pandas: powerful Python data analysis toolkit

Release 1.1.1

Wes McKinney and the Pandas Development Team

Aug 20, 2020
## CONTENTS

### 1 Getting started
- **1.1 Installation** ................................................................. 3
- **1.2 Intro to pandas** .......................................................... 3
- **1.3 Coming from** .............................................................. 5
- **1.4 Tutorials** ................................................................. 5
  - **1.4.1 Installation** ........................................................... 5
  - **1.4.2 Package overview** .................................................. 10
  - **1.4.3 Getting started tutorials** ........................................... 13
  - **1.4.4 Comparison with other tools** .................................... 58
  - **1.4.5 Community tutorials** ............................................ 110

### 2 User Guide
- **2.1 10 minutes to pandas** .................................................. 113
  - **2.1.1 Object creation** ..................................................... 113
  - **2.1.2 Viewing data** ....................................................... 115
  - **2.1.3 Selection** ............................................................ 117
  - **2.1.4 Missing data** ....................................................... 122
  - **2.1.5 Operations** .......................................................... 122
  - **2.1.6 Merge** ............................................................... 125
  - **2.1.7 Grouping** ............................................................ 127
  - **2.1.8 Reshaping** .......................................................... 128
  - **2.1.9 Time series** .......................................................... 130
  - **2.1.10 Categoricals** ....................................................... 132
  - **2.1.11 Plotting** ............................................................. 133
  - **2.1.12 Getting data in/out** .............................................. 135
  - **2.1.13 Gotchas** ............................................................. 137
- **2.2 Intro to data structures** ................................................ 137
  - **2.2.1 Series** ............................................................... 137
  - **2.2.2 DataFrame** .......................................................... 143
- **2.3 Essential basic functionality** ........................................... 160
  - **2.3.1 Head and tail** ....................................................... 160
  - **2.3.2 Attributes and underlying data** ................................ 161
  - **2.3.3 Accelerated operations** .......................................... 163
  - **2.3.4 Flexible binary operations** ...................................... 163
  - **2.3.5 Descriptive statistics** ............................................ 172
  - **2.3.6 Function application** ............................................. 180
  - **2.3.7 Reindexing and altering labels** .................................. 193
  - **2.3.8 Iteration** ............................................................. 202
  - **2.3.9 .dt accessor** ........................................................ 205
  - **2.3.10 Vectorized string methods** ..................................... 209

---

i
2.3.11 Sorting ............................................................... 209
2.3.12 Copying ............................................................. 216
2.3.13 dtypes .............................................................. 216
2.3.14 Selecting columns based on *dtype* ................................ 227

2.4 IO tools (text, CSV, HDF5, ...) ........................................... 230
2.4.1 CSV & text files .................................................. 230
2.4.2 JSON ............................................................... 266
2.4.3 HTML ............................................................... 280
2.4.4 Excel files ........................................................ 289
2.4.5 OpenDocument Spreadsheets ....................................... 295
2.4.6 Binary Excel (.xlsx) files ......................................... 295
2.4.7 Clipboard .......................................................... 296
2.4.8 Pickling ............................................................. 297
2.4.9 msgpack ............................................................ 300
2.4.10 HDF5 (PyTables) ................................................ 300
2.4.11 Feather ............................................................ 327
2.4.12 Parquet ............................................................. 328
2.4.13 ORC ................................................................. 331
2.4.14 SQL queries ....................................................... 331
2.4.15 Google BigQuery ................................................ 339
2.4.16 Stata format ....................................................... 339
2.4.17 SAS formats ........................................................ 342
2.4.18 SPSS formats ...................................................... 342
2.4.19 Other file formats ............................................... 343
2.4.20 Performance considerations ...................................... 343

2.5 Indexing and selecting data .............................................. 346
2.5.1 Different choices for indexing .................................... 347
2.5.2 Basics .............................................................. 347
2.5.3 Attribute access .................................................. 350
2.5.4 Slicing ranges ..................................................... 352
2.5.5 Selection by label ................................................ 353
2.5.6 Selection by position .............................................. 357
2.5.7 Selection by callable ............................................. 360
2.5.8 IX indexer is deprecated ......................................... 362
2.5.9 Indexing with list with missing labels is deprecated .......... 363
2.5.10 Selecting random samples ....................................... 365
2.5.11 Setting with enlargement ....................................... 367
2.5.12 Fast scalar value getting and setting ......................... 368
2.5.13 Boolean indexing ............................................... 369
2.5.14 Indexing with isin ............................................... 371
2.5.15 The *where()* Method and Masking ............................ 373
2.5.16 The *query()* Method ........................................ 377
2.5.17 Duplicate data ................................................... 387
2.5.18 Dictionary-like *get()* method ................................ 390
2.5.19 The *lookup()* method ....................................... 390
2.5.20 Index objects ..................................................... 390
2.5.21 Set / reset index ................................................ 394
2.5.22 Returning a view versus a copy ................................ 396

2.6 MultiIndex / advanced indexing ....................................... 400
2.6.1 Hierarchical indexing (MultiIndex) ............................ 400
2.6.2 Advanced indexing with hierarchical index .................... 406
2.6.3 Sorting a MultiIndex ............................................. 417
2.6.4 Take methods ..................................................... 420
2.6.5 Index types ........................................................ 422
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.6.6</td>
<td>Miscellaneous indexing FAQ</td>
<td>431</td>
</tr>
<tr>
<td>2.7</td>
<td>Merge, join, concatenate and compare</td>
<td>436</td>
</tr>
<tr>
<td>2.7.1</td>
<td>Concatenating objects</td>
<td>436</td>
</tr>
<tr>
<td>2.7.2</td>
<td>Database-style DataFrame or named Series joining/merging</td>
<td>448</td>
</tr>
<tr>
<td>2.7.3</td>
<td>Timeseries friendly merging</td>
<td>467</td>
</tr>
<tr>
<td>2.7.4</td>
<td>Comparing objects</td>
<td>469</td>
</tr>
<tr>
<td>2.8</td>
<td>Reshaping and pivot tables</td>
<td>471</td>
</tr>
<tr>
<td>2.8.1</td>
<td>Reshaping by pivoting DataFrame objects</td>
<td>471</td>
</tr>
<tr>
<td>2.8.2</td>
<td>Reshaping by stacking and unstacking</td>
<td>473</td>
</tr>
<tr>
<td>2.8.3</td>
<td>Reshaping by melt</td>
<td>481</td>
</tr>
<tr>
<td>2.8.4</td>
<td>Combining with stats and GroupBy</td>
<td>483</td>
</tr>
<tr>
<td>2.8.5</td>
<td>Pivot tables</td>
<td>484</td>
</tr>
<tr>
<td>2.8.6</td>
<td>Cross tabulations</td>
<td>487</td>
</tr>
<tr>
<td>2.8.7</td>
<td>Tiling</td>
<td>490</td>
</tr>
<tr>
<td>2.8.8</td>
<td>Computing indicator / dummy variables</td>
<td>490</td>
</tr>
<tr>
<td>2.8.9</td>
<td>Factorizing values</td>
<td>494</td>
</tr>
<tr>
<td>2.8.10</td>
<td>Examples</td>
<td>494</td>
</tr>
<tr>
<td>2.8.11</td>
<td>Exploding a list-like column</td>
<td>497</td>
</tr>
<tr>
<td>2.9</td>
<td>Working with text data</td>
<td>499</td>
</tr>
<tr>
<td>2.9.1</td>
<td>Text data types</td>
<td>499</td>
</tr>
<tr>
<td>2.9.2</td>
<td>String methods</td>
<td>502</td>
</tr>
<tr>
<td>2.9.3</td>
<td>Splitting and replacing strings</td>
<td>504</td>
</tr>
<tr>
<td>2.9.4</td>
<td>Concatenation</td>
<td>508</td>
</tr>
<tr>
<td>2.9.5</td>
<td>Indexing with .str</td>
<td>513</td>
</tr>
<tr>
<td>2.9.6</td>
<td>Extracting substrings</td>
<td>514</td>
</tr>
<tr>
<td>2.9.7</td>
<td>Testing for strings that match or contain a pattern</td>
<td>518</td>
</tr>
<tr>
<td>2.9.8</td>
<td>Creating indicator variables</td>
<td>519</td>
</tr>
<tr>
<td>2.9.9</td>
<td>Method summary</td>
<td>520</td>
</tr>
<tr>
<td>2.10</td>
<td>Working with missing data</td>
<td>521</td>
</tr>
<tr>
<td>2.10.1</td>
<td>Values considered “missing”</td>
<td>521</td>
</tr>
<tr>
<td>2.10.2</td>
<td>Inserting missing data</td>
<td>524</td>
</tr>
<tr>
<td>2.10.3</td>
<td>Calculations with missing data</td>
<td>525</td>
</tr>
<tr>
<td>2.10.4</td>
<td>Sum/prod of empties/nans</td>
<td>526</td>
</tr>
<tr>
<td>2.10.5</td>
<td>NA values in GroupBy</td>
<td>527</td>
</tr>
<tr>
<td>2.10.6</td>
<td>Filling missing values: fillna</td>
<td>527</td>
</tr>
<tr>
<td>2.10.7</td>
<td>Filling with a PandasObject</td>
<td>529</td>
</tr>
<tr>
<td>2.10.8</td>
<td>Dropping axis labels with missing data: dropna</td>
<td>530</td>
</tr>
<tr>
<td>2.10.9</td>
<td>Interpolation</td>
<td>531</td>
</tr>
<tr>
<td>2.10.10</td>
<td>Replacing generic values</td>
<td>540</td>
</tr>
<tr>
<td>2.10.11</td>
<td>String/regular expression replacement</td>
<td>541</td>
</tr>
<tr>
<td>2.10.12</td>
<td>Numeric replacement</td>
<td>543</td>
</tr>
<tr>
<td>2.10.13</td>
<td>Experimental NA scalar to denote missing values</td>
<td>547</td>
</tr>
<tr>
<td>2.11</td>
<td>Categorical data</td>
<td>551</td>
</tr>
<tr>
<td>2.11.1</td>
<td>Object creation</td>
<td>551</td>
</tr>
<tr>
<td>2.11.2</td>
<td>CategoricalDtype</td>
<td>556</td>
</tr>
<tr>
<td>2.11.3</td>
<td>Description</td>
<td>557</td>
</tr>
<tr>
<td>2.11.4</td>
<td>Working with categories</td>
<td>558</td>
</tr>
<tr>
<td>2.11.5</td>
<td>Sorting and order</td>
<td>562</td>
</tr>
<tr>
<td>2.11.6</td>
<td>Comparisons</td>
<td>565</td>
</tr>
<tr>
<td>2.11.7</td>
<td>Operations</td>
<td>567</td>
</tr>
<tr>
<td>2.11.8</td>
<td>Data munging</td>
<td>568</td>
</tr>
<tr>
<td>2.11.9</td>
<td>Getting data in/out</td>
<td>576</td>
</tr>
<tr>
<td>2.11.10</td>
<td>Missing data</td>
<td>577</td>
</tr>
<tr>
<td>2.11.11</td>
<td>Differences to R’s factor</td>
<td>578</td>
</tr>
</tbody>
</table>
3.8 Date offsets ............................................................... 2038
3.8.1 DateOffset ........................................................ 2038
3.8.2 BusinessDay ...................................................... 2043
3.8.3 BusinessHour ..................................................... 2048
3.8.4 CustomBusinessDay ........................................... 2052
3.8.5 CustomBusinessHour .......................................... 2057
3.8.6 MonthEnd ........................................................ 2061
3.8.7 MonthBegin ...................................................... 2065
3.8.8 BusinessMonthEnd ............................................. 2069
3.8.9 BusinessMonthBegin ........................................... 2073
3.8.10 CustomBusinessMonthEnd .................................... 2077
3.8.11 CustomBusinessMonthBegin .................................. 2082
3.8.12 SemiMonthEnd .................................................. 2087
3.8.13 SemiMonthBegin ............................................... 2090
3.8.14 Week ............................................................ 2094
3.8.15 WeekOfMonth .................................................... 2098
3.8.16 LastWeekOfMonth .............................................. 2102
3.8.17 BQuarterEnd .................................................... 2107
3.8.18 BQuarterBegin .................................................. 2110
3.8.19 QuarterEnd ...................................................... 2114
3.8.20 QuarterBegin .................................................... 2118
3.8.21 BYearEnd ........................................................ 2122

3.7 Index objects ......................................................... 1886
3.7.1 Index ............................................................ 1886
3.7.2 Numeric Index .................................................... 1950
3.7.3 CategoricalIndex ............................................... 1954
3.7.4 IntervalIndex .................................................... 1963
3.7.5 MultiIndex ....................................................... 1975
3.7.6 DatetimeIndex ................................................... 1992
3.7.7 TimedeltaIndex .................................................. 2022
3.7.8 PeriodIndex ...................................................... 2031
3.7.9 Sparse data ....................................................... 1880
3.7.10 Text data ......................................................... 1882
3.7.11 Boolean data with missing values ............................ 1884

3.6 Panel ................................................................. 1886

3.5 pandas arrays ....................................................... 1808
3.5.1 pandas.array ..................................................... 1808
3.5.2 Datetime data .................................................... 1811
3.5.3 Timedelta data .................................................... 1831
3.5.4 Timespan data .................................................... 1840
3.5.5 Period ............................................................ 1840
3.5.6 Interval data ..................................................... 1855
3.5.7 Nullable integer .................................................. 1869
3.5.8 Categorical data ................................................. 1874
3.5.9 Sparse data ....................................................... 1880
3.5.10 Text data ........................................................ 1882
3.5.11 Boolean data with missing values ............................ 1884
3.5.12 DateOffset ....................................................... 2038
3.5.13 Index objects .................................................... 1886
3.5.14 Computations / descriptive stats ............................. 1747
3.5.15 Sparse accessor .................................................. 1803
3.5.16 Serialization / IO / conversion ................................ 1807
3.5.17 Time Series-related ............................................ 1750
3.5.18 Combining / comparing / joining / merging ................. 1750
3.5.19 Reshaping, sorting, transposing .............................. 1749
3.5.20 Reindexing / selection / label manipulation ................. 1748
3.5.21 Pandas array ..................................................... 1808
3.4.16 Serialization / IO / conversion ................................ 1807
3.4.15 Sparse accessor .................................................. 1803
3.4.14 Plotting .......................................................... 1751
3.4.13 Metadata ......................................................... 1751
3.4.12 Time Series-related ............................................ 1750
3.4.11 Combining / comparing / joining / merging ................. 1750
3.4.10 Reshaping, sorting, transposing .............................. 1749
3.4.9 Missing data handling ........................................... 1749
3.4.8 Reindexing / selection / label manipulation ................. 1748
3.4.7 Computations / descriptive stats ............................... 1747

vii
3.8.22 BYearBegin ........................................... 2126
3.8.23 YearEnd ............................................ 2130
3.8.24 YearBegin ........................................... 2134
3.8.25 FY5253 .................................................. 2138
3.8.26 FY5253Quarter ....................................... 2143
3.8.27 Easter .................................................. 2149
3.8.28 Tick ..................................................... 2152
3.8.29 Day ..................................................... 2156
3.8.30 Hour ..................................................... 2160
3.8.31 Minute ................................................... 2164
3.8.32 Second ................................................... 2168
3.8.33 Milli ..................................................... 2172
3.8.34 Micro .................................................... 2176
3.8.35 Nano ..................................................... 2180
3.9 Frequencies ................................................. 2184
  3.9.1 pandas.tseries.frequencies.to_offset ................. 2184
3.10 Window .................................................... 2185
  3.10.1 Standard moving window functions .................. 2185
  3.10.2 Standard expanding window functions ............... 2203
  3.10.3 Exponentially-weighted moving window functions ... 2216
  3.10.4 Window indexer ........................................... 2218
3.11 GroupBy .................................................. 2221
  3.11.1 Indexing, iteration .................................... 2221
  3.11.2 Function application .................................. 2226
  3.11.3 Computations / descriptive stats .................... 2236
3.12 Resampling ............................................... 2286
  3.12.1 Indexing, iteration .................................... 2286
  3.12.2 Function application .................................. 2289
  3.12.3 Upsampling ............................................. 2294
  3.12.4 Computations / descriptive stats .................... 2305
3.13 Style .................................................... 2311
  3.13.1 Styler constructor ................................... 2311
  3.13.2 Styler properties ..................................... 2326
  3.13.3 Style application ..................................... 2326
  3.13.4 Built-in styles ....................................... 2326
  3.13.5 Style export and import ................................ 2327
3.14 Plotting .................................................. 2327
  3.14.1 pandas.plotting.andrews_curves ...................... 2327
  3.14.2 pandas.plotting.autocorrelation_plot ................ 2329
  3.14.3 pandas.plotting.bootstrap_plot ....................... 2330
  3.14.4 pandas.plotting.boxplot ............................... 2330
  3.14.5 pandas.plotting.deregister_matplotlib_converters .... 2338
  3.14.6 pandas.plotting.lag_plot .............................. 2338
  3.14.7 pandas.plotting.parallel_coordinates ............... 2338
  3.14.8 pandas.plotting.plot_params ......................... 2341
  3.14.9 pandas.plotting.radviz ............................... 2341
  3.14.10 pandas.plotting.register_matplotlib_converters ..... 2343
  3.14.11 pandas.plotting.scatter_matrix ..................... 2345
  3.14.12 pandas.plotting.table ................................ 2345
3.15 General utility functions ................................ 2347
  3.15.1 Working with options ................................ 2347
  3.15.2 Testing functions ................................... 2361
  3.15.3 Exceptions and warnings ............................ 2365
  3.15.4 Data types related functionality ..................... 2369
### Development

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.15.5 Bug report function</td>
<td>2395</td>
</tr>
<tr>
<td>3.16 Extensions</td>
<td>2396</td>
</tr>
<tr>
<td>3.16.1 pandas.api.extensions.register_extension_dtype</td>
<td>2396</td>
</tr>
<tr>
<td>3.16.2 pandas.api.extensions.register_dataframe_accessor</td>
<td>2396</td>
</tr>
<tr>
<td>3.16.3 pandas.api.extensions.register_series_accessor</td>
<td>2398</td>
</tr>
<tr>
<td>3.16.4 pandas.api.extensions.register_index_accessor</td>
<td>2399</td>
</tr>
<tr>
<td>3.16.5 pandas.api.extensions.ExtensionDtype</td>
<td>2400</td>
</tr>
<tr>
<td>3.16.6 pandas.api.extensions.ExtensionArray</td>
<td>2403</td>
</tr>
<tr>
<td>3.16.7 pandas.arrays.PandasArray</td>
<td>2415</td>
</tr>
<tr>
<td>3.16.8 pandas.api.indexers.check_array_indexer</td>
<td>2416</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>4 Development</td>
<td>2419</td>
</tr>
<tr>
<td>4.1 Contributing to pandas</td>
<td>2419</td>
</tr>
<tr>
<td>4.1.1 Where to start?</td>
<td>2420</td>
</tr>
<tr>
<td>4.1.2 Bug reports and enhancement requests</td>
<td>2421</td>
</tr>
<tr>
<td>4.1.3 Working with the code</td>
<td>2421</td>
</tr>
<tr>
<td>4.1.4 Contributing to the documentation</td>
<td>2426</td>
</tr>
<tr>
<td>4.1.5 Contributing to the code base</td>
<td>2444</td>
</tr>
<tr>
<td>4.1.6 Contributing your changes to pandas</td>
<td>2457</td>
</tr>
<tr>
<td>4.1.7 Tips for a successful pull request</td>
<td>2460</td>
</tr>
<tr>
<td>4.2 pandas code style guide</td>
<td>2460</td>
</tr>
<tr>
<td>4.2.1 Patterns</td>
<td>2461</td>
</tr>
<tr>
<td>4.2.2 String formatting</td>
<td>2461</td>
</tr>
<tr>
<td>4.2.3 Imports (aim for absolute)</td>
<td>2463</td>
</tr>
<tr>
<td>4.2.4 Miscellaneous</td>
<td>2463</td>
</tr>
<tr>
<td>4.3 pandas maintenance</td>
<td>2463</td>
</tr>
<tr>
<td>4.3.1 Roles</td>
<td>2463</td>
</tr>
<tr>
<td>4.3.2 Tasks</td>
<td>2464</td>
</tr>
<tr>
<td>4.3.3 Issue triage</td>
<td>2464</td>
</tr>
<tr>
<td>4.3.4 Closing issues</td>
<td>2465</td>
</tr>
<tr>
<td>4.3.5 Reviewing pull requests</td>
<td>2465</td>
</tr>
<tr>
<td>4.3.6 Cleaning up old issues</td>
<td>2465</td>
</tr>
<tr>
<td>4.3.7 Cleaning up old pull requests</td>
<td>2466</td>
</tr>
<tr>
<td>4.3.8 Becoming a pandas maintainer</td>
<td>2466</td>
</tr>
<tr>
<td>4.4 Internals</td>
<td>2466</td>
</tr>
<tr>
<td>4.4.1 Indexing</td>
<td>2466</td>
</tr>
<tr>
<td>4.4.2 Subclassing pandas data structures</td>
<td>2468</td>
</tr>
<tr>
<td>4.5 Extending pandas</td>
<td>2468</td>
</tr>
<tr>
<td>4.5.1 Registering custom accessors</td>
<td>2468</td>
</tr>
<tr>
<td>4.5.2 Extension types</td>
<td>2469</td>
</tr>
<tr>
<td>4.5.3 Subclassing pandas data structures</td>
<td>2472</td>
</tr>
<tr>
<td>4.5.4 Plotting backends</td>
<td>2475</td>
</tr>
<tr>
<td>4.6 Developer</td>
<td>2476</td>
</tr>
<tr>
<td>4.6.1 Storing pandas DataFrame objects in Apache Parquet format</td>
<td>2476</td>
</tr>
<tr>
<td>4.7 Policies</td>
<td>2478</td>
</tr>
<tr>
<td>4.7.1 Version policy</td>
<td>2478</td>
</tr>
<tr>
<td>4.7.2 Python support</td>
<td>2479</td>
</tr>
<tr>
<td>4.8 Roadmap</td>
<td>2479</td>
</tr>
<tr>
<td>4.8.1 Extensibility</td>
<td>2479</td>
</tr>
<tr>
<td>4.8.2 String data type</td>
<td>2480</td>
</tr>
<tr>
<td>4.8.3 Apache Arrow interoperability</td>
<td>2480</td>
</tr>
<tr>
<td>4.8.4 Block manager rewrite</td>
<td>2480</td>
</tr>
<tr>
<td>4.8.5 Decoupling of indexing and internals</td>
<td>2481</td>
</tr>
<tr>
<td>4.8.6 Numba-accelerated operations</td>
<td>2481</td>
</tr>
</tbody>
</table>
5 Release notes

5.1 Version 1.1
  5.1.1 What’s new in 1.1.1 (August 20, 2020)
  5.1.2 What’s new in 1.1.0 (July 28, 2020)

5.2 Version 1.0
  5.2.1 What’s new in 1.0.5 (June 17, 2020)
  5.2.2 What’s new in 1.0.4 (May 28, 2020)
  5.2.3 What’s new in 1.0.3 (March 17, 2020)
  5.2.4 What’s new in 1.0.2 (March 12, 2020)
  5.2.5 What’s new in 1.0.1 (February 5, 2020)
  5.2.6 What’s new in 1.0.0 (January 29, 2020)

5.3 Version 0.25
  5.3.1 What’s new in 0.25.3 (October 31, 2019)
  5.3.2 What’s new in 0.25.2 (October 15, 2019)
  5.3.3 What’s new in 0.25.1 (August 21, 2019)
  5.3.4 What’s new in 0.25.0 (July 18, 2019)

5.4 Version 0.24
  5.4.1 What’s new in 0.24.2 (March 12, 2019)
  5.4.2 What’s new in 0.24.1 (February 3, 2019)
  5.4.3 What’s new in 0.24.0 (January 25, 2019)

5.5 Version 0.23
  5.5.1 What’s new in 0.23.4 (August 3, 2018)
  5.5.2 What’s new in 0.23.3 (July 7, 2018)
  5.5.3 What’s new in 0.23.2 (July 5, 2018)
  5.5.4 What’s new in 0.23.1 (June 12, 2018)
  5.5.5 What’s new in 0.23.0 (May 15, 2018)

5.6 Version 0.22
  5.6.1 v0.22.0 (December 29, 2017)

5.7 Version 0.21
  5.7.1 Version 0.21.1 (December 12, 2017)
  5.7.2 Version 0.21.0 (October 27, 2017)

5.8 Version 0.20
  5.8.1 Version 0.20.3 (July 7, 2017)
  5.8.2 Version 0.20.2 (June 4, 2017)
  5.8.3 Version 0.20.1 (May 5, 2017)

5.9 Version 0.19
  5.9.1 Version 0.19.2 (December 24, 2016)
  5.9.2 Version 0.19.1 (November 3, 2016)
  5.9.3 Version 0.19.0 (October 2, 2016)

5.10 Version 0.18
  5.10.1 Version 0.18.1 (May 3, 2016)
  5.10.2 Version 0.18.0 (March 13, 2016)

5.11 Version 0.17
  5.11.1 Version 0.17.1 (November 21, 2015)
  5.11.2 Version 0.17.0 (October 9, 2015)

5.12 Version 0.16
  5.12.1 Version 0.16.2 (June 12, 2015)
**pandas** is an open source, BSD-licensed library providing high-performance, easy-to-use data structures and data analysis tools for the Python programming language.

*To the getting started guides*

*To the user guide*

*To the reference guide*

*To the development guide*
CHAPTER
ONE

GETTING STARTED

1.1 Installation

pandas is part of the Anaconda distribution and can be installed with Anaconda or Miniconda:

```
conda install pandas
```

pandas can be installed via pip from PyPI.

```
pip install pandas
```

Learn more

1.2 Intro to pandas

*Straight to tutorial…*

When working with tabular data, such as data stored in spreadsheets or databases, pandas is the right tool for you. pandas will help you to explore, clean and process your data. In pandas, a data table is called a DataFrame.

*To introduction tutorial*

*To user guide*

*Straight to tutorial…*

pandas supports the integration with many file formats or data sources out of the box (csv, excel, sql, json, parquet,…). Importing data from each of these data sources is provided by function with the prefix `read_*`. Similarly, the `to_*` methods are used to store data.

*To introduction tutorial*

*To user guide*

*Straight to tutorial…*

Selecting or filtering specific rows and/or columns? Filtering the data on a condition? Methods for slicing, selecting, and extracting the data you need are available in pandas.

*To introduction tutorial*
pandas provides plotting your data out of the box, using the power of Matplotlib. You can pick the plot type (scatter, bar, boxplot, . . . ) corresponding to your data.

There is no need to loop over all rows of your data table to do calculations. Data manipulations on a column work elementwise. Adding a column to a DataFrame based on existing data in other columns is straightforward.

Basic statistics (mean, median, min, max, counts . . . ) are easily calculable. These or custom aggregations can be applied on the entire data set, a sliding window of the data or grouped by categories. The latter is also known as the split-apply-combine approach.

Change the structure of your data table in multiple ways. You can melt() your data table from wide to long/tidy form or pivot() from long to wide format. With aggregations built-in, a pivot table is created with a single command.

Multiple tables can be concatenated both column wise as row wise and database-like join/merge operations are provided to combine multiple tables of data.

pandas has great support for time series and has an extensive set of tools for working with dates, times, and time-indexed data.
Data sets do not only contain numerical data. pandas provides a wide range of functions to cleaning textual data and extract useful information from it.

To introduction tutorial
To user guide

1.3 Coming from...

Are you familiar with other software for manipulating tabular data? Learn the pandas-equivalent operations compared to software you already know:

Learn more
Learn more
Learn more
Learn more

1.4 Tutorials

For a quick overview of pandas functionality, see 10 Minutes to pandas.

You can also reference the pandas cheat sheet for a succinct guide for manipulating data with pandas.

The community produces a wide variety of tutorials available online. Some of the material is enlisted in the community contributed Community tutorials.

1.4.1 Installation

The easiest way to install pandas is to install it as part of the Anaconda distribution, a cross platform distribution for data analysis and scientific computing. This is the recommended installation method for most users.

Instructions for installing from source, PyPI, ActivePython, various Linux distributions, or a development version are also provided.

Python version support

Officially Python 3.6.1 and above, 3.7, and 3.8.

Installing pandas

Installing with Anaconda

Installing pandas and the rest of the NumPy and SciPy stack can be a little difficult for inexperienced users.

The simplest way to install not only pandas, but Python and the most popular packages that make up the SciPy stack (IPython, NumPy, Matplotlib, ...) is with Anaconda, a cross-platform (Linux, Mac OS X, Windows) Python distribution for data analytics and scientific computing.

After running the installer, the user will have access to pandas and the rest of the SciPy stack without needing to install anything else, and without needing to wait for any software to be compiled.

1.3. Coming from...
Installation instructions for Anaconda can be found here.
A full list of the packages available as part of the Anaconda distribution can be found here.
Another advantage to installing Anaconda is that you don’t need admin rights to install it. Anaconda can install in the user’s home directory, which makes it trivial to delete Anaconda if you decide (just delete that folder).

Installing with Miniconda

The previous section outlined how to get pandas installed as part of the Anaconda distribution. However this approach means you will install well over one hundred packages and involves downloading the installer which is a few hundred megabytes in size.

If you want to have more control on which packages, or have a limited internet bandwidth, then installing pandas with Miniconda may be a better solution.

Conda is the package manager that the Anaconda distribution is built upon. It is a package manager that is both cross-platform and language agnostic (it can play a similar role to a pip and virtualenv combination).

Miniconda allows you to create a minimal self contained Python installation, and then use the Conda command to install additional packages.

First you will need Conda to be installed and downloading and running the Miniconda will do this for you. The installer can be found here.

The next step is to create a new conda environment. A conda environment is like a virtualenv that allows you to specify a specific version of Python and set of libraries. Run the following commands from a terminal window:

```
conda create -n name_of_my_env python
```

This will create a minimal environment with only Python installed in it. To put your self inside this environment run:

```
source activate name_of_my_env
```

On Windows the command is:

```
activate name_of_my_env
```

The final step required is to install pandas. This can be done with the following command:

```
conda install pandas
```

To install a specific pandas version:

```
conda install pandas=0.20.3
```

To install other packages, IPython for example:

```
conda install ipython
```

To install the full Anaconda distribution:

```
conda install anaconda
```

If you need packages that are available to pip but not conda, then install pip, and then use pip to install those packages:

```
conda install pip
django
```
Installing from PyPI

pandas can be installed via pip from PyPI.

```
pip install pandas
```

Installing with ActivePython

Installation instructions for ActivePython can be found here. Versions 2.7, 3.5 and 3.6 include pandas.

Installing using your Linux distribution’s package manager.

The commands in this table will install pandas for Python 3 from your distribution.

<table>
<thead>
<tr>
<th>Distribution</th>
<th>Status</th>
<th>Download / Repository Link</th>
<th>Install method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Debian</td>
<td>stable</td>
<td>official Debian repository</td>
<td>sudo apt-get install python3-pandas</td>
</tr>
<tr>
<td>Debian &amp; Ubuntu</td>
<td>unstable</td>
<td>NeuroDebian</td>
<td>sudo apt-get install python3-pandas</td>
</tr>
<tr>
<td>Ubuntu</td>
<td>stable</td>
<td>official Ubuntu repository</td>
<td>sudo apt-get install python3-pandas</td>
</tr>
<tr>
<td>OpenSuse</td>
<td>stable</td>
<td>OpenSuse Repository</td>
<td>zypper in python3-pandas</td>
</tr>
<tr>
<td>Fedora</td>
<td>stable</td>
<td>official Fedora repository</td>
<td>dnf install python3-pandas</td>
</tr>
<tr>
<td>Centos/RHEL</td>
<td>stable</td>
<td>EPEL repository</td>
<td>yum install python3-pandas</td>
</tr>
</tbody>
</table>

However, the packages in the linux package managers are often a few versions behind, so to get the newest version of pandas, it’s recommended to install using the pip or conda methods described above.

Handling ImportErrors

If you encounter an ImportError, it usually means that Python couldn’t find pandas in the list of available libraries. Python internally has a list of directories it searches through, to find packages. You can obtain these directories with:

```
import sys
sys.path
```

One way you could be encountering this error is if you have multiple Python installations on your system and you don’t have pandas installed in the Python installation you’re currently using. In Linux/Mac you can run `which python` on your terminal and it will tell you which Python installation you’re using. If it’s something like “/usr/bin/python”, you’re using the Python from the system, which is not recommended.

It is highly recommended to use conda, for quick installation and for package and dependency updates. You can find simple installation instructions for pandas in this document: [installation instructions](https://pandas.pydata.org/pandas-docs/stable/getting_started.html).
Installing from source

See the contributing guide for complete instructions on building from the git source tree. Further, see creating a development environment if you wish to create a pandas development environment.

Running the test suite

pandas is equipped with an exhaustive set of unit tests, covering about 97% of the code base as of this writing. To run it on your machine to verify that everything is working (and that you have all of the dependencies, soft and hard, installed), make sure you have pytest >= 5.0.1 and Hypothesis >= 3.58, then run:

```
>>> pd.test()
running: pytest --skip-slow --skip-network C:\Users\TP\Anaconda3\envs\py36\lib\site-packages\pandas
================================= test session starts =================================
platform win32 -- Python 3.6.2, pytest-3.6.0, py-1.4.34, pluggy-0.4.0
rootdir: C:\Users\TP\Documents\Python\pandas\pandasdev\pandas, inifile: setup.cfg
collected 12145 items / 3 skipped

.....................................................................S...........................
........................................................................

================================== 12130 passed, 12 skipped in 368.339 seconds =================
```

Dependencies

<table>
<thead>
<tr>
<th>Package</th>
<th>Minimum supported version</th>
</tr>
</thead>
<tbody>
<tr>
<td>setuptools</td>
<td>24.2.0</td>
</tr>
<tr>
<td>NumPy</td>
<td>1.15.4</td>
</tr>
<tr>
<td>python-dateutil</td>
<td>2.7.3</td>
</tr>
<tr>
<td>pytz</td>
<td>2017.2</td>
</tr>
</tbody>
</table>

Recommended dependencies

- **numexpr**: for accelerating certain numerical operations. numexpr uses multiple cores as well as smart chunking and caching to achieve large speedups. If installed, must be Version 2.6.2 or higher.

- **bottleneck**: for accelerating certain types of nan evaluations. bottleneck uses specialized cython routines to achieve large speedups. If installed, must be Version 1.2.1 or higher.

**Note**: You are highly encouraged to install these libraries, as they provide speed improvements, especially when working with large data sets.
Optional dependencies

Pandas has many optional dependencies that are only used for specific methods. For example, `pandas.read_hdf()` requires the `pytables` package, while `DataFrame.to_markdown()` requires the `tabulate` package. If the optional dependency is not installed, pandas will raise an `ImportError` when the method requiring that dependency is called.

<table>
<thead>
<tr>
<th>Dependency</th>
<th>Minimum Version</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>BeautifulSoup4</td>
<td>4.6.0</td>
<td>HTML parser for <code>read_html</code> (see note)</td>
</tr>
<tr>
<td>Jinja2</td>
<td></td>
<td>Conditional formatting with <code>DataFrame.style</code></td>
</tr>
<tr>
<td>PyQt5</td>
<td></td>
<td>Clipboard I/O</td>
</tr>
<tr>
<td>PyTables</td>
<td>3.4.3</td>
<td>HDF5-based reading / writing</td>
</tr>
<tr>
<td>SQLAlchemy</td>
<td>1.1.4</td>
<td>SQL support for databases other than sqlite</td>
</tr>
<tr>
<td>SciPy</td>
<td>0.19.0</td>
<td>Miscellaneous statistical functions</td>
</tr>
<tr>
<td>XLsxWriter</td>
<td>0.9.8</td>
<td>Excel writing</td>
</tr>
<tr>
<td>blosc</td>
<td></td>
<td>Compression for HDF5</td>
</tr>
<tr>
<td>fsspec</td>
<td>0.7.4</td>
<td>Handling files aside from local and HTTP</td>
</tr>
<tr>
<td>fastparquet</td>
<td>0.3.2</td>
<td>Parquet reading / writing</td>
</tr>
<tr>
<td>gcsfs</td>
<td>0.6.0</td>
<td>Google Cloud Storage access</td>
</tr>
<tr>
<td>html5lib</td>
<td></td>
<td>HTML parser for <code>read_html</code> (see note)</td>
</tr>
<tr>
<td>lxml</td>
<td>3.8.0</td>
<td>HTML parser for <code>read_html</code> (see note)</td>
</tr>
<tr>
<td>matplotlib</td>
<td>2.2.2</td>
<td>Visualization</td>
</tr>
<tr>
<td>numba</td>
<td>0.46.0</td>
<td>Alternative execution engine for rolling operations</td>
</tr>
<tr>
<td>openpyxl</td>
<td>2.5.7</td>
<td>Reading / writing for xlsx files</td>
</tr>
<tr>
<td>pandas-gbq</td>
<td>0.12.0</td>
<td>Google Big Query access</td>
</tr>
<tr>
<td>psycopg2</td>
<td>0.12.0</td>
<td>PostgreSQL engine for <code>sqlalchemy</code></td>
</tr>
<tr>
<td>pyarrow</td>
<td>0.12.0</td>
<td>Parquet, ORC (requires 0.13.0), and feather reading / writing</td>
</tr>
<tr>
<td>pymysql</td>
<td>0.7.11</td>
<td>MySQL engine for <code>sqlalchemy</code></td>
</tr>
<tr>
<td>pyreadstat</td>
<td></td>
<td>SPSS files (.sav) reading</td>
</tr>
<tr>
<td>pytables</td>
<td>3.4.3</td>
<td>HDF5 reading / writing</td>
</tr>
<tr>
<td>pyxlsb</td>
<td>1.0.6</td>
<td>Reading for xlsx files</td>
</tr>
<tr>
<td>qtpy</td>
<td></td>
<td>Clipboard I/O</td>
</tr>
<tr>
<td>s3fs</td>
<td>0.4.0</td>
<td>Amazon S3 access</td>
</tr>
<tr>
<td>tabulate</td>
<td>0.8.3</td>
<td>Printing in Markdown-friendly format (see <code>tabulate</code>)</td>
</tr>
<tr>
<td>xarray</td>
<td>0.8.2</td>
<td>pandas-like API for N-dimensional data</td>
</tr>
<tr>
<td>xclip</td>
<td></td>
<td>Clipboard I/O on linux</td>
</tr>
<tr>
<td>xlrd</td>
<td>1.1.0</td>
<td>Excel reading</td>
</tr>
<tr>
<td>xltw</td>
<td>1.2.0</td>
<td>Excel writing</td>
</tr>
<tr>
<td>xsel</td>
<td></td>
<td>Clipboard I/O on linux</td>
</tr>
<tr>
<td>zlib</td>
<td></td>
<td>Compression for HDF5</td>
</tr>
</tbody>
</table>
Optional dependencies for parsing HTML

One of the following combinations of libraries is needed to use the top-level `read_html()` function:

Changed in version 0.23.0.

- BeautifulSoup4 and html5lib
- BeautifulSoup4 and lxml
- BeautifulSoup4 and html5lib and lxml
- Only lxml, although see HTML Table Parsing for reasons as to why you should probably not take this approach.

**Warning:**
- if you install BeautifulSoup4 you must install either lxml or html5lib or both. `read_html()` will not work with only BeautifulSoup4 installed.
- You are highly encouraged to read HTML Table Parsing gotchas. It explains issues surrounding the installation and usage of the above three libraries.

1.4.2 Package overview

**pandas** is a Python package providing fast, flexible, and expressive data structures designed to make working with “relational” or “labeled” data both easy and intuitive. It aims to be the fundamental high-level building block for doing practical, real world data analysis in Python. Additionally, it has the broader goal of becoming the most powerful and flexible open source data analysis / manipulation tool available in any language. It is already well on its way toward this goal.

pandas is well suited for many different kinds of data:

- Tabular data with heterogeneously-typed columns, as in an SQL table or Excel spreadsheet
- Ordered and unordered (not necessarily fixed-frequency) time series data.
- Arbitrary matrix data (homogeneously typed or heterogeneous) with row and column labels
- Any other form of observational / statistical data sets. The data actually need not be labeled at all to be placed into a pandas data structure

The two primary data structures of pandas, `Series` (1-dimensional) and `DataFrame` (2-dimensional), handle the vast majority of typical use cases in finance, statistics, social science, and many areas of engineering. For R users, `DataFrame` provides everything that R’s `data.frame` provides and much more. pandas is built on top of NumPy and is intended to integrate well within a scientific computing environment with many other 3rd party libraries.

Here are just a few of the things that pandas does well:

- Easy handling of missing data (represented as NaN) in floating point as well as non-floating point data
- Size mutability: columns can be inserted and deleted from DataFrame and higher dimensional objects
- Automatic and explicit data alignment: objects can be explicitly aligned to a set of labels, or the user can simply ignore the labels and let `Series`, `DataFrame`, etc. automatically align the data for you in computations
- Powerful, flexible group by functionality to perform split-apply-combine operations on data sets, for both aggregating and transforming data
- Make it easy to convert ragged, differently-indexed data in other Python and NumPy data structures into DataFrame objects
• Intelligent label-based slicing, fancy indexing, and subsetting of large data sets
• Intuitive merging and joining data sets
• Flexible reshaping and pivoting of data sets
• Hierarchical labeling of axes (possible to have multiple labels per tick)
• Robust IO tools for loading data from flat files (CSV and delimited), Excel files, databases, and saving / loading data from the ultrafast HDF5 format
• Time series-specific functionality: date range generation and frequency conversion, moving window statistics, date shifting and lagging.

Many of these principles are here to address the shortcomings frequently experienced using other languages / scientific research environments. For data scientists, working with data is typically divided into multiple stages: munging and cleaning data, analyzing / modeling it, then organizing the results of the analysis into a form suitable for plotting or tabular display. pandas is the ideal tool for all of these tasks.

Some other notes
• pandas is fast. Many of the low-level algorithmic bits have been extensively tweaked in Cython code. However, as with anything else generalization usually sacrifices performance. So if you focus on one feature for your application you may be able to create a faster specialized tool.
• pandas is a dependency of statsmodels, making it an important part of the statistical computing ecosystem in Python.
• pandas has been used extensively in production in financial applications.

Data structures

<table>
<thead>
<tr>
<th>Dimensions</th>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Series</td>
<td>1D labeled homogeneously-typed array</td>
</tr>
<tr>
<td>2</td>
<td>DataFrame</td>
<td>General 2D labeled, size-mutable tabular structure with potentially</td>
</tr>
<tr>
<td></td>
<td></td>
<td>heterogeneous-typed column</td>
</tr>
</tbody>
</table>

Why more than one data structure?

The best way to think about the pandas data structures is as flexible containers for lower dimensional data. For example, DataFrame is a container for Series, and Series is a container for scalars. We would like to be able to insert and remove objects from these containers in a dictionary-like fashion.

Also, we would like sensible default behaviors for the common API functions which take into account the typical orientation of time series and cross-sectional data sets. When using ndarrays to store 2- and 3-dimensional data, a burden is placed on the user to consider the orientation of the data set when writing functions; axes are considered more or less equivalent (except when C- or Fortran-contiguousness matters for performance). In pandas, the axes are intended to lend more semantic meaning to the data; i.e., for a particular data set there is likely to be a “right” way to orient the data. The goal, then, is to reduce the amount of mental effort required to code up data transformations in downstream functions.

For example, with tabular data (DataFrame) it is more semantically helpful to think of the index (the rows) and the columns rather than axis 0 and axis 1. Iterating through the columns of the DataFrame thus results in more readable code:
for col in df.columns:
    series = df[col]
    # do something with series

**Mutability and copying of data**

All pandas data structures are value-mutable (the values they contain can be altered) but not always size-mutable. The length of a Series cannot be changed, but, for example, columns can be inserted into a DataFrame. However, the vast majority of methods produce new objects and leave the input data untouched. In general we like to favor immutability where sensible.

**Getting support**

The first stop for pandas issues and ideas is the Github Issue Tracker. If you have a general question, pandas community experts can answer through Stack Overflow.

**Community**

pandas is actively supported today by a community of like-minded individuals around the world who contribute their valuable time and energy to help make open source pandas possible. Thanks to all of our contributors.

If you’re interested in contributing, please visit the contributing guide.

pandas is a NumFOCUS sponsored project. This will help ensure the success of development of pandas as a world-class open-source project, and makes it possible to donate to the project.

**Project governance**

The governance process that pandas project has used informally since its inception in 2008 is formalized in Project Governance documents. The documents clarify how decisions are made and how the various elements of our community interact, including the relationship between open source collaborative development and work that may be funded by for-profit or non-profit entities.

Wes McKinney is the Benevolent Dictator for Life (BDFL).

**Development team**

The list of the Core Team members and more detailed information can be found on the people’s page of the governance repo.

**Institutional partners**

The information about current institutional partners can be found on pandas website page.
License

BSD 3-Clause License

Copyright (c) 2008-2011, AQR Capital Management, LLC, Lambda Foundry, Inc. and PyData Development Team
All rights reserved.

Copyright (c) 2011-2020, Open source contributors.

Redistribution and use in source and binary forms, with or without modification, are permitted provided that the following conditions are met:

- Redistributions of source code must retain the above copyright notice, this list of conditions and the following disclaimer.
- Redistributions in binary form must reproduce the above copyright notice, this list of conditions and the following disclaimer in the documentation and/or other materials provided with the distribution.
- Neither the name of the copyright holder nor the names of its contributors may be used to endorse or promote products derived from this software without specific prior written permission.

THIS SOFTWARE IS PROVIDED BY THE COPYRIGHT HOLDERS AND CONTRIBUTORS "AS IS" AND ANY EXPRESS OR IMPLIED WARRANTIES, INCLUDING, BUT NOT LIMITED TO, THE IMPLIED WARRANTIES OF MERCHANTABILITY AND FITNESS FOR A PARTICULAR PURPOSE ARE DISCLAIMED. IN NO EVENT SHALL THE COPYRIGHT HOLDER OR CONTRIBUTORS BE LIABLE FOR ANY DIRECT, INDIRECT, INCIDENTAL, SPECIAL, EXEMPLARY, OR CONSEQUENTIAL DAMAGES (INCLUDING, BUT NOT LIMITED TO, PROCUREMENT OF SUBSTITUTE GOODS OR SERVICES; LOSS OF USE, DATA, OR PROFITS; OR BUSINESS INTERRUPTION) HOWEVER CAUSED AND ON ANY THEORY OF LIABILITY, WHETHER IN CONTRACT, STRICT LIABILITY, OR TORT (INCLUDING NEGLIGENCE OR OTHERWISE) ARISING IN ANY WAY OUT OF THE USE OF THIS SOFTWARE, EVEN IF ADVISED OF THE POSSIBILITY OF SUCH DAMAGE.

1.4.3 Getting started tutorials

What kind of data does pandas handle?

I want to start using pandas

```
In [1]: import pandas as pd
```

To load the pandas package and start working with it, import the package. The community agreed alias for pandas is pd, so loading pandas as pd is assumed standard practice for all of the pandas documentation.
pandas data table representation

I want to store passenger data of the Titanic. For a number of passengers, I know the name (characters), age (integers) and sex (male/female) data.

```python
In [2]: df = pd.DataFrame(
    ...:     {
    ...:         "Name": ["Braund, Mr. Owen Harris", 
    ...:                     "Allen, Mr. William Henry", 
    ...:                     "Bonnell, Miss. Elizabeth"], 
    ...:         "Age": [22, 35, 58], 
    ...:         "Sex": ["male", "male", "female"]
    ...:     })
```

```python
In [3]: df
```

<table>
<thead>
<tr>
<th>Name</th>
<th>Age</th>
<th>Sex</th>
</tr>
</thead>
<tbody>
<tr>
<td>Braund, Mr. Owen Harris</td>
<td>22</td>
<td>male</td>
</tr>
<tr>
<td>Allen, Mr. William Henry</td>
<td>35</td>
<td>male</td>
</tr>
<tr>
<td>Bonnell, Miss. Elizabeth</td>
<td>58</td>
<td>female</td>
</tr>
</tbody>
</table>

To manually store data in a table, create a DataFrame. When using a Python dictionary of lists, the dictionary keys will be used as column headers and the values in each list as columns of the DataFrame.

A DataFrame is a 2-dimensional data structure that can store data of different types (including characters, integers, floating point values, categorical data and more) in columns. It is similar to a spreadsheet, a SQL table or the data.frame in R.

- The table has 3 columns, each of them with a column label. The column labels are respectively Name, Age and Sex.
- The column Name consists of textual data with each value a string, the column Age are numbers and the column Sex is textual data.

In spreadsheet software, the table representation of our data would look very similar:
Each column in a DataFrame is a Series

I’m just interested in working with the data in the column Age

```
In [4]: df["Age"]
Out[4]:
0  22
1  35
2  58
Name: Age, dtype: int64
```

When selecting a single column of a pandas DataFrame, the result is a pandas Series. To select the column, use the column label in between square brackets [].

**Note:** If you are familiar to Python dictionaries, the selection of a single column is very similar to selection of dictionary values based on the key.

You can create a Series from scratch as well:

```
In [5]: ages = pd.Series([22, 35, 58], name="Age")
In [6]: ages
Out[6]:
0  22
1  35
2  58
Name: Age, dtype: int64
```
A pandas Series has no column labels, as it is just a single column of a DataFrame. A Series does have row labels.

**Do something with a DataFrame or Series**

I want to know the maximum Age of the passengers

We can do this on the DataFrame by selecting the Age column and applying \texttt{max()}:  

\begin{verbatim}
In [7]: df["Age"].max()
Out[7]: 58
\end{verbatim}

Or to the Series:

\begin{verbatim}
In [8]: ages.max()
Out[8]: 58
\end{verbatim}

As illustrated by the \texttt{max()} method, you can do things with a DataFrame or Series. pandas provides a lot of functionalities, each of them a \textit{method} you can apply to a DataFrame or Series. As methods are functions, do not forget to use parentheses ().

I’m interested in some basic statistics of the numerical data of my data table:

\begin{verbatim}
In [9]: df.describe()
Out [9]:
         Age
count 3.000000
mean  38.333333
std   18.230012
min   22.000000
25%   28.500000
50%   35.000000
75%   46.500000
max   58.000000
\end{verbatim}

The \texttt{describe()} method provides a quick overview of the numerical data in a DataFrame. As the Name and Sex columns are textual data, these are by default not taken into account by the \texttt{describe()} method.

Many pandas operations return a DataFrame or a Series. The \texttt{describe()} method is an example of a pandas operation returning a pandas Series.

Check more options on \texttt{describe} in the user guide section about \textit{aggregations with describe}

\textbf{Note:} This is just a starting point. Similar to spreadsheet software, pandas represents data as a table with columns and rows. Apart from the representation, also the data manipulations and calculations you would do in spreadsheet software are supported by pandas. Continue reading the next tutorials to get started!

- Import the package, aka \texttt{import pandas as pd}
- A table of data is stored as a pandas DataFrame
- Each column in a DataFrame is a Series
- You can do things by applying a method to a DataFrame or Series

A more extended explanation to DataFrame and Series is provided in the introduction to data structures.
This tutorial uses the Titanic data set, stored as CSV. The data consists of the following data columns:

- **PassengerId**: Id of every passenger.
- **Survived**: This feature have value 0 and 1. 0 for not survived and 1 for survived.
- **Pclass**: There are 3 classes: Class 1, Class 2 and Class 3.
- **Name**: Name of passenger.
- **Sex**: Gender of passenger.
- **Age**: Age of passenger.
- **SibSp**: Indication that passenger have siblings and spouse.
- **Parch**: Whether a passenger is alone or have family.
- **Ticket**: Ticket number of passenger.
- **Fare**: Indicating the fare.
- **Cabin**: The cabin of passenger.
- **Embarked**: The embarked category.

### How do I read and write tabular data?

I want to analyze the Titanic passenger data, available as a CSV file.

```python
In [2]: titanic = pd.read_csv("data/titanic.csv")
```

pandas provides the `read_csv()` function to read data stored as a csv into a pandas DataFrame. pandas supports many different file formats or data sources out of the box (csv, excel, sql, json, parquet, ...), each of them with the prefix `read_*`.

Make sure to always have a check on the data after reading in the data. When displaying a DataFrame, the first and last 5 rows will be shown by default:
I want to see the first 8 rows of a pandas DataFrame.

```python
In [4]: titanic.head(8)
Out[4]:
   PassengerId  Survived  Pclass     Name                                Sex  Age  SibSp  Parch   Ticket     Fare Cabin Embarked
0           1          0       3    Braund, Mr. Owen Harris    male  22.0       0       0   A/5 21171    7.2500   NaN      S
1           2          1       1  Cumings, Mrs. John Bradley (Florence Briggs Th... female 38.0       1       1     PC 17599  71.2833     C5          C
2           3          1       3          Heikkinen, Miss. Laina female 26.0       3       1  STON/O2. 3101282  7.9250   NaN      S
3           4          1       1  Futrelle, Mrs. Jacques Heath (Lily May Peel) female 35.0       1       1  113803     53.1000   C123      S
4           5          0       3           Allen, Mr. William Henry male  35.0       0       3  373450     8.0500   NaN      S
5           6          0       3          Moran, Mr. James male  19.0       0       3  330877     8.4583   NaN      Q
6           7          0       3    McCarthy, Mr. Timothy J male  30.0       0       3  17463      51.8625   E46      S
7           8          0       3 Palsson, Master. Gosta Leonard male  22.0       0       3  349909    21.0750   NaN      S
```

To see the first N rows of a DataFrame, use the `head()` method with the required number of rows (in this case 8) as argument.

**Note:** Interested in the last N rows instead? pandas also provides a `tail()` method. For example, `titanic.tail(10)` will return the last 10 rows of the DataFrame.

A check on how pandas interpreted each of the column data types can be done by requesting the pandas `dtypes` attribute:

```python
In [5]: titanic.dtypes
Out[5]:
PassengerId    int64
Survived       int64
Pclass         int64
Name           object
Sex            object
Age            float64
SibSp          int64
Parch          int64
dtype: object
```

(continues on next page)
For each of the columns, the used data type is enlisted. The data types in this DataFrame are integers (int64), floats (float64) and strings (object).

**Note:** When asking for the dtypes, no brackets are used! dtypes is an attribute of a DataFrame and Series. Attributes of DataFrame or Series do not need brackets. Attributes represent a characteristic of a DataFrame/Series, whereas a method (which requires brackets) do something with the DataFrame/Series as introduced in the first tutorial.

My colleague requested the Titanic data as a spreadsheet.

```python
In [6]: titanic.to_excel('titanic.xlsx', sheet_name='passengers', index=False)
```

Whereas read_* functions are used to read data to pandas, the to_* methods are used to store data. The to_excel() method stores the data as an excel file. In the example here, the sheet_name is named passengers instead of the default Sheet1. By setting index=False the row index labels are not saved in the spreadsheet.

The equivalent read function read_excel() will reload the data to a DataFrame:

```python
In [7]: titanic = pd.read_excel('titanic.xlsx', sheet_name='passengers')
```

```
In [8]: titanic.head()
Out[8]:
   PassengerId  Survived  Pclass  Name                      Sex   ...   Fare  Cabin  Embarked
0          1         0       3     Braund, Mr. Owen Harris    male ...  7.25 NaN    S
1          2         1       1     Cumings, Mrs. John Bradley  female ... 71.28 C85   C
2          3         0       3      Heikkinen, Miss. Laina    female ...  7.92 NaN    S
3          4         1       1   Futrelle, Mrs. Jacques Heath  female ... 53.10 C123  S
4          5         0       3       Allen, Mr. William Henry    male ...  8.05 NaN    S

[5 rows x 12 columns]
```

I’m interested in a technical summary of a DataFrame

```python
In [9]: titanic.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
#    Column Non-Null Count  Dtype
---  ------ -------------- ------
 0    PassengerId     891 non-null   int64
 1    Survived       891 non-null   int64
 2    Pclass         891 non-null   int64
```
The method `info()` provides technical information about a DataFrame, so let's explain the output in more detail:

- It is indeed a DataFrame.
- There are 891 entries, i.e. 891 rows.
- Each row has a row label (aka the index) with values ranging from 0 to 890.
- The table has 12 columns. Most columns have a value for each of the rows (all 891 values are non-null). Some columns do have missing values and less than 891 non-null values.
- The columns Name, Sex, Cabin and Embarked consists of textual data (strings, aka object). The other columns are numerical data with some of them whole numbers (aka integer) and others are real numbers (aka float).
- The kind of data (characters, integers,...) in the different columns are summarized by listing the dtypes.
- The approximate amount of RAM used to hold the DataFrame is provided as well.
- Getting data in to pandas from many different file formats or data sources is supported by read_* functions.
- Exporting data out of pandas is provided by different to_* methods.
- The head/tail/info methods and the dtypes attribute are convenient for a first check.

For a complete overview of the input and output possibilities from and to pandas, see the user guide section about reader and writer functions.

```
In [1]: import pandas as pd
```

This tutorial uses the Titanic data set, stored as CSV. The data consists of the following data columns:

- PassengerId: Id of every passenger.
- Survived: This feature have value 0 and 1. 0 for not survived and 1 for survived.
- Pclass: There are 3 classes: Class 1, Class 2 and Class 3.
- Name: Name of passenger.
- Sex: Gender of passenger.
- Age: Age of passenger.
- SibSp: Indication that passenger have siblings and spouse.
- Parch: Whether a passenger is alone or have family.
- Ticket: Ticket number of passenger.
- Fare: Indicating the fare.
- Cabin: The cabin of passenger.
• Embarked: The embarked category.

```python
In [2]: titanic = pd.read_csv("data/titanic.csv")
```

```python
In [3]: titanic.head()
Out[3]:
   PassengerId  Survived  Pclass   Name                           ...
0            1       0        3  Braund, Mr. Owen Harris              ...
1            2       1        1  Cumings, Mrs. John Bradley (Florence Briggs Th... ...
2            3       0        3  Heikkinen, Miss. Laina                ...
3            4       1        1  Futrelle, Mrs. Jacques Heath (Lily May Peel) ...
4            5       0        3  Allen, Mr. William Henry              ...
```

[5 rows x 12 columns]

**How do I select a subset of a DataFrame?**

**How do I select specific columns from a DataFrame?**

I’m interested in the age of the Titanic passengers.

```python
In [4]: ages = titanic["Age"]

In [5]: ages.head()
Out[5]:
0   22.0
1   38.0
2   26.0
3   35.0
4   35.0
Name: Age, dtype: float64
```

To select a single column, use square brackets [] with the column name of the column of interest. Each column in a DataFrame is a Series. As a single column is selected, the returned object is a pandas Series. We can verify this by checking the type of the output:

```python
In [6]: type(titanic["Age"])
Out[6]: pandas.core.series.Series
```

And have a look at the shape of the output:

```python
In [7]: titanic["Age"].shape
Out[7]: (891,)
```

DataFrame.shape is an attribute (remember tutorial on reading and writing, do not use parentheses for attributes) of a pandas Series and DataFrame containing the number of rows and columns: (nrows, ncols). A pandas Series is 1-dimensional and only the number of rows is returned.

I’m interested in the age and sex of the Titanic passengers.

1.4. Tutorials
In [8]: age_sex = titanic["Age", "Sex"]

In [9]: age_sex.head()
Out[9]:
   Age  Sex
0  22.0  male
1  38.0  female
2  26.0  female
3  35.0  female
4  35.0  male

To select multiple columns, use a list of column names within the selection brackets [].

Note: The inner square brackets define a Python list with column names, whereas the outer brackets are used to select the data from a pandas DataFrame as seen in the previous example.

The returned data type is a pandas DataFrame:

In [10]: type(titanic["Age", "Sex")
Out[10]: pandas.core.frame.DataFrame

In [11]: titanic["Age", "Sex").shape
Out[11]: (891, 2)

The selection returned a DataFrame with 891 rows and 2 columns. Remember, a DataFrame is 2-dimensional with both a row and column dimension.

For basic information on indexing, see the user guide section on indexing and selecting data.

**How do I filter specific rows from a DataFrame?**

I’m interested in the passengers older than 35 years.

In [12]: above_35 = titanic[titanic["Age"] > 35]

In [13]: above_35.head()
Out[13]:
   PassengerId  Survived  Pclass     Name        Sex  ...   Fare  Cabin  Embarked
   ---  --------  ------  -------  -------  ...  -----  -----  -------
  1      2       1      1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  ...  0  C85  C
  2      7       0      1  McCarthy, Mr. Timothy J  male  ...  0  E46  S
  3     11       1      1  Bonnell, Miss. Elizabeth  female  ...  0  C103  S
  4     14       0      3  Andersson, Mr. Anders Johan  male  ...  5  NaN  NaN
  5     16       1      2  Hewlett, Mrs. (Mary D Kingcome)  female  ...  0  NaN  S

[5 rows x 12 columns]

To select rows based on a conditional expression, use a condition inside the selection brackets [].
The condition inside the selection brackets `titanic["Age"] > 35` checks for which rows the Age column has a value larger than 35:

```
In [14]: titanic["Age"] > 35
Out[14]:
0    False
1     True
2    False
3    False
4    False
...   ...
886   False
887   False
888   False
889   False
890   False
Name: Age, Length: 891, dtype: bool
```

The output of the conditional expression (>, but also ==, !=, <, <=,... would work) is actually a pandas Series of boolean values (either True or False) with the same number of rows as the original DataFrame. Such a Series of boolean values can be used to filter the DataFrame by putting it in between the selection brackets []. Only rows for which the value is True will be selected.

We know from before that the original Titanic DataFrame consists of 891 rows. Let's have a look at the amount of rows which satisfy the condition by checking the `shape` attribute of the resulting DataFrame `above_35`:

```
In [15]: above_35.shape
Out[15]: (217, 12)
```

I'm interested in the Titanic passengers from cabin class 2 and 3.

```
In [16]: class_23 = titanic[titanic["Pclass"].isin([2, 3])]
In [17]: class_23.head()
```

```
PassengerId  Survived  Pclass  Name       Sex  Age  SibSp  Parch  Ticket  Fare  Cabin  Embarked
0              1        3    Braund, Mr. Owen Harris    male 22.0     0    0        A/5 21171  7.2500 NaN      S
2              3        3  Heikkinen, Miss. Laina    female 26.0     0    0  STON/O2. 3101282  7.9250 NaN      S
4              5        3    Allen, Mr. William Henry   male 35.0     0    0          373450  8.0500 NaN      S
5              6        3      Moran, Mr. James    male  NaN     0    0          330877  8.4583 NaN      Q
7              8        3   Palsson, Master. Gosta Leonard    male 2.0     3    0          349909 21.0750 NaN      S
```

Similar to the conditional expression, the `isin()` conditional function returns a True for each row the values are in the provided list. To filter the rows based on such a function, use the conditional function inside the selection brackets[]. In this case, the condition inside the selection brackets `titanic["Pclass"].isin([2, 3])` checks for which rows the Pclass column is either 2 or 3.

The above is equivalent to filtering by rows for which the class is either 2 or 3 and combining the two statements with an `|` (or) operator:

```
In [18]: class_23 = titanic["Pclass"] == 2 | (titanic["Pclass"] == 3)
```
In [19]: class_23.head()
Out[19]:
   PassengerId  Survived  Pclass  Name             Sex  Age  SibSp  Parch  Ticket  Fare  Cabin  Embarked
0           1         0      3  Braund, Mr. Owen Harris     male  22.0     1       0  A/5  21171   7.2500   NaN      S
1           2         1      3  Heikkinen, Miss. Laina    female  26.0     0       0  STON/O2. 3101282 7.9250   NaN      S
2           3         1      3     Moran, Mr. James       male  NaN      0       0 330877  8.4583   NaN      Q
3           5         0      3  Palsson, Master. Gosta Leonard  male   2.0     3       0 349909 21.0750   NaN      S
4           1         0      3  Allen, Mr. William Henry     male  35.0     0       0 373450  8.0500   NaN      S

Note: When combining multiple conditional statements, each condition must be surrounded by parentheses ()
Moreover, you can not use or/and but need to use the or operator | and the and operator &.

See the dedicated section in the user guide about boolean indexing or about the isin function.

I want to work with passenger data for which the age is known.

In [20]: age_no_na = titanic[titanic["Age"].notna()]

In [21]: age_no_na.head()
Out[21]:
   PassengerId  Survived  Pclass  Name             Sex  Age  SibSp  Parch  Ticket  Fare  Cabin  Embarked
0           1         0      3  Braund, Mr. Owen Harris     male  22.0     1       0  A/5  21171   7.2500   NaN      S
1           2         1      3  Cumings, Mrs. John Bradley (Florence Briggs Th...  female   38.9600     0       0  PC 17599 71.2833  C85      C
2           3         1      3  Heikkinen, Miss. Laina    female  26.0     0       0  STON/O2. 3101282 7.9250   NaN      S
3           4         1      3  Futrelle, Mrs. Jacques Heath (Lily May Peel) female   38.4200     0       0 113803  53.1000  C123      S
4           5         0      3  Allen, Mr. William Henry     male  35.0     0       0 373450  8.0500   NaN      S

The notna() conditional function returns a True for each row the values are not an Null value. As such, this can be combined with the selection brackets [] to filter the data table.

You might wonder what actually changed, as the first 5 lines are still the same values. One way to verify is to check if the shape has changed:

In [22]: age_no_na.shape
Out[22]: (714, 12)

For more dedicated functions on missing values, see the user guide section about handling missing data.
How do I select specific rows and columns from a DataFrame?

I’m interested in the names of the passengers older than 35 years.

```
In [23]: adult_names = titanic.loc[titanic["Age"] > 35, "Name"]
```

```
In [24]: adult_names.head()
Out[24]:
   1  Cumings, Mrs. John Bradley (Florence Briggs Th...  
   6  McCarthy, Mr. Timothy J
   11  Bonnell, Miss. Elizabeth
   13  Andersson, Mr. Anders Johan
   15  Hewlett, Mrs. (Mary D Kingcome)
Name: Name, dtype: object
```

In this case, a subset of both rows and columns is made in one go and just using selection brackets [] is not sufficient anymore. The `loc/iloc` operators are required in front of the selection brackets[]. When using `loc/iloc`, the part before the comma is the rows you want, and the part after the comma is the columns you want to select.

When using the column names, row labels or a condition expression, use the `loc` operator in front of the selection brackets[]. For both the part before and after the comma, you can use a single label, a list of labels, a slice of labels, a conditional expression or a colon. Using a colon specifies you want to select all rows or columns.

I’m interested in rows 10 till 25 and columns 3 to 5.

```
In [25]: titanic.iloc[9:25, 2:5]
Out[25]:
      Pclass  Name       Sex
     9       2  Nasser, Mrs. Nicholas (Adele Achem)  female
     10      3  Sandstrom, Miss. Marguerite Rut  female
     11       1  Bonnell, Miss. Elizabeth        female
     12       3  Saundercoc, Mr. William Henry  male
     13       3    Andersson, Mr. Anders Johan   male
     ...    ...          ...       ...
     20      2    Fynney, Mr. Joseph J         male
     21      2  Beesley, Mr. Lawrence           male
     22      3    McGowan, Miss. Anna "Annie"  female
     23      1    Sloper, Mr. William Thompson  male
     24      3  Palsson, Miss. Torborg Danira   female
```

Again, a subset of both rows and columns is made in one go and just using selection brackets [] is not sufficient anymore. When specifically interested in certain rows and/or columns based on their position in the table, use the `iloc` operator in front of the selection brackets[].

When selecting specific rows and/or columns with `loc` or `iloc`, new values can be assigned to the selected data. For example, to assign the name `anonymous` to the first 3 elements of the third column:

```
In [26]: titanic.iloc[0:3, 3] = "anonymous"
In [27]: titanic.head()
Out[27]:
   PassengerId  Survived  Pclass  Name       Sex ... Parch  Ticket  Fare  Cabin  Embarked   anonymous
            0         1      3 anonymous  male ... 0  A/5 21171  7.2500 NaN          S
            (continues on next page)
See the user guide section on different choices for indexing to get more insight in the usage of `loc` and `iloc`.

- When selecting subsets of data, square brackets `[]` are used.
- Inside these brackets, you can use a single column/row label, a list of column/row labels, a slice of labels, a conditional expression or a colon.
- Select specific rows and/or columns using `loc` when using the row and column names.
- Select specific rows and/or columns using `iloc` when using the positions in the table.
- You can assign new values to a selection based on `loc`/`iloc`.

A full overview about indexing is provided in the user guide pages on indexing and selecting data.

```python
In [1]: import pandas as pd

In [2]: import matplotlib.pyplot as plt

For this tutorial, air quality data about $NO_2$ is used, made available by openaq and using the py-openaq package. The `air_quality_no2.csv` data set provides $NO_2$ values for the measurement stations FR04014, BETR801 and London Westminster in respectively Paris, Antwerp and London.

```python
In [3]: air_quality = pd.read_csv("data/air_quality_no2.csv",
...:                          index_col=0, parse_dates=True)
...:

In [4]: air_quality.head()
```

```
Out[4]:
station_antwerp  station_paris  station_london
datetime
2019-05-07 02:00:00  NaN        NaN          23.0
2019-05-07 03:00:00  50.5        25.0          19.0
2019-05-07 04:00:00  45.0        27.7          19.0
2019-05-07 05:00:00  NaN        50.4           16.0
2019-05-07 06:00:00  NaN        61.9          NaN
```

Note: The usage of the `index_col` and `parse_dates` parameters of the `read_csv` function to define the first (0th) column as index of the resulting DataFrame and convert the dates in the column to `Timestamp` objects, respectively.
How to create plots in pandas?

I want a quick visual check of the data.

```python
In [5]: air_quality.plot()
Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe2a79fdeb0>
```

With a DataFrame, pandas creates by default one line plot for each of the columns with numeric data.

I want to plot only the columns of the data table with the data from Paris.

```python
In [6]: air_quality["station_paris"].plot()
Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe2a7cc9670>
```
To plot a specific column, use the selection method of the *subset data tutorial* in combination with the `plot()` method. Hence, the `plot()` method works on both Series and DataFrame.

I want to visually compare the \( N_{02} \) values measured in London versus Paris.

```python
In [7]: air_quality.plot.scatter(x="station_london",
                      y="station_paris",
                      alpha=0.5)
```

```
Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe2a7c31e20>
```
Apart from the default line plot when using the `plot` function, a number of alternatives are available to plot data. Let’s use some standard Python to get an overview of the available plot methods:

```python
In [8]: [method_name for method_name in dir(air_quality.plot) if not method_name.startswith('_')]
...:
Out[8]:
['area',
'bar',
'barh',
'boxcap',
'density',
'hexbin',
'hist',
'kde',
'line',
'pie',
'scatter']
```

**Note:** In many development environments as well as ipython and jupyter notebook, use the TAB button to get an overview of the available methods, for example `air_quality.plot.+TAB`.

One of the options is `DataFrame.plot.box()`, which refers to a boxplot. The box method is applicable on the air quality example data:
For an introduction to plots other than the default line plot, see the user guide section about *supported plot styles*. I want each of the columns in a separate subplot.

```python
In [10]: axs = air_quality.plot.area(figsize=(12, 4), subplots=True)
```

Separate subplots for each of the data columns is supported by the `subplots` argument of the `plot` functions. The built-in options available in each of the pandas plot functions that are worthwhile to have a look.
Some more formatting options are explained in the user guide section on plot formatting.

I want to further customize, extend or save the resulting plot.

```py
In [11]: fig, axs = plt.subplots(figsize=(12, 4));
In [12]: air_quality.plot.area(ax=axs);
In [13]: axs.set_ylabel("NO$_2$ concentration");
In [14]: fig.savefig("no2_concentrations.png")
```

Each of the plot objects created by pandas are a matplotlib object. As Matplotlib provides plenty of options to customize plots, making the link between pandas and Matplotlib explicit enables all the power of matplotlib to the plot. This strategy is applied in the previous example:

```py
fig, axs = plt.subplots(figsize=(12, 4))  # Create an empty matplotlib Figure and Axes
air_quality.plot.area(ax=axs)  # Use pandas to put the area plot on the prepared Figure/Axes
axs.set_ylabel("NO$_2$ concentration")  # Do any matplotlib customization you like
fig.savefig("no2_concentrations.png")  # Save the Figure/Axes using the existing matplotlib method.
```

- The `.plot.*` methods are applicable on both Series and DataFrames
- By default, each of the columns is plotted as a different element (line, boxplot,...)
- Any plot created by pandas is a Matplotlib object.

A full overview of plotting in pandas is provided in the visualization pages.

```py
In [1]: import pandas as pd
```

For this tutorial, air quality data about $NO_2$ is used, made available by openaq and using the py-openaq package. The `air_quality_no2.csv` data set provides $NO_2$ values for the measurement stations FR04014, BETR801 and London Westminster in respectively Paris, Antwerp and London.

```py
In [2]: air_quality = pd.read_csv("data/air_quality_no2.csv",
   ...:   index_col=0, parse_dates=True)
   ...
In [3]: air_quality.head()
```

(continues on next page)
Out[3]:

<table>
<thead>
<tr>
<th>station_antwerp</th>
<th>station_paris</th>
<th>station_london</th>
<th>datetime</th>
</tr>
</thead>
<tbody>
<tr>
<td>2019-05-07 02:00:00</td>
<td>NaN</td>
<td>NaN</td>
<td>23.0</td>
</tr>
<tr>
<td>2019-05-07 03:00:00</td>
<td>50.5</td>
<td>25.0</td>
<td>19.0</td>
</tr>
<tr>
<td>2019-05-07 04:00:00</td>
<td>45.0</td>
<td>27.7</td>
<td>19.0</td>
</tr>
<tr>
<td>2019-05-07 05:00:00</td>
<td>NaN</td>
<td>50.4</td>
<td>16.0</td>
</tr>
<tr>
<td>2019-05-07 06:00:00</td>
<td>NaN</td>
<td>61.9</td>
<td>NaN</td>
</tr>
</tbody>
</table>

How to create new columns derived from existing columns?

I want to express the $NO_2$ concentration of the station in London in mg/m$^3$.

(If we assume temperature of 25 degrees Celsius and pressure of 1013 hPa, the conversion factor is 1.882)

In [4]: air_quality["london_mg_per_cubic"] = air_quality["station_london"] * 1.882

In [5]: air_quality.head()

Out[5]:

<table>
<thead>
<tr>
<th>station_antwerp</th>
<th>station_paris</th>
<th>station_london</th>
<th>london_mg_per_cubic</th>
</tr>
</thead>
<tbody>
<tr>
<td>2019-05-07 02:00:00</td>
<td>NaN</td>
<td>NaN</td>
<td>23.0 43.286</td>
</tr>
<tr>
<td>2019-05-07 03:00:00</td>
<td>50.5</td>
<td>25.0</td>
<td>19.0 35.758</td>
</tr>
<tr>
<td>2019-05-07 04:00:00</td>
<td>45.0</td>
<td>27.7</td>
<td>19.0 35.758</td>
</tr>
<tr>
<td>2019-05-07 05:00:00</td>
<td>NaN</td>
<td>50.4</td>
<td>16.0 30.712</td>
</tr>
<tr>
<td>2019-05-07 06:00:00</td>
<td>NaN</td>
<td>61.9</td>
<td>NaN</td>
</tr>
</tbody>
</table>

To create a new column, use the [ ] brackets with the new column name at the left side of the assignment.

Note: The calculation of the values is done element wise. This means all values in the given column are multiplied by the value 1.882 at once. You do not need to use a loop to iterate each of the rows!

I want to check the ratio of the values in Paris versus Antwerp and save the result in a new column

In [6]: air_quality["ratio_paris_antwerp"] = \ 
               ...: air_quality["station_paris"] / air_quality["station_antwerp"]

In [7]: air_quality.head()

Out[7]:

<table>
<thead>
<tr>
<th>station_antwerp</th>
<th>station_paris</th>
<th>station_london</th>
<th>london_mg_per_cubic</th>
<th>ratio_paris_antwerp</th>
</tr>
</thead>
<tbody>
<tr>
<td>2019-05-07 02:00:00</td>
<td>NaN</td>
<td>NaN</td>
<td>23.0 43.286</td>
<td></td>
</tr>
<tr>
<td>2019-05-07 03:00:00</td>
<td>50.5</td>
<td>25.0</td>
<td>19.0 35.758</td>
<td></td>
</tr>
<tr>
<td>2019-05-07 04:00:00</td>
<td>45.0</td>
<td>27.7</td>
<td>19.0 35.758</td>
<td></td>
</tr>
<tr>
<td>2019-05-07 05:00:00</td>
<td>NaN</td>
<td>50.4</td>
<td>16.0 30.712</td>
<td></td>
</tr>
<tr>
<td>2019-05-07 06:00:00</td>
<td>NaN</td>
<td>61.9</td>
<td>NaN</td>
<td></td>
</tr>
</tbody>
</table>

(continues on next page)
The calculation is again element-wise, so the `/` is applied for the values in each row.

Also other mathematical operators (`, `-`, `*`, `/`) or logical operators (`<`, `>`, `=`, `!=`) work element wise. The latter was already used in the subset data tutorial to filter rows of a table using a conditional expression.

I want to rename the data columns to the corresponding station identifiers used by openAQ

```
In [8]: air_quality_renamed = air_quality.rename(
    ...:     columns={'station_antwerp': 'BETR801',
    ...:                 'station_paris':  'FR04014',
    ...:                 'station_london': 'London Westminster'})
```

```
In [9]: air_quality_renamed.head()
Out[9]:
          BETR801  FR04014 London Westminster      london_mg_per_cubic  ratio_
         ----------------------  ---------  -----------------------------------------------
    datetime
  2019-05-07 02:00:00 NaN       NaN                23.0                    43.286
  2019-05-07 03:00:00 50.5      25.0                19.0                    35.758
  2019-05-07 04:00:00 45.0      27.7                19.0                    35.758
  2019-05-07 05:00:00 NaN       NaN                50.4                    16.0
  2019-05-07 06:00:00 NaN       NaN                61.9                    NaN
```

The `rename()` function can be used for both row labels and column labels. Provide a dictionary with the keys the current names and the values the new names to update the corresponding names.

The mapping should not be restricted to fixed names only, but can be a mapping function as well. For example, converting the column names to lowercase letters can be done using a function as well:

```
In [10]: air_quality_renamed = air_quality_renamed.rename(columns=str.lower)
In [11]: air_quality_renamed.head()
Out[11]:
          betr801 fr04014 london westminster      london_mg_per_cubic  ratio_
         ----------------------  ---------  -----------------------------------------------
    datetime
  2019-05-07 02:00:00 NaN       NaN                23.0                    43.286
  2019-05-07 03:00:00 50.5      25.0                19.0                    35.758
  2019-05-07 04:00:00 45.0      27.7                19.0                    35.758
  2019-05-07 05:00:00 NaN       NaN                50.4                    16.0
  2019-05-07 06:00:00 NaN       NaN                61.9                    NaN
```

(continues on next page)
Details about column or row label renaming is provided in the user guide section on renaming labels.

- Create a new column by assigning the output to the DataFrame with a new column name in between the [].
- Operations are element-wise, no need to loop over rows.
- Use rename with a dictionary or function to rename row labels or column names.

The user guide contains a separate section on column addition and deletion.

This tutorial uses the Titanic data set, stored as CSV. The data consists of the following data columns:

- PassengerId: Id of every passenger.
- Survived: This feature have value 0 and 1. 0 for not survived and 1 for survived.
- Pclass: There are 3 classes: Class 1, Class 2 and Class 3.
- Name: Name of passenger.
- Sex: Gender of passenger.
- Age: Age of passenger.
- SibSp: Indication that passenger have siblings and spouse.
- Parch: Whether a passenger is alone or have family.
- Ticket: Ticket number of passenger.
- Fare: Indicating the fare.
- Cabin: The cabin of passenger.
- Embarked: The embarked category.

```python
In [1]: import pandas as pd

In [2]: titanic = pd.read_csv("data/titanic.csv")

In [3]: titanic.head()
```

<table>
<thead>
<tr>
<th>PassengerId</th>
<th>Survived</th>
<th>Pclass</th>
<th>Name</th>
<th>Sex</th>
<th>Parch</th>
<th>Ticket</th>
<th>Fare</th>
<th>Cabin</th>
<th>Embarked</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>3</td>
<td>Braund, Mr. Owen Harris</td>
<td>male</td>
<td>0</td>
<td>A/5 21171</td>
<td>7.2500</td>
<td>NaN</td>
<td>S</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>1</td>
<td>Cumings, Mrs. John Bradley (Florence Briggs Th...</td>
<td>female</td>
<td>2</td>
<td>PC 17599</td>
<td>71.2833</td>
<td>C</td>
<td>C</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>3</td>
<td>Heikkinen, Miss. Laina</td>
<td>female</td>
<td>3</td>
<td>STON/O2. 3101282</td>
<td>7.9250</td>
<td>NaN</td>
<td>S</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>1</td>
<td>Futrelle, Mrs. Jacques Heath (Lily May Peel)</td>
<td>female</td>
<td>4</td>
<td>113803</td>
<td>53.1000</td>
<td>C123</td>
<td>S</td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>3</td>
<td>Allen, Mr. William Henry</td>
<td>male</td>
<td>5</td>
<td>373450</td>
<td>8.0500</td>
<td>NaN</td>
<td>S</td>
</tr>
</tbody>
</table>
How to calculate summary statistics?

Aggregating statistics

What is the average age of the Titanic passengers?

```
In [4]: titanic["Age"].mean()
Out[4]: 29.6991764705882
```

Different statistics are available and can be applied to columns with numerical data. Operations in general exclude missing data and operate across rows by default.

What is the median age and ticket fare price of the Titanic passengers?

```
In [5]: titanic[["Age", "Fare"]].median()
Out[5]:
Age 28.0000
Fare 14.4542
dtype: float64
```

The statistic applied to multiple columns of a DataFrame (the selection of two columns return a DataFrame, see the subset data tutorial) is calculated for each numeric column.

The aggregating statistic can be calculated for multiple columns at the same time. Remember the describe function from first tutorial tutorial?

```
In [6]: titanic[["Age", "Fare"]].describe()
Out[6]:
     Age  Fare
count 714.0000  891.0000
mean 29.6991  32.2042
std 14.5265  49.6934
min 0.4200  0.0000
25% 20.1250  7.9104
50% 28.0000  14.4542
75% 38.0000  31.0000
max 80.0000  512.3292
```

Instead of the predefined statistics, specific combinations of aggregating statistics for given columns can be defined using the DataFrame.agg() method:

```
In [7]: titanic.agg({'Age': ['min', 'max', 'median', 'skew'],
                      ...
                      'Fare': ['min', 'max', 'median', 'mean']})
Out[7]:
   Age  Fare
max  80.0000  512.3292
mean NaN     32.2042
```

(continues on next page)
median 28.000000 14.454200
min 0.420000 0.000000
skew 0.389108 NaN

Details about descriptive statistics are provided in the user guide section on descriptive statistics.

**Aggregating statistics grouped by category**

What is the average age for male versus female Titanic passengers?

```python
In [8]: titanic["Sex", "Age"].groupby("Sex").mean()
Out [8]:
    Sex   Age
females 27.915709
males  30.726645
```

As our interest is the average age for each gender, a subselection on these two columns is made first: `titanic[["Sex", "Age"]].`. Next, the `groupby()` method is applied on the `Sex` column to make a group per category. The average age for each gender is calculated and returned.

Calculating a given statistic (e.g. mean age) for each category in a column (e.g. male/female in the `Sex` column) is a common pattern. The `groupby` method is used to support this type of operations. More general, this fits in the more general split-apply-combine pattern:

- **Split** the data into groups
- **Apply** a function to each group independently
- **Combine** the results into a data structure

The apply and combine steps are typically done together in pandas.

In the previous example, we explicitly selected the 2 columns first. If not, the `mean` method is applied to each column containing numerical columns:

```python
In [9]: titanic.groupby("Sex").mean()
Out [9]:
    PassengerId  Survived  Pclass  Age  SibSp  Parch    Fare
Sex  female  431.028662  0.742038  2.159236  27.915709  0.694268  0.649682  44.479818
    male  454.147314  0.188908  2.389948  30.726645  0.429809  0.235702  25.523893
```

It does not make much sense to get the average value of the `Pclass` if we are only interested in the average age for each gender, the selection of columns (rectangular brackets `[]` as usual) is supported on the grouped data as well:

```python
In [10]: titanic.groupby("Sex")["Age"].mean()
Out [10]:
    Sex
females 27.915709
males  30.726645
Name: Age, dtype: float64
```
Note: The Pclass column contains numerical data but actually represents 3 categories (or factors) with respectively the labels ‘1’, ‘2’ and ‘3’. Calculating statistics on these does not make much sense. Therefore, pandas provides a Categorical data type to handle this type of data. More information is provided in the user guide Categorical data section.

What is the mean ticket fare price for each of the sex and cabin class combinations?

```
In [11]: titanic.groupby(['Sex', 'Pclass'])['Fare'].mean()
Out[11]:
            Sex   Pclass
female 1     106.125798
           2      21.970121
           3      16.118810
male    1     67.226127
           2      19.741782
           3      12.661633
Name: Fare, dtype: float64
```

Grouping can be done by multiple columns at the same time. Provide the column names as a list to the groupby() method.

A full description on the split-apply-combine approach is provided in the user guide section on groupby operations.

Count number of records by category

What is the number of passengers in each of the cabin classes?

```
In [12]: titanic['Pclass'].value_counts()
Out[12]:
3     491
1     216
2     184
Name: Pclass, dtype: int64
```

The value_counts() method counts the number of records for each category in a column.

The function is a shortcut, as it is actually a groupby operation in combination with counting of the number of records within each group:

```
In [13]: titanic.groupby('Pclass')['Pclass'].count()
Out[13]:
Pclass
1    216
2    184
3    491
Name: Pclass, dtype: int64
```

Note: Both size and count can be used in combination with groupby. Whereas size includes NaN values and just provides the number of rows (size of the table), count excludes the missing values. In the value_counts method, use the dropna argument to include or exclude the NaN values.

The user guide has a dedicated section on value_counts, see page on discretization.
pandas: powerful Python data analysis toolkit, Release 1.1.1

- Aggregation statistics can be calculated on entire columns or rows
- `groupby` provides the power of the `split-apply-combine` pattern
- `value_counts` is a convenient shortcut to count the number of entries in each category of a variable

A full description on the `split-apply-combine` approach is provided in the user guide pages about `groupby operations`.

```python
In [1]: import pandas as pd
```

This tutorial uses the Titanic data set, stored as CSV. The data consists of the following data columns:

- PassengerId: Id of every passenger.
- Survived: This feature have value 0 and 1. 0 for not survived and 1 for survived.
- Pclass: There are 3 classes: Class 1, Class 2 and Class 3.
- Name: Name of passenger.
- Sex: Gender of passenger.
- Age: Age of passenger.
- SibSp: Indication that passenger have siblings and spouse.
- Parch: Whether a passenger is alone or have family.
- Ticket: Ticket number of passenger.
- Fare: Indicating the fare.
- Cabin: The cabin of passenger.
- Embarked: The embarked category.

```python
In [2]: titanic = pd.read_csv("data/titanic.csv")
```

```python
In [3]: titanic.head()
```

<table>
<thead>
<tr>
<th>PassengerId</th>
<th>Survived</th>
<th>Pclass</th>
<th>Name</th>
<th>Sex</th>
<th>Parch</th>
<th>Ticket</th>
<th>Fare</th>
<th>Cabin</th>
<th>Embarked</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
<td>1</td>
<td>Braund, Mr. Owen Harris</td>
<td>male</td>
<td>0</td>
<td>A/5 21171</td>
<td>7.2500</td>
<td>NaN</td>
<td>S</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>1</td>
<td>Cumings, Mrs. John Bradley (Florence Briggs Th...</td>
<td>female</td>
<td>0</td>
<td>1 Cumings, Mrs. John Bradley (Florence Briggs Th...</td>
<td>female</td>
<td>0</td>
<td>C41 13317</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>1</td>
<td>Heikkinen, Miss. Laina</td>
<td>female</td>
<td>3</td>
<td>STON/O2. 3101282</td>
<td>7.9250</td>
<td>NaN</td>
<td>S</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>1</td>
<td>Futrelle, Mrs. Jacques Heath (Lily May Peel)</td>
<td>female</td>
<td>1</td>
<td>113803</td>
<td>53.1000</td>
<td>C123</td>
<td>S</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>1</td>
<td>Allen, Mr. William Henry</td>
<td>male</td>
<td>0</td>
<td>373450</td>
<td>8.0500</td>
<td>NaN</td>
<td>S</td>
</tr>
</tbody>
</table>

[5 rows x 12 columns]

This tutorial uses air quality data about $NO_2$ and Particulate matter less than 2.5 micrometers, made available by openaq and using the py-openaq package. The `air_quality_long.csv` data set provides $NO_2$ and $PM_{2.5}$ values for the measurement stations FR04014, BETR801 and London Westminster in respectively Paris, Antwerp and London.

The air-quality data set has the following columns:

- city: city where the sensor is used, either Paris, Antwerp or London
- country: country where the sensor is used, either FR, BE or GB
• location: the id of the sensor, either FR04014, BETR801 or London Westminster
• parameter: the parameter measured by the sensor, either $NO_2$ or Particulate matter
• value: the measured value
• unit: the unit of the measured parameter, in this case ‘$\mu$g/m$^3$’

and the index of the DataFrame is datetime, the datetime of the measurement.

**Note:** The air-quality data is provided in a so-called *long format* data representation with each observation on a separate row and each variable a separate column of the data table. The long/narrow format is also known as the tidy data format.

```python
In [4]: air_quality = pd.read_csv("data/air_quality_long.csv", ...: index_col="date.utc", parse_dates=True)
...
In [5]: air_quality.head()
Out[5]:
<table>
<thead>
<tr>
<th>city</th>
<th>country</th>
<th>location</th>
<th>parameter</th>
<th>value</th>
<th>unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Antwerpen</td>
<td>BE</td>
<td>BETR801</td>
<td>pm25</td>
<td>18.0</td>
<td>$\mu$g/m$^3$</td>
</tr>
<tr>
<td>Antwerpen</td>
<td>BE</td>
<td>BETR801</td>
<td>pm25</td>
<td>6.5</td>
<td>$\mu$g/m$^3$</td>
</tr>
<tr>
<td>Antwerpen</td>
<td>BE</td>
<td>BETR801</td>
<td>pm25</td>
<td>18.5</td>
<td>$\mu$g/m$^3$</td>
</tr>
<tr>
<td>Antwerpen</td>
<td>BE</td>
<td>BETR801</td>
<td>pm25</td>
<td>16.0</td>
<td>$\mu$g/m$^3$</td>
</tr>
<tr>
<td>Antwerpen</td>
<td>BE</td>
<td>BETR801</td>
<td>pm25</td>
<td>7.5</td>
<td>$\mu$g/m$^3$</td>
</tr>
</tbody>
</table>
```

**How to reshape the layout of tables?**

**Sort table rows**

I want to sort the Titanic data according to the age of the passengers.

```python
In [6]: titanic.sort_values(by="Age").head()
Out[6]:
<table>
<thead>
<tr>
<th>PassengerId</th>
<th>Survived</th>
<th>Pclass</th>
<th>Name</th>
<th>Sex</th>
<th>Age</th>
</tr>
</thead>
<tbody>
<tr>
<td>803</td>
<td>1</td>
<td>3</td>
<td>Thomas, Master. Assad Alexander</td>
<td>male</td>
<td>0.42</td>
</tr>
<tr>
<td>755</td>
<td>1</td>
<td>2</td>
<td>Hamalainen, Master. Viljo</td>
<td>male</td>
<td>0.67</td>
</tr>
<tr>
<td>644</td>
<td>1</td>
<td>3</td>
<td>Baclini, Miss. Eugenie</td>
<td>female</td>
<td>0.75</td>
</tr>
<tr>
<td>469</td>
<td>0</td>
<td>1</td>
<td>Baclini, Miss. Helene Barbara</td>
<td>female</td>
<td>0.75</td>
</tr>
<tr>
<td>78</td>
<td>0</td>
<td>2</td>
<td>Caldwell, Master. Alden Gates</td>
<td>male</td>
<td>0.83</td>
</tr>
</tbody>
</table>
```

I want to sort the Titanic data according to the cabin class and age in descending order.

```python
In [7]: titanic.sort_values(by=['Pclass', 'Age'], ascending=False).head()
Out[7]:
<table>
<thead>
<tr>
<th>PassengerId</th>
<th>Survived</th>
<th>Pclass</th>
<th>Name</th>
<th>Sex</th>
<th>Age</th>
</tr>
</thead>
<tbody>
<tr>
<td>248738</td>
<td>2</td>
<td>2</td>
<td>Caldwell, Master. Alden Gates</td>
<td>male</td>
<td>0.83</td>
</tr>
<tr>
<td>2666</td>
<td>1</td>
<td>1</td>
<td>Baclini, Miss. Helene Barbara</td>
<td>female</td>
<td>0.75</td>
</tr>
<tr>
<td>2666</td>
<td>1</td>
<td>1</td>
<td>Baclini, Miss. Eugenie</td>
<td>female</td>
<td>0.75</td>
</tr>
<tr>
<td>250649</td>
<td>1</td>
<td>3</td>
<td>Baclini, Miss. Helene Barbara</td>
<td>female</td>
<td>0.75</td>
</tr>
<tr>
<td>756</td>
<td>2</td>
<td>2</td>
<td>Hamalainen, Master. Viljo</td>
<td>male</td>
<td>0.67</td>
</tr>
</tbody>
</table>
```

(continues on next page)
With `Series.sort_values()`, the rows in the table are sorted according to the defined column(s). The index will follow the row order.

More details about sorting of tables is provided in the using guide section on sorting data.

### Long to wide table format

Let’s use a small subset of the air quality data set. We focus on $NO_2$ data and only use the first two measurements of each location (i.e. the head of each group). The subset of data will be called `no2_subset`

```python
# filter for no2 data only
In [8]: no2 = air_quality[air_quality["parameter"] == "no2"]
# use 2 measurements (head) for each location (groupby)
In [9]: no2_subset = no2.sort_index().groupby(["location"]).head(2)
```

```
<table>
<thead>
<tr>
<th>date.utc</th>
<th>city</th>
<th>country</th>
<th>location</th>
<th>parameter</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2019-04-09 01:00:00+00:00</td>
<td>Antwerpen</td>
<td>BE</td>
<td>BETR801</td>
<td>no2</td>
<td>22.5</td>
</tr>
<tr>
<td>2019-04-09 01:00:00+00:00</td>
<td>Paris</td>
<td>FR</td>
<td>FR04014</td>
<td>no2</td>
<td>24.4</td>
</tr>
<tr>
<td>2019-04-09 02:00:00+00:00</td>
<td>London</td>
<td>GB</td>
<td>London Westminster</td>
<td>no2</td>
<td>67.0</td>
</tr>
<tr>
<td>2019-04-09 02:00:00+00:00</td>
<td>Antwerpen</td>
<td>BE</td>
<td>BETR801</td>
<td>no2</td>
<td>53.5</td>
</tr>
<tr>
<td>2019-04-09 02:00:00+00:00</td>
<td>Paris</td>
<td>FR</td>
<td>FR04014</td>
<td>no2</td>
<td>27.4</td>
</tr>
<tr>
<td>2019-04-09 03:00:00+00:00</td>
<td>London</td>
<td>GB</td>
<td>London Westminster</td>
<td>no2</td>
<td>67.0</td>
</tr>
</tbody>
</table>
```

I want the values for the three stations as separate columns next to each other

```python
In [11]: no2_subset.pivot(columns="location", values="value")
```

```
<table>
<thead>
<tr>
<th>location</th>
<th>BETR801</th>
<th>FR04014</th>
<th>London Westminster</th>
</tr>
</thead>
<tbody>
<tr>
<td>date.utc</td>
<td>2019-04-09 01:00:00+00:00</td>
<td>22.5</td>
<td>24.4</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>NaN</td>
</tr>
</tbody>
</table>
```

(continues on next page)
The `pivot()` function is purely reshaping of the data: a single value for each index/column combination is required. As pandas support plotting of multiple columns (see plotting tutorial) out of the box, the conversion from long to wide table format enables the plotting of the different time series at the same time:

```python
In [12]: no2.head()
Out[12]:
   city country location parameter value unit
date.utc
2019-06-21 00:00:00+00:00 Paris FR FR04014 no2 20.0 µg/m³
2019-06-20 23:00:00+00:00 Paris FR FR04014 no2 21.8 µg/m³
2019-06-20 22:00:00+00:00 Paris FR FR04014 no2 26.5 µg/m³
2019-06-20 21:00:00+00:00 Paris FR FR04014 no2 24.9 µg/m³
2019-06-20 20:00:00+00:00 Paris FR FR04014 no2 21.4 µg/m³
```

```python
In [13]: no2.pivot(columns="location", values="value").plot()
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe2a7ab8ee0>
```

Note: When the `index` parameter is not defined, the existing index (row labels) is used.
I want the mean concentrations for \( NO_2 \) and \( PM_{2.5} \) in each of the stations in table form

```
In [14]: air_quality.pivot_table(values="value", index="location",
                           ....:       columns="parameter", aggfunc="mean")
   ....:
Out[14]:
   parameter  no2     pm25
   location
   BETR801    26.950920 23.169492
   FR04014    29.374284  NaN
   London Westminster 29.740050 13.443568
```

In the case of `pivot()`, the data is only rearranged. When multiple values need to be aggregated (in this specific case, the values on different time steps) `pivot_table()` can be used, providing an aggregation function (e.g. mean) on how to combine these values.

Pivot table is a well known concept in spreadsheet software. When interested in summary columns for each variable separately as well, put the `margins` parameter to `True`:

```
In [15]: air_quality.pivot_table(values="value", index="location",
                           ....:       columns="parameter", aggfunc="mean",
                           ....:       margins=True)
   ....:
Out[15]:
   parameter  no2     pm25    All
   location
   BETR801    26.950920 23.169492 24.982353
   FR04014    29.374284  NaN      29.374284
   All        29.430316 14.386849 24.222743
```

For more information about `pivot_table()`, see the user guide section on pivot tables.

**Note:** In case you are wondering, `pivot_table()` is indeed directly linked to `groupby()`. The same result can be derived by grouping on both `parameter` and `location`:

```
air_quality.groupby(["parameter", "location"]).mean()
```

Have a look at `groupby()` in combination with `unstack()` at the user guide section on combining stats and groupby.
Wide to long format

Starting again from the wide format table created in the previous section:

```python
In [16]: no2_pivoted = no2.pivot(columns="location", values="value").reset_index()

In [17]: no2_pivoted.head()
Out[17]:
<table>
<thead>
<tr>
<th>location</th>
<th>date.utc</th>
<th>BETR801</th>
<th>FR04014</th>
<th>London Westminster</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2019-04-09</td>
<td>01:00:00</td>
<td>01:00:00</td>
<td>01:00:00</td>
</tr>
<tr>
<td></td>
<td>2019-04-09</td>
<td>02:00:00</td>
<td>02:00:00</td>
<td>02:00:00</td>
</tr>
<tr>
<td></td>
<td>2019-04-09</td>
<td>03:00:00</td>
<td>03:00:00</td>
<td>03:00:00</td>
</tr>
<tr>
<td></td>
<td>2019-04-09</td>
<td>04:00:00</td>
<td>04:00:00</td>
<td>04:00:00</td>
</tr>
<tr>
<td></td>
<td>2019-04-09</td>
<td>05:00:00</td>
<td>05:00:00</td>
<td>05:00:00</td>
</tr>
</tbody>
</table>
```

I want to collect all air quality $NO_2$ measurements in a single column (long format)

```python
In [18]: no_2 = no2_pivoted.melt(id_vars="date.utc")

In [19]: no_2.head()
Out[19]:
<table>
<thead>
<tr>
<th>date.utc</th>
<th>location</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2019-04-09</td>
<td>BETR801</td>
<td>22.5</td>
</tr>
<tr>
<td>2019-04-09</td>
<td>BETR801</td>
<td>53.5</td>
</tr>
<tr>
<td>2019-04-09</td>
<td>BETR801</td>
<td>54.5</td>
</tr>
<tr>
<td>2019-04-09</td>
<td>BETR801</td>
<td>34.5</td>
</tr>
<tr>
<td>2019-04-09</td>
<td>BETR801</td>
<td>46.5</td>
</tr>
</tbody>
</table>
```

The `pandas.melt()` method on a DataFrame converts the data table from wide format to long format. The column headers become the variable names in a newly created column.

The solution is the short version on how to apply `pandas.melt()`. The method will *melt* all columns NOT mentioned in `id_vars` together into two columns: A column with the column header names and a column with the values itself. The latter column gets by default the name `value`.

The `pandas.melt()` method can be defined in more detail:

```python
In [20]: no_2 = no2_pivoted.melt(id_vars="date.utc",
                            value_vars=["BETR801",
                            "FR04014",
                            "London Westminster"],
                            value_name="NO_2",
                            var_name="id_location")

In [21]: no_2.head()
Out[21]:
<table>
<thead>
<tr>
<th>date.utc</th>
<th>id_location</th>
<th>NO_2</th>
</tr>
</thead>
<tbody>
<tr>
<td>2019-04-09</td>
<td>BETR801</td>
<td>22.5</td>
</tr>
<tr>
<td>2019-04-09</td>
<td>BETR801</td>
<td>53.5</td>
</tr>
<tr>
<td>2019-04-09</td>
<td>BETR801</td>
<td>54.5</td>
</tr>
<tr>
<td>2019-04-09</td>
<td>BETR801</td>
<td>34.5</td>
</tr>
<tr>
<td>2019-04-09</td>
<td>BETR801</td>
<td>46.5</td>
</tr>
</tbody>
</table>
```

The result in the same, but in more detail defined:

- `value_vars` defines explicitly which columns to *melt* together
pandas: powerful Python data analysis toolkit, Release 1.1.1

- value_name provides a custom column name for the values column instead of the default column name value
- var_name provides a custom column name for the column collecting the column header names. Otherwise it takes the index name or a default variable

Hence, the arguments value_name and var_name are just user-defined names for the two generated columns. The columns to melt are defined by id_vars and value_vars.

Conversion from wide to long format with pandas.melt() is explained in the user guide section on reshaping by melt.

- Sorting by one or more columns is supported by sort_values
- The pivot function is purely restructuring of the data, pivot_table supports aggregations
- The reverse of pivot (long to wide format) is melt (wide to long format)

A full overview is available in the user guide on the pages about reshaping and pivoting.

In [1]: import pandas as pd

For this tutorial, air quality data about NO2 is used, made available by openaq and downloaded using the py-openaq package.

The air_quality_no2_long.csv data set provides NO2 values for the measurement stations FR04014, BETR801 and London Westminster in respectively Paris, Antwerp and London.

In [2]: air_quality_no2 = pd.read_csv("data/air_quality_no2_long.csv",
   ...: parse_dates=True)
   ...

In [3]: air_quality_no2 = air_quality_no2["date.utc", "location",
   ...: "parameter", "value"]
   ...

In [4]: air_quality_no2.head()

Out[4]:

<table>
<thead>
<tr>
<th>date.utc</th>
<th>location</th>
<th>parameter</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2019-06-21</td>
<td>FR04014</td>
<td>no2</td>
<td>20.0</td>
</tr>
<tr>
<td>2019-06-20</td>
<td>FR04014</td>
<td>no2</td>
<td>21.8</td>
</tr>
<tr>
<td>2019-06-20</td>
<td>FR04014</td>
<td>no2</td>
<td>26.5</td>
</tr>
<tr>
<td>2019-06-20</td>
<td>FR04014</td>
<td>no2</td>
<td>24.9</td>
</tr>
<tr>
<td>2019-06-20</td>
<td>FR04014</td>
<td>no2</td>
<td>21.4</td>
</tr>
</tbody>
</table>

For this tutorial, air quality data about Particulate matter less than 2.5 micrometers is used, made available by openaq and downloaded using the py-openaq package.

The air_quality_pm25_long.csv data set provides PM25 values for the measurement stations FR04014, BETR801 and London Westminster in respectively Paris, Antwerp and London.

In [5]: air_quality_pm25 = pd.read_csv("data/air_quality_pm25_long.csv",
   ...: parse_dates=True)
   ...

In [6]: air_quality_pm25 = air_quality_pm25["date.utc", "location",
   ...: "parameter", "value"]
   ...

In [7]: air_quality_pm25.head()
How to combine data from multiple tables?

Concatenating objects

I want to combine the measurements of $NO_2$ and $PM_{25}$, two tables with a similar structure, in a single table:

```
In [8]: air_quality = pd.concat([air_quality_pm25, air_quality_no2], axis=0)

In [9]: air_quality.head()
```

```
Out[9]:
<table>
<thead>
<tr>
<th>date.utc</th>
<th>location</th>
<th>parameter</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2019-06-18 06:00:00+00:00</td>
<td>BETR801</td>
<td>pm25</td>
<td>18.0</td>
</tr>
<tr>
<td>2019-06-17 08:00:00+00:00</td>
<td>BETR801</td>
<td>pm25</td>
<td>6.5</td>
</tr>
<tr>
<td>2019-06-17 07:00:00+00:00</td>
<td>BETR801</td>
<td>pm25</td>
<td>18.5</td>
</tr>
<tr>
<td>2019-06-17 06:00:00+00:00</td>
<td>BETR801</td>
<td>pm25</td>
<td>16.0</td>
</tr>
<tr>
<td>2019-06-17 05:00:00+00:00</td>
<td>BETR801</td>
<td>pm25</td>
<td>7.5</td>
</tr>
</tbody>
</table>
```

The `concat()` function performs concatenation operations of multiple tables along one of the axis (row-wise or column-wise).

By default concatenation is along axis 0, so the resulting table combines the rows of the input tables. Let’s check the shape of the original and the concatenated tables to verify the operation:

```
In [10]: print('Shape of the `air_quality_pm25` table: ', air_quality_pm25.shape)
Shape of the `air_quality_pm25` table:  (1110, 4)

In [11]: print('Shape of the `air_quality_no2` table: ', air_quality_no2.shape)
Shape of the `air_quality_no2` table:  (2068, 4)

In [12]: print('Shape of the resulting `air_quality` table: ', air_quality.shape)
Shape of the resulting `air_quality` table:  (3178, 4)
```

Hence, the resulting table has $3178 = 1110 + 2068$ rows.

**Note:** The `axis` argument will return in a number of pandas methods that can be applied along an axis. A DataFrame has two corresponding axes: the first running vertically downwards across rows (axis 0), and the second running horizontally across columns (axis 1). Most operations like concatenation or summary statistics are by default across rows (axis 0), but can be applied across columns as well.

Sorting the table on the datetime information illustrates also the combination of both tables, with the parameter column defining the origin of the table (either `no2` from table `air_quality_no2` or `pm25` from table `air_quality_pm25`):
In [13]: `air_quality = air_quality.sort_values("date.utc")`

In [14]: `air_quality.head()`

Out[14]:

<table>
<thead>
<tr>
<th>date.utc</th>
<th>location</th>
<th>parameter</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2019-05-07 01:00:00</td>
<td>London Westminster</td>
<td>no2</td>
<td>23.0</td>
</tr>
<tr>
<td>2019-05-07 01:00:00</td>
<td>FR04014</td>
<td>no2</td>
<td>25.0</td>
</tr>
<tr>
<td>2019-05-07 01:00:00</td>
<td>BETR801</td>
<td>pm25</td>
<td>12.5</td>
</tr>
<tr>
<td>2019-05-07 01:00:00</td>
<td>BETR801</td>
<td>no2</td>
<td>50.5</td>
</tr>
<tr>
<td>2019-05-07 01:00:00</td>
<td>London Westminster</td>
<td>pm25</td>
<td>8.0</td>
</tr>
</tbody>
</table>

In this specific example, the `parameter` column provided by the data ensures that each of the original tables can be identified. This is not always the case. the `concat` function provides a convenient solution with the `keys` argument, adding an additional (hierarchical) row index. For example:

In [15]: `air_quality_ = pd.concat([air_quality_pm25, air_quality_no2], keys=["PM25", "NO2"],)`

In [16]: `air_quality_.head()`

Out[16]:

<table>
<thead>
<tr>
<th>date.utc</th>
<th>location</th>
<th>parameter</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2019-06-18 06:00:00</td>
<td>BETR801</td>
<td>pm25</td>
<td>18.0</td>
</tr>
<tr>
<td>2019-06-17 08:00:00</td>
<td>BETR801</td>
<td>pm25</td>
<td>6.5</td>
</tr>
<tr>
<td>2019-06-17 07:00:00</td>
<td>BETR801</td>
<td>pm25</td>
<td>18.5</td>
</tr>
<tr>
<td>2019-06-17 06:00:00</td>
<td>BETR801</td>
<td>pm25</td>
<td>16.0</td>
</tr>
<tr>
<td>2019-06-17 05:00:00</td>
<td>BETR801</td>
<td>pm25</td>
<td>7.5</td>
</tr>
</tbody>
</table>

Note: The existence of multiple row/column indices at the same time has not been mentioned within these tutorials. Hierarchical indexing or MultiIndex is an advanced and powerful pandas feature to analyze higher dimensional data. Multi-indexing is out of scope for this pandas introduction. For the moment, remember that the function `reset_index` can be used to convert any level of an index to a column, e.g. `air_quality.reset_index(level=0)`

Feel free to dive into the world of multi-indexing at the user guide section on advanced indexing.

More options on table concatenation (row and column wise) and how `concat` can be used to define the logic (union or intersection) of the indexes on the other axes is provided at the section on object concatenation.

Join tables using a common identifier

Add the station coordinates, provided by the stations metadata table, to the corresponding rows in the measurements table.

Warning: The air quality measurement station coordinates are stored in a data file `air_quality_stations.csv`, downloaded using the `py-openaq` package.

In [17]: `stations_coord = pd.read_csv("data/air_quality_stations.csv")`
In [18]: stations_coord.head()

Out[18]:
<table>
<thead>
<tr>
<th>location</th>
<th>coordinates.latitude</th>
<th>coordinates.longitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>BELAL01</td>
<td>51.23619</td>
<td>4.38522</td>
</tr>
<tr>
<td>BELHB23</td>
<td>51.17030</td>
<td>4.34100</td>
</tr>
<tr>
<td>BELLD01</td>
<td>51.10998</td>
<td>5.00486</td>
</tr>
<tr>
<td>BELLD02</td>
<td>51.12038</td>
<td>5.02155</td>
</tr>
<tr>
<td>BELR833</td>
<td>51.32766</td>
<td>4.36226</td>
</tr>
</tbody>
</table>

Note: The stations used in this example (FR04014, BETR801 and London Westminster) are just three entries enlisted in the metadata table. We only want to add the coordinates of these three to the measurements table, each on the corresponding rows of the `air_quality` table.

In [19]: air_quality.head()

Out[19]:
<table>
<thead>
<tr>
<th>date.utc</th>
<th>location</th>
<th>parameter</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2019-05-07 01:00:00+00:00</td>
<td>London Westminster</td>
<td>no2</td>
<td>23.0</td>
</tr>
<tr>
<td>2019-05-07 01:00:00+00:00</td>
<td>FR04014</td>
<td>no2</td>
<td>25.0</td>
</tr>
<tr>
<td>2019-05-07 01:00:00+00:00</td>
<td>BETR801</td>
<td>pm25</td>
<td>12.5</td>
</tr>
<tr>
<td>2019-05-07 01:00:00+00:00</td>
<td>BETR801</td>
<td>no2</td>
<td>50.5</td>
</tr>
<tr>
<td>2019-05-07 01:00:00+00:00</td>
<td>London Westminster</td>
<td>pm25</td>
<td>8.0</td>
</tr>
</tbody>
</table>

In [20]: air_quality = pd.merge(air_quality, stations_coord,

   ....:    how='left', on='location')

In [21]: air_quality.head()

Out[21]:
<table>
<thead>
<tr>
<th>date.utc</th>
<th>location</th>
<th>parameter</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2019-05-07 01:00:00+00:00</td>
<td>London Westminster</td>
<td>no2</td>
<td>23.0</td>
</tr>
<tr>
<td>2019-05-07 01:00:00+00:00</td>
<td>FR04014</td>
<td>no2</td>
<td>25.0</td>
</tr>
<tr>
<td>2019-05-07 01:00:00+00:00</td>
<td>BETR801</td>
<td>pm25</td>
<td>12.5</td>
</tr>
<tr>
<td>2019-05-07 01:00:00+00:00</td>
<td>BETR801</td>
<td>no2</td>
<td>50.5</td>
</tr>
<tr>
<td>2019-05-07 01:00:00+00:00</td>
<td>London Westminster</td>
<td>pm25</td>
<td>8.0</td>
</tr>
</tbody>
</table>

Using the `merge()` function, for each of the rows in the `air_quality` table, the corresponding coordinates are added from the `air_quality_stations_coord` table. Both tables have the column `location` in common which is used as a key to combine the information. By choosing the `left` join, only the locations available in the `air_quality` (left) table, i.e. FR04014, BETR801 and London Westminster, end up in the resulting table. The `merge` function supports multiple join options similar to database-style operations.

Add the parameter full description and name, provided by the parameters metadata table, to the measurements table

Warning: The air quality parameters metadata are stored in a data file `air_quality_parameters.csv`, downloaded using the `py-openaq` package.
In [22]: air_quality_parameters = pd.read_csv("data/air_quality_parameters.csv")

In [23]: air_quality_parameters.head()
Out[23]:
   id  description    name
0  bc  Black Carbon  BC
1  co  Carbon Monoxide  CO
2  no2  Nitrogen Dioxide  NO2
3  o3      Ozone      O3
4  pm10 Particulate matter less than 10 micrometers in...  PM10

In [24]: air_quality = pd.merge(air_quality, air_quality_parameters,
....:       how='left', left_on='parameter', right_on='id')
....:

In [25]: air_quality.head()
Out[25]:
   date.utc location parameter ... id
   description name
0  2019-05-07 01:00:00+00:00 London Westminster  no2 ... no2
1  2019-05-07 01:00:00+00:00 Nitrogen Dioxide  NO2
2  2019-05-07 01:00:00+00:00 Nitrogen Dioxide  NO2
3  2019-05-07 01:00:00+00:00 Nitrogen Dioxide  NO2
4  2019-05-07 01:00:00+00:00 BETR801 Particulate...  PM2.5
   description name
0  Nitrogen Dioxide  NO2
1  Nitrogen Dioxide  NO2
2  Nitrogen Dioxide  NO2
3  Particulate matter less than 2.5 micrometers in...  PM2.5
4  Nitrogen Dioxide  NO2

Compared to the previous example, there is no common column name. However, the parameter column in the air_quality table and the id column in the air_quality_parameters_name both provide the measured variable in a common format. The left_on and right_on arguments are used here (instead of just on) to make the link between the two tables.

pandas supports also inner, outer, and right joins. More information on join/merge of tables is provided in the user guide section on database style merging of tables. Or have a look at the comparison with SQL page.

• Multiple tables can be concatenated both column-wise and row-wise using the concat function.
  • For database-like merging/joining of tables, use the merge function.

See the user guide for a full description of the various facilities to combine data tables.

In [1]: import pandas as pd

In [2]: import matplotlib.pyplot as plt

For this tutorial, air quality data about NO₂ and Particulate matter less than 2.5 micrometers is used, made available by openaq and downloaded using the py-openaq package. The air_quality_no2_long.csv" data set provides NO₂ values for the measurement stations FR04014, BETR801 and London Westminster in respectively Paris, Antwerp and London.

In [3]: air_quality = pd.read_csv("data/air_quality_no2_long.csv")

In [4]: air_quality = air_quality.rename(columns={"date.utc": "datetime"})
How to handle time series data with ease?

Using pandas datetime properties

I want to work with the dates in the column `datetime` as datetime objects instead of plain text.

```
In [7]: air_quality["datetime"] = pd.to_datetime(air_quality["datetime"])  
Out[8]:
```

Initially, the values in `datetime` are character strings and do not provide any datetime operations (e.g. extract the year, day of the week,...). By applying the `to_datetime` function, pandas interprets the strings and convert these to datetime (i.e. `datetime64[ns, UTC]`) objects. In pandas we call these datetime objects similar to `datetime` from the standard library as `pandas.Timestamp`.

**Note:** As many data sets do contain datetime information in one of the columns, pandas input function like `pandas.read_csv()` and `pandas.read_json()` can do the transformation to dates when reading the data using the `parse_dates` parameter with a list of the columns to read as Timestamp:

```
pd.read_csv("../data/air_quality_no2_long.csv", parse_dates=["datetime"])  
```

Why are these `pandas.Timestamp` objects useful? Let’s illustrate the added value with some example cases.

What is the start and end date of the time series data set we are working with?
Using `pandas.Timestamp` for datetimes enables us to calculate with date information and make them comparable. Hence, we can use this to get the length of our time series:

```python
In [10]: air_quality["datetime"].max() - air_quality["datetime"].min()
Out[10]: Timedelta('44 days 23:00:00')
```

The result is a `pandas.Timedelta` object, similar to `datetime.timedelta` from the standard Python library and defining a time duration.

The various time concepts supported by pandas are explained in the user guide section on time related concepts.

I want to add a new column to the DataFrame containing only the month of the measurement

```python
In [11]: air_quality["month"] = air_quality["datetime"].dt.month
In [12]: air_quality.head()
```

<table>
<thead>
<tr>
<th>city</th>
<th>country</th>
<th>datetime</th>
<th>location</th>
<th>parameter</th>
<th>value</th>
<th>unit</th>
<th>month</th>
</tr>
</thead>
<tbody>
<tr>
<td>Paris</td>
<td>FR</td>
<td>2019-06-21 00:00:00+0000</td>
<td>FR04014</td>
<td>no2</td>
<td>20.0</td>
<td>µg/m³</td>
<td>6</td>
</tr>
<tr>
<td>Paris</td>
<td>FR</td>
<td>2019-06-20 23:00:00+0000</td>
<td>FR04014</td>
<td>no2</td>
<td>21.8</td>
<td>µg/m³</td>
<td>6</td>
</tr>
<tr>
<td>Paris</td>
<td>FR</td>
<td>2019-06-20 22:00:00+0000</td>
<td>FR04014</td>
<td>no2</td>
<td>26.5</td>
<td>µg/m³</td>
<td>6</td>
</tr>
<tr>
<td>Paris</td>
<td>FR</td>
<td>2019-06-20 21:00:00+0000</td>
<td>FR04014</td>
<td>no2</td>
<td>24.9</td>
<td>µg/m³</td>
<td>6</td>
</tr>
<tr>
<td>Paris</td>
<td>FR</td>
<td>2019-06-20 20:00:00+0000</td>
<td>FR04014</td>
<td>no2</td>
<td>21.4</td>
<td>µg/m³</td>
<td>6</td>
</tr>
</tbody>
</table>

By using Timestamp objects for dates, a lot of time-related properties are provided by pandas. For example the month, but also year, weekofyear, quarter... All of these properties are accessible by the `dt` accessor.

An overview of the existing date properties is given in the time and date components overview table. More details about the `dt` accessor to return datetime like properties are explained in a dedicated section on the `dt accessor`.

What is the average $NO_2$ concentration for each day of the week for each of the measurement locations?

```python
In [13]: air_quality.groupby(
      ....: [air_quality["datetime"].dt.weekday, "location"])
       ....: ["value"]).mean()
Out[13]:
```

<table>
<thead>
<tr>
<th>datetime</th>
<th>location</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2019-05-07 01:00:00+0000</td>
<td>BETR801</td>
<td>27.875000</td>
</tr>
<tr>
<td>2019-05-07 01:00:00+0000</td>
<td>FR04014</td>
<td>24.856250</td>
</tr>
<tr>
<td>2019-05-07 01:00:00+0000</td>
<td>London Westminster</td>
<td>23.969697</td>
</tr>
<tr>
<td>2019-05-07 01:00:00+0000</td>
<td>BETR801</td>
<td>22.214286</td>
</tr>
<tr>
<td>2019-05-07 01:00:00+0000</td>
<td>FR04014</td>
<td>30.999359</td>
</tr>
<tr>
<td>2019-05-07 01:00:00+0000</td>
<td>London Westminster</td>
<td>24.859155</td>
</tr>
<tr>
<td>2019-05-07 01:00:00+0000</td>
<td>BETR801</td>
<td>21.896552</td>
</tr>
<tr>
<td>2019-05-07 01:00:00+0000</td>
<td>FR04014</td>
<td>23.274306</td>
</tr>
<tr>
<td>2019-05-07 01:00:00+0000</td>
<td>London Westminster</td>
<td>24.859155</td>
</tr>
</tbody>
</table>

Remember the split-apply-combine pattern provided by `groupby` from the tutorial on statistics calculation? Here, we want to calculate a given statistic (e.g. mean $NO_2$) for each weekday and for each measurement location. To group on weekdays, we use the datetime property `weekday` (with Monday=0 and Sunday=6) of pandas Timestamp,
which is also accessible by the dt accessor. The grouping on both locations and weekdays can be done to split the calculation of the mean on each of these combinations.

**Danger:** As we are working with a very short time series in these examples, the analysis does not provide a long-term representative result!

Plot the typical $NO_2$ pattern during the day of our time series of all stations together. In other words, what is the average value for each hour of the day?

```python
In [14]: fig, axs = plt.subplots(figsize=(12, 4))

In [15]: air_quality.groupby(......: air_quality["datetime"].dt.hour)["value"].mean().plot(kind='bar',......: rot=0,......: ax=axs)

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe2a7c8ff70>

In [16]: plt.xlabel("Hour of the day"); # custom x label using matplotlib

In [17]: plt.ylabel("$NO_2 (\mu g/m^3)$");
```

Similar to the previous case, we want to calculate a given statistic (e.g. mean $NO_2$) for each hour of the day and we can use the split-apply-combine approach again. For this case, we use the datetime property hour of pandas Timestamp, which is also accessible by the dt accessor.

**Datet ime as index**

In the tutorial on reshaping, pivot() was introduced to reshape the data table with each of the measurements locations as a separate column:

```python
In [18]: no_2 = air_quality.pivot(index="datetime", columns="location", values="value ")

In [19]: no_2.head()
Out[19]:
<table>
<thead>
<tr>
<th>location</th>
<th>BETR801</th>
<th>FR04014</th>
<th>London Westminster</th>
</tr>
</thead>
<tbody>
<tr>
<td>datetime</td>
<td>2019-05-07 01:00:00+00:00</td>
<td>50.5</td>
<td>25.0</td>
</tr>
</tbody>
</table>

(continues on next page)
2019-05-07 02:00:00+00:00 45.0 27.7 19.0
2019-05-07 03:00:00+00:00 NaN 50.4 19.0
2019-05-07 04:00:00+00:00 NaN 61.9 16.0
2019-05-07 05:00:00+00:00 NaN 72.4 NaN

Note: By pivoting the data, the datetime information became the index of the table. In general, setting a column as an index can be achieved by the `set_index` function.

Working with a datetime index (i.e. `DateTimeIndex`) provides powerful functionalities. For example, we do not need the `dt` accessor to get the time series properties, but have these properties available on the index directly:

```
In [20]: no_2.index.year, no_2.index.weekday
Out[20]:
(Int64Index([2019, 2019, 2019, 2019, 2019, 2019, 2019, 2019, 2019, 2019,
             ...
            dtype='int64', name='datetime', length=1033),
Int64Index([1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
             ...
             3, 3, 3, 3, 3, 3, 3, 3, 4],
            dtype='int64', name='datetime', length=1033))
```

Some other advantages are the convenient subsetting of time period or the adapted time scale on plots. Let’s apply this on our data.

Create a plot of the NO₂ values in the different stations from the 20th of May till the end of 21st of May

```
In [21]: no_2["2019-05-20":"2019-05-21"].plot();
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

By providing a **string that parses to a datetime**, a specific subset of the data can be selected on a `DatetimeIndex`. More information on the `DatetimeIndex` and the slicing by using strings is provided in the section on time series indexing.

### Resample a time series to another frequency

Aggregate the current hourly time series values to the monthly maximum value in each of the stations.

```
In [22]: monthly_max = no_2.resample("M").max()
```

```
In [23]: monthly_max
```

```
Out[23]:

<table>
<thead>
<tr>
<th>location</th>
<th>BETR801</th>
<th>FR04014</th>
<th>London Westminster</th>
</tr>
</thead>
<tbody>
<tr>
<td>location</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>datetime</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2019-05-31 00:00:00</td>
<td>74.5</td>
<td>97.0</td>
<td>97.0</td>
</tr>
<tr>
<td>2019-06-30 00:00:00</td>
<td>52.5</td>
<td>84.7</td>
<td>52.0</td>
</tr>
</tbody>
</table>
```

A very powerful method on time series data with a datetime index, is the ability to `resample()` time series to another frequency (e.g., converting secondly data into 5-minutely data).

The `resample()` method is similar to a groupby operation:

- it provides a time-based grouping, by using a string (e.g. M, 5H,...) that defines the target frequency
- it requires an aggregation function such as `mean`, `max`,...
An overview of the aliases used to define time series frequencies is given in the offset aliases overview table. When defined, the frequency of the time series is provided by the `freq` attribute:

```python
In [24]: monthly_max.index.freq
Out[24]: <MonthEnd>
```

Make a plot of the daily mean NO₂ value in each of the stations.

```python
In [25]: no_2.resample("D").mean().plot(style="-o", figsize=(10, 5));
```

More details on the power of time series resampling is provided in the user guide section on resampling.

- Valid date strings can be converted to datetime objects using `to_datetime` function or as part of read functions.
- Datetime objects in pandas support calculations, logical operations and convenient date-related properties using the `dt` accessor.
- A `DatetimeIndex` contains these date-related properties and supports convenient slicing.
- `Resample` is a powerful method to change the frequency of a time series.

A full overview on time series is given on the pages on time series and date functionality.

```python
In [1]: import pandas as pd
```

This tutorial uses the Titanic data set, stored as CSV. The data consists of the following data columns:

- **PassengerId**: Id of every passenger.
- **Survived**: This feature have value 0 and 1. 0 for not survived and 1 for survived.
- **Pclass**: There are 3 classes: Class 1, Class 2 and Class 3.
- **Name**: Name of passenger.
- **Sex**: Gender of passenger.
- **Age**: Age of passenger.
• SibSp: Indication that passenger have siblings and spouse.
• Parch: Whether a passenger is alone or have family.
• Ticket: Ticket number of passenger.
• Fare: Indicating the fare.
• Cabin: The cabin of passenger.
• Embarked: The embarked category.

```python
In [2]: titanic = pd.read_csv("data/titanic.csv")

In [3]: titanic.head()
Out[3]:
   PassengerId  Survived  Pclass       Name                  Sex  ...  Parch Ticket  Fare    Cabin  Embarked
0           1         0        3  Braund, Mr. Owen Harris  male ...  0   A/5 21171   7.2500 NaN    S
1           2         1        1  Cumings, Mrs. John Bradley  female ...  0    PC 17599  71.2833   C85   C
2           3         1        3  Heikkinen, Miss. Laina  female ...  0 STON/O2.3101282   7.9250 NaN    S
3           4         1        1  Futrelle, Mrs. Jacques Heath (Lily May Peel)  female ...  0   113803  53.1000  C123   S
4           5         0        3  Allen, Mr. William Henry  male ...  0   373450   8.0500 NaN    S

[5 rows x 12 columns]
```

How to manipulate textual data?

Make all name characters lowercase

```python
In [4]: titanic["Name"].str.lower()
Out[4]:
0 braund, mr. owen harris
1 cumings, mrs. john bradley (florence briggs th...
2 heikkinen, miss. laina
3 futrelle, mrs. jacques heath (lily may peel)
4 allen, mr. william henry
...
886 montvila, rev. juozas
887 graham, miss. margaret edith
888 johnston, miss. catherine helen "carrie"
889 behr, mr. karl howell
890 dooley, mr. patrick
Name: Name, Length: 891, dtype: object
```

To make each of the strings in the Name column lowercase, select the Name column (see tutorial on selection of data), add the str accessor and apply the lower method. As such, each of the strings is converted element wise.

Similar to datetime objects in the time series tutorial having a dt accessor, a number of specialized string methods are available when using the str accessor. These methods have in general matching names with the equivalent built-in string methods for single elements, but are applied element-wise (remember element wise calculations?) on each of the values of the columns.

Create a new column Surname that contains the surname of the Passengers by extracting the part before the comma.
Using the `Series.str.split()` method, each of the values is returned as a list of 2 elements. The first element is the part before the comma and the second element is the part after the comma.

As we are only interested in the first part representing the surname (element 0), we can again use the `str` accessor and apply `Series.str.get()` to extract the relevant part. Indeed, these string functions can be concatenated to combine multiple functions at once!

More information on extracting parts of strings is available in the user guide section on *splitting and replacing strings*.

Extract the passenger data about the Countesses on board of the Titanic.
In [9]: titanic[titanic["Name"].str.contains("Countess")]
Out[9]:
<table>
<thead>
<tr>
<th>PassengerId</th>
<th>Survived</th>
<th>Pclass</th>
<th>Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>759</td>
<td>760</td>
<td>1</td>
<td>Rothes, the Countess. of (Lucy Noel Martha Dye...</td>
</tr>
</tbody>
</table>


The string method `Series.str.contains()` checks for each of the values in the column `Name` if the string contains the word `Countess` and returns for each of the values `True` (`Countess` is part of the name) or `False` (`Countess` is not part of the name). This output can be used to subselect the data using conditional (boolean) indexing introduced in the subsetting of data tutorial. As there was only one Countess on the Titanic, we get one row as a result.

**Note:** More powerful extractions on strings are supported, as the `Series.str.contains()` and `Series.str.extract()` methods accept regular expressions, but out of scope of this tutorial.

More information on extracting parts of strings is available in the user guide section on string matching and extracting.

Which passenger of the Titanic has the longest name?

In [10]: titanic["Name"].str.len()
Out[10]:
<table>
<thead>
<tr>
<th></th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>23</td>
<td>51</td>
<td>22</td>
<td>44</td>
<td>24</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>866</td>
<td>21</td>
<td>28</td>
<td>40</td>
<td>21</td>
<td>19</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Name: Name, Length: 891, dtype: int64

To get the longest name we first have to get the lengths of each of the names in the `Name` column. By using pandas string methods, the `Series.str.len()` function is applied to each of the names individually (element-wise).

In [11]: titanic["Name"].str.len().idxmax()
Out[11]:

Next, we need to get the corresponding location, preferably the index label, in the table for which the name length is the largest. The `idxmax()` method does exactly that. It is not a string method and is applied to integers, so no `str` is used.

In [12]: titanic.loc[titanic["Name"].str.len().idxmax(), "Name"]
Out[12]: 'Penasco y Castellana, Mrs. Victor de Satode (Maria Josefa Perez de Soto y Vallejo)'

Based on the index name of the row (307) and the column (Name), we can do a selection using the `loc` operator, introduced in the tutorial on subsetting.

In the “Sex” column, replace values of “male” by “M” and values of “female” by “F”
Whereas `replace()` is not a string method, it provides a convenient way to use mappings or vocabularies to translate certain values. It requires a dictionary to define the mapping `{from: to}`.

**Warning:** There is also a `replace()` method available to replace a specific set of characters. However, when having a mapping of multiple values, this would become:

```python
In [13]: titanic["Sex_short"] = titanic["Sex"].str.replace("female", "F")
In [14]: titanic["Sex_short"]
```

This would become cumbersome and easily lead to mistakes. Just think (or try out yourself) what would happen if those two statements are applied in the opposite order...

- String methods are available using the `str` accessor.
- String methods work element wise and can be used for conditional indexing.
- The `replace` method is a convenient method to convert values according to a given dictionary.

A full overview is provided in the user guide pages on *working with text data*.

### 1.4.4 Comparison with other tools

#### Comparison with R / R libraries

Since pandas aims to provide a lot of the data manipulation and analysis functionality that people use R for, this page was started to provide a more detailed look at the R language and its many third party libraries as they relate to pandas. In comparisons with R and CRAN libraries, we care about the following things:

- **Functionality / flexibility:** what can/cannot be done with each tool
- **Performance:** how fast are operations. Hard numbers/benchmarks are preferable
- **Ease-of-use:** Is one tool easier/harder to use (you may have to be the judge of this, given side-by-side code comparisons)

This page is also here to offer a bit of a translation guide for users of these R packages.

For transfer of DataFrame objects from pandas to R, one option is to use HDF5 files, see *External compatibility* for an example.
Quick reference

We’ll start off with a quick reference guide pairing some common R operations using **dplyr** with pandas equivalents.

### Querying, filtering, sampling

<table>
<thead>
<tr>
<th>R</th>
<th>pandas</th>
</tr>
</thead>
<tbody>
<tr>
<td>dim(df)</td>
<td>df.shape</td>
</tr>
<tr>
<td>head(df)</td>
<td>df.head()</td>
</tr>
<tr>
<td>slice(df, 1:10)</td>
<td>df.iloc[:9]</td>
</tr>
<tr>
<td>filter(df, coll == 1, col2 == 1)</td>
<td>df.query('coll == 1 &amp; col2 == 1')</td>
</tr>
<tr>
<td>df[df$coll == 1 &amp; df$col2 == 1,]</td>
<td>df[(df.$coll == 1) &amp; (df.$col2 == 1)]</td>
</tr>
<tr>
<td>select(df, col1, col2)</td>
<td>df[['col1', 'col2']]]</td>
</tr>
<tr>
<td>select(df, col1:col3)</td>
<td>df.loc[:,'col1':'col3']</td>
</tr>
<tr>
<td>select(df, -(col1:col3))</td>
<td>df.drop(cols_to_drop, axis=1) but see</td>
</tr>
<tr>
<td>distinct(select(df, col1))</td>
<td>df[['col1']].drop_duplicates()</td>
</tr>
<tr>
<td>distinct(select(df, col1, col2))</td>
<td>df[['col1', 'col2']].drop_duplicates()</td>
</tr>
<tr>
<td>sample_n(df, 10)</td>
<td>df.sample(n=10)</td>
</tr>
<tr>
<td>sample_frac(df, 0.01)</td>
<td>df.sample(frac=0.01)</td>
</tr>
</tbody>
</table>

### Sorting

<table>
<thead>
<tr>
<th>R</th>
<th>pandas</th>
</tr>
</thead>
<tbody>
<tr>
<td>arrange(df, col1, col2)</td>
<td>df.sort_values(['col1', 'col2'])</td>
</tr>
<tr>
<td>arrange(df, desc(col1))</td>
<td>df.sort_values('col1', ascending=False)</td>
</tr>
</tbody>
</table>

### Transforming

<table>
<thead>
<tr>
<th>R</th>
<th>pandas</th>
</tr>
</thead>
<tbody>
<tr>
<td>select(df, col_one = col1)</td>
<td>df.rename(columns={'col1': 'col_one'})[['col_one']]</td>
</tr>
<tr>
<td>rename(df, col_one = col1)</td>
<td>df.rename(columns={'col1': 'col_one'})</td>
</tr>
<tr>
<td>mutate(df, c=a-b)</td>
<td>df.assign(c=df['a']-df['b'])</td>
</tr>
</tbody>
</table>

---

1. R’s shorthand for a subrange of columns (select(df, col1:col3)) can be approached cleanly in pandas, if you have the list of columns, for example df[cols[1:3]] or df.drop(cols[1:3]), but doing this by column name is a bit messy.
Grouping and summarizing

<table>
<thead>
<tr>
<th>R</th>
<th>pandas</th>
</tr>
</thead>
<tbody>
<tr>
<td>summary(df)</td>
<td>df.describe()</td>
</tr>
<tr>
<td>gdf &lt;- group_by(df, col1)</td>
<td>gdf = df.groupby('col1')</td>
</tr>
<tr>
<td>summarise(gdf, avg=mean(col1, na.</td>
<td>df.groupby('col1').agg({'col1': 'mean'})</td>
</tr>
<tr>
<td>rm=TRUE))</td>
<td></td>
</tr>
<tr>
<td>summarise(gdf, total=sum(col1))</td>
<td>df.groupby('col1').sum()</td>
</tr>
</tbody>
</table>

Base R

Slicing with R's c

R makes it easy to access data.frame columns by name

```r
df <- data.frame(a=rnorm(5), b=rnorm(5), c=rnorm(5), d=rnorm(5), e=rnorm(5))
df[, c("a", "c", "e")]
```

or by integer location

```r
df <- data.frame(matrix(rnorm(1000), ncol=100))
df[, c(1:10, 25:30, 40, 50:100)]
```

Selecting multiple columns by name in pandas is straightforward

```python
In [1]: df = pd.DataFrame(np.random.randn(10, 3), columns=list('abc'))
In [2]: df[['a', 'c']]  
Out[2]:      a         c
0  0.469112  -1.509059
1 -1.135632  -0.173215
2  0.119209   0.861849
3 -2.104569   1.071804
4  0.721555  -1.039575
5  0.271860   0.567020
6  0.276232  -0.673690
7  0.113648   0.524988
8  0.404705  -1.715002
9 -1.039268  -1.157892
```

```python
In [3]: df.loc[:, ['a', 'c']]  
Out[3]:      a         c
0  0.469112  -1.509059
1 -1.135632  -0.173215
2  0.119209   0.861849
3 -2.104569   1.071804
4  0.721555  -1.039575
5  0.271860   0.567020
6  0.276232  -0.673690
7  0.113648   0.524988
8  0.404705  -1.715002
9 -1.039268  -1.157892
```
Selecting multiple noncontiguous columns by integer location can be achieved with a combination of the `iloc` indexer attribute and `numpy.r_`.

```python
In [4]: named = list('abcdefg')
In [5]: n = 30
In [6]: columns = named + np.arange(len(named), n).tolist()
In [7]: df = pd.DataFrame(np.random.randn(n, n), columns=columns)
In [8]: df.iloc[:, np.r_[:10, 24:30]]
```

Out[8]:

```
  a   b   c   d   e   f   g ...  
--- --- --- --- --- --- --- ... ---
 0  1.344312  0.844885  1.075770 -0.109050  1.643563  -1.469388  0.357021 ... -0.248447  0.432390  1.519970 -0.493460  0.600178  0.274230  0.132885 -0.023688  2.410179  1.450520  0.206053 -0.251905 -2.213588  0.00...```

[30 rows x 16 columns]

aggregate

In R you may want to split data into subsets and compute the mean for each. Using a `data.frame` called `df` and splitting it into groups by `by1` and `by2`:

```r
df <- data.frame(
  v1 = c(1,3,5,7,8,3,5,NA,4,5,7,9),
  v2 = c(11,33,55,77,88,33,55,NA,44,55,77,99),
  by1 = c("red", "blue", 1, 2, NA, "big", 1, 2, \"red\", 1, NA, 12),
  by2 = c("wet", \"dry\", 99, 95, NA, \"damp\", 95, 99, \"red\", 99, NA, NA))
aggregate(x=df[, c("v1", \"v2\")], by=list(mydf2$by1, mydf2$by2), FUN = mean)
```

The `groupby()` method is similar to base R `aggregate` function.
...:  
  'v2': [11, 33, 55, 77, 88, 33, 55, np.nan, 44, 55, 77, 99],
  'by1': ["red", "blue", 1, 2, np.nan, "big", 1, 2, "red", 1, np.nan, 12],
  'by2': ["wet", "dry", 99, 95, np.nan, "damp", 95, 99, "red", 99, np.nan, np.nan])

In [10]: g = df.groupby(['by1', 'by2'])

In [11]: g[['v1', 'v2']].mean()

Out[11]:

<table>
<thead>
<tr>
<th>by1</th>
<th>by2</th>
<th>v1</th>
<th>v2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>95</td>
<td>5.0</td>
<td>55.0</td>
</tr>
<tr>
<td>2</td>
<td>95</td>
<td>7.0</td>
<td>77.0</td>
</tr>
<tr>
<td>99</td>
<td>NaN</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>big</td>
<td>damp</td>
<td>3.0</td>
<td>33.0</td>
</tr>
<tr>
<td>blue</td>
<td>dry</td>
<td>3.0</td>
<td>33.0</td>
</tr>
<tr>
<td>red</td>
<td>red</td>
<td>4.0</td>
<td>44.0</td>
</tr>
<tr>
<td>wet</td>
<td></td>
<td>1.0</td>
<td>11.0</td>
</tr>
</tbody>
</table>

For more details and examples see the **groupby documentation**.

**match/%in%**

A common way to select data in R is using `%in%` which is defined using the function `match`. The operator `%in%` is used to return a logical vector indicating if there is a match or not:

```r
s <- 0:4
s %in% c(2,4)
```

The `isin()` method is similar to R `%in%` operator:

```python
In [12]: s = pd.Series(np.arange(5), dtype=np.float32)
In [13]: s.isin([2, 4])
```

The `match` function returns a vector of the positions of matches of its first argument in its second:

```python
s <- 0:4
match(s, c(2,4))
```

For more details and examples see the **reshaping documentation**.
tapply

tapply is similar to aggregate, but data can be in a ragged array, since the subclass sizes are possibly irregular. Using a data.frame called baseball, and retrieving information based on the array team:

```r
baseball <-
  data.frame(team = gl(5, 5,
                 labels = paste("Team", LETTERS[1:5]),
                 player = sample(letters, 25),
                 batting.average = runif(25, .200, .400))
tapply(baseball$batting.average, baseball.example$team,
       max)
```

In pandas we may use `pivot_table()` method to handle this:

```python
In [14]: import random
In [15]: import string
In [16]: baseball = pd.DataFrame(
   .....:   {'team': ['team %d' % (x + 1) for x in range(5)] * 5,
   .....:   'player': random.sample(list(string.ascii_lowercase), 25),
   .....:   'batting avg': np.random.uniform(.200, .400, 25))
In [17]: baseball.pivot_table(values='batting avg', columns='team', aggfunc=np.max)
```

For more details and examples see the reshaping documentation.

subset

The `query()` method is similar to the base R `subset` function. In R you might want to get the rows of a data.frame where one column’s values are less than another column’s values:

```r
df <- data.frame(a=rnorm(10), b=rnorm(10))
subset(df, a <= b)
df[df$a <= df$b,]  # note the comma
```

In pandas, there are a few ways to perform subsetting. You can use `query()` or pass an expression as if it were an index/slice as well as standard boolean indexing:

```python
In [18]: df = pd.DataFrame({'a': np.random.randn(10), 'b': np.random.randn(10)})
In [19]: df.query('a <= b')
Out[19]:
   a    b
1  1.174950  0.552887
2 -0.023167  0.148084
3 -0.495291 -0.300218
4 -0.860736  0.197378
5  1.134146  1.720780
6 -0.290098  0.083515
```

(continues on next page)
For more details and examples see [the query documentation](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html).

**with**

An expression using a data.frame called `df` in R with the columns `a` and `b` would be evaluated using `with` like so:

```r
df <- data.frame(a=rnorm(10), b=rnorm(10))
with(df, a + b)
```

In pandas the equivalent expression, using the `eval()` method, would be:

```python
In [22]: df = pd.DataFrame({'a': np.random.randn(10), 'b': np.random.randn(10)})
In [23]: df.eval('a + b')
Out[23]:
   a    b
0 -0.091430
1 -2.483890
2 -0.252728
3 -0.626444
4 -0.261740
5  2.149503
6 -0.332214
7  0.799331
8 -2.377245
9  2.104677
dtype: float64
```

```python
In [24]: df['a'] + df['b']  # same as the previous expression
Out[24]:
   0 -0.091430
   1 -2.483890
   2 -0.252728
   3 -0.626444
   4 -0.261740
   5  2.149503
   6 -0.332214
   7  0.799331
   8 -2.377245
   9  2.104677
```

(continues on next page)
pandas: powerful Python data analysis toolkit, Release 1.1.1

In certain cases `eval()` will be much faster than evaluation in pure Python. For more details and examples see the `eval` documentation.

plyr

plyr is an R library for the split-apply-combine strategy for data analysis. The functions revolve around three data structures in R, `a` for arrays, `l` for lists, and `d` for data.frame. The table below shows how these data structures could be mapped in Python.

<table>
<thead>
<tr>
<th>R</th>
<th>Python</th>
</tr>
</thead>
<tbody>
<tr>
<td>array</td>
<td>list</td>
</tr>
<tr>
<td>lists</td>
<td>dictionary or list of objects</td>
</tr>
<tr>
<td>data.frame</td>
<td>dataframe</td>
</tr>
</tbody>
</table>

dplyp

An expression using a data.frame called df in R where you want to summarize `x` by `month`:

```r
require(plyr)
df <- data.frame(
    x = runif(120, 1, 168),
    y = runif(120, 7, 334),
    z = runif(120, 1.7, 20.7),
    month = rep(c(5, 6, 7, 8), 30),
    week = sample(1:4, 120, TRUE)
)
dply(df, .(month, week), summarize,
    mean = round(mean(x), 2),
    sd = round(sd(x), 2))
```

In pandas the equivalent expression, using the `groupby()` method, would be:

```python
In [25]: df = pd.DataFrame({'x': np.random.uniform(1., 168., 120),
                        'y': np.random.uniform(7., 334., 120),
                        'z': np.random.uniform(1.7, 20.7, 120),
                        'month': [5, 6, 7, 8] * 30,
                        'week': np.random.randint(1, 4, 120)})

In [26]: grouped = df.groupby(['month', 'week'])
```

(continues on next page)
In [27]: grouped['x'].agg([np.mean, np.std])
Out[27]:

<table>
<thead>
<tr>
<th></th>
<th>mean</th>
<th>std</th>
</tr>
</thead>
<tbody>
<tr>
<td>month week</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>63.653367</td>
<td>40.601965</td>
</tr>
<tr>
<td>2</td>
<td>78.126605</td>
<td>53.342400</td>
</tr>
<tr>
<td>3</td>
<td>92.091886</td>
<td>57.630110</td>
</tr>
<tr>
<td>6</td>
<td>81.747070</td>
<td>54.339218</td>
</tr>
<tr>
<td>2</td>
<td>70.971205</td>
<td>54.687287</td>
</tr>
<tr>
<td>3</td>
<td>100.968344</td>
<td>54.010081</td>
</tr>
<tr>
<td>7</td>
<td>61.576332</td>
<td>38.844274</td>
</tr>
<tr>
<td>2</td>
<td>61.733510</td>
<td>48.209013</td>
</tr>
<tr>
<td>3</td>
<td>71.688795</td>
<td>37.595638</td>
</tr>
<tr>
<td>8</td>
<td>62.741922</td>
<td>34.618153</td>
</tr>
<tr>
<td>2</td>
<td>91.774627</td>
<td>49.790202</td>
</tr>
<tr>
<td>3</td>
<td>73.936856</td>
<td>60.773900</td>
</tr>
</tbody>
</table>

For more details and examples see the groupby documentation.

**reshape / reshape2**

**melt.array**

An expression using a 3 dimensional array called `a` in R where you want to melt it into a data.frame:

```r
a <- array(c(1:23, NA, c(2,3,4))
data.frame(melt(a))
```

In Python, since `a` is a list, you can simply use list comprehension.

```python
In [28]: a = np.array(list(range(1, 24)) + [np.NAN]).reshape(2, 3, 4)

In [29]: pd.DataFrame([tuple(list(x) + [val]) for x, val in np.ndenumerate(a)])
Out[29]:

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>19</td>
<td>1</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>20</td>
<td>1</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>21</td>
<td>1</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>22</td>
<td>1</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>23</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
</tbody>
</table>

[24 rows x 4 columns]
melt.list

An expression using a list called `a` in R where you want to melt it into a data.frame:

```r
a <- as.list(c(1:4, NA))
data.frame(melt(a))
```

In Python, this list would be a list of tuples, so `DataFrame()` method would convert it to a dataframe as required.

```python
In [30]: a = list(enumerate(list(range(1, 5)) + [np.NAN]))
In [31]: pd.DataFrame(a)
Out[31]:
   0 1
0 0 1.0
1 1 2.0
2 2 3.0
3 3 4.0
4 4 NaN
```

For more details and examples see the Into to Data Structures documentation.

melt.data.frame

An expression using a data.frame called `cheese` in R where you want to reshape the data.frame:

```r
cheese <- data.frame(
  first = c('John', 'Mary'),
  last = c('Doe', 'Bo'),
  height = c(5.5, 6.0),
  weight = c(130, 150)
)
melt(cheese, id=c("first", "last"))
```

In Python, the `melt()` method is the R equivalent:

```python
In [32]: cheese = pd.DataFrame({'first': ['John', 'Mary'],
                          'last': ['Doe', 'Bo'],
                          'height': [5.5, 6.0],
                          'weight': [130, 150]})
In [33]: pd.melt(cheese, id_vars=['first', 'last'])
Out[33]:
   first last variable value
0   John Doe   height   5.5
1   Mary   Bo   height   6.0
2   John Doe     weight  130.0
3   Mary   Bo     weight  150.0
```

In [34]: cheese.set_index(['first', 'last']).stack()  # alternative way
```

(continues on next page)

1.4. Tutorials

67
weight 150.0
dtype: float64

For more details and examples see the reshaping documentation.

**cast**

In R `acast` is an expression using a data.frame called `df` in R to cast into a higher dimensional array:

```r
df <- data.frame(
  x = runif(12, 1, 168),
  y = runif(12, 7, 334),
  z = runif(12, 1.7, 20.7),
  month = rep(c(5, 6, 7), 4),
  week = rep(c(1, 2), 6)
)

mdf <- melt(df, id=c("month", "week"))
acast(mdf, week ~ month ~ variable, mean)
```

In Python the best way is to make use of `pivot_table()`:

```python
In [35]: df = pd.DataFrame({'x': np.random.uniform(1., 168., 12),
                   'y': np.random.uniform(7., 334., 12),
                   'z': np.random.uniform(1.7, 20.7, 12),
                   'month': [5, 6, 7] * 4,
                   'week': [1, 2] * 6})

In [36]: mdf = pd.melt(df, id_vars=['month', 'week'])

In [37]: pd.pivot_table(mdf, values='value', index=['variable', 'week'],
                   columns=['month'], aggfunc=np.mean)
```

```
Out[37]:

<table>
<thead>
<tr>
<th>variable</th>
<th>week</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>x</td>
<td>1</td>
<td>93.888747</td>
<td>98.762034</td>
<td>55.219673</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>94.391427</td>
<td>38.112932</td>
<td>83.942781</td>
</tr>
<tr>
<td>y</td>
<td>1</td>
<td>94.306912</td>
<td>279.454811</td>
<td>227.840449</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>87.392662</td>
<td>193.028166</td>
<td>173.899260</td>
</tr>
<tr>
<td>z</td>
<td>1</td>
<td>11.016009</td>
<td>10.079307</td>
<td>16.170549</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>8.476111</td>
<td>17.638509</td>
<td>19.003494</td>
</tr>
</tbody>
</table>
```

Similarly for `dcast` which uses a data.frame called `df` in R to aggregate information based on `Animal` and `FeedType`:

```r
df <- data.frame(
  Animal = c('Animal1', 'Animal2', 'Animal3', 'Animal2', 'Animal1',
             'Animal2', 'Animal3'),
  FeedType = c('A', 'B', 'A', 'A', 'B', 'B', 'A'),
  Amount = c(10, 7, 4, 2, 5, 6, 2)
)

dcast(df, Animal ~ FeedType, sum, fill=NaN)
```

(continues on next page)
Python can approach this in two different ways. Firstly, similar to above using `pivot_table()`:

```
In [38]: df = pd.DataFrame(
    ....:     'Animal': ['Animal1', 'Animal2', 'Animal3', 'Animal2', 'Animal1',
    ....:                     'Animal2', 'Animal3'],
    ....:     'FeedType': ['A', 'B', 'A', 'A', 'B', 'B', 'A'],
    ....:     'Amount': [10, 7, 4, 2, 5, 6, 2],
    ....:     'Animal': [
    ....:     'Animal1', 'Animal2', 'Animal3', 'Animal2', 'Animal1',
    ....:     'Animal2', 'Animal3'],
    ....: )

In [39]: df.pivot_table(values='Amount', index='Animal', columns='FeedType',
    ....:     aggfunc='sum')
```

```
Out[39]:
FeedType  A  B
Animal
Animal1  10.0  5.0
Animal2  2.0  13.0
Animal3  6.0  NaN
```

The second approach is to use the `groupby()` method:

```
In [40]: df.groupby(['Animal', 'FeedType'])['Amount'].sum()
```

```
Out[40]:
Animal  FeedType
Animal1 A       10
        B       5
Animal2 A       2
        B      13
Animal3 A       6
Name: Amount, dtype: int64
```

For more details and examples see the reshaping documentation or the groupby documentation.

**factor**

pandas has a data type for categorical data.

```
cut(c(1,2,3,4,5,6), 3)
factor(c(1,2,3,2,2,3))
```

In pandas this is accomplished with `pd.cut` and `astype("category")`:

```
In [41]: pd.cut(pd.Series([1, 2, 3, 4, 5, 6]), 3)
```

```
Out[41]:
0 (0.995, 2.667]
1 (0.995, 2.667]
2 (2.667, 4.333]
3 (2.667, 4.333]
4 (4.333, 6.0]
5 (4.333, 6.0]
dtype: category
```
For more details and examples see categorical introduction and the API documentation. There is also a documentation regarding the differences to R’s factor.

Comparison with SQL

Since many potential pandas users have some familiarity with SQL, this page is meant to provide some examples of how various SQL operations would be performed using pandas.

If you’re new to pandas, you might want to first read through 10 Minutes to pandas to familiarize yourself with the library.

As is customary, we import pandas and NumPy as follows:

```python
In [1]: import pandas as pd

In [2]: import numpy as np
```

Most of the examples will utilize the tips dataset found within pandas tests. We’ll read the data into a DataFrame called tips and assume we have a database table of the same name and structure.

```python
In [3]: url = ('https://raw.github.com/pandas-dev/pandas/master/pandas/tests/io/data/csv/tips.csv')

In [4]: tips = pd.read_csv(url)

In [5]: tips.head()
```

```output
Out[5]:
      total_bill  tip     sex  smoker  day   time  size
0    16.990000  1.01  Female    No  Sun  Dinner    2
1    10.340000  1.66    Male    No  Sun  Dinner    3
2    21.010000  3.50    Male    No  Sun  Dinner    3
3    23.680000  3.31    Male    No  Sun  Dinner    2
4    24.590000  3.61  Female    No  Sun  Dinner    4
```
**SELECT**

In SQL, selection is done using a comma-separated list of columns you’d like to select (or a `*` to select all columns):

```sql
SELECT total_bill, tip, smoker, time
FROM tips
LIMIT 5;
```

With pandas, column selection is done by passing a list of column names to your DataFrame:

```python
In [6]: tips[['total_bill', 'tip', 'smoker', 'time']].head(5)
Out[6]:
          total_bill  tip  smoker time
0       16.9900  1.01  No  Dinner
1       10.3400  1.66  No  Dinner
2       21.0100  3.50  No  Dinner
3       23.6800  3.31  No  Dinner
4       24.5900  3.61  No  Dinner
```

Calling the DataFrame without the list of column names would display all columns (akin to SQL’s `*`).

In SQL, you can add a calculated column:

```sql
SELECT *, tip/total_bill as tip_rate
FROM tips
LIMIT 5;
```

With pandas, you can use the `DataFrame.assign()` method of a DataFrame to append a new column:

```python
In [7]: tips.assign(tip_rate=tips['tip'] / tips['total_bill']).head(5)
Out[7]:
     total_bill  tip  sex  smoker day    time  size  tip_rate
0  16.990000  1.01 Female  No  Sun Dinner  2 0.059447
1  10.340000  1.66  Male  No  Sun Dinner  3 0.160542
2  21.010000  3.50  Male  No  Sun Dinner  3 0.166587
3  23.680000  3.31  Male  No  Sun Dinner  2 0.139780
4  24.590000  3.61 Female  No  Sun Dinner  4 0.146808
```

**WHERE**

Filtering in SQL is done via a WHERE clause.

```sql
SELECT *
FROM tips
WHERE time = 'Dinner'
LIMIT 5;
```

DataFrames can be filtered in multiple ways; the most intuitive of which is using boolean indexing

```python
In [8]: tips[tips['time'] == 'Dinner'].head(5)
Out[8]:
          total_bill  tip  sex  smoker day    time  size
0  16.990000  1.01 Female  No  Sun Dinner  2
1  10.340000  1.66  Male  No  Sun Dinner  3
2  21.010000  3.50  Male  No  Sun Dinner  3
```

(continues on next page)
The above statement is simply passing a Series of True/False objects to the DataFrame, returning all rows with True.

In [9]: is_dinner = tips['time'] == 'Dinner'
In [10]: is_dinner.value_counts()
Out[10]:
   True  176
  False   68
Name: time, dtype: int64
In [11]: tips[is_dinner].head(5)
Out[11]:
   total_bill  tip   sex  smoker  day    time  size
0     16.99  1.01  Female   No  Sun  Dinner   2
1     10.34  1.66    Male   No  Sun  Dinner   3
2     21.01  3.50    Male   No  Sun  Dinner   3
3     23.68  3.31    Male   No  Sun  Dinner   2
4     24.59  3.61  Female   No  Sun  Dinner   4

Just like SQL's OR and AND, multiple conditions can be passed to a DataFrame using | (OR) and & (AND).

-- tips of more than $5.00 at Dinner meals
SELECT *
FROM tips
WHERE time = 'Dinner' AND tip > 5.00;

# tips of more than $5.00 at Dinner meals
In [12]: tips[(tips['time'] == 'Dinner') & (tips['tip'] > 5.00)]
Out[12]:
   total_bill  tip   sex  smoker  day    time  size
  23    39.42  7.58    Male   No  Sat  Dinner   4
  44    30.40  5.60    Male   No  Sun  Dinner   4
  47    32.40  6.00    Male   No  Sun  Dinner   4
  52    34.81  5.20  Female   No  Sun  Dinner   4
  59    48.27  6.73    Male   No  Sun  Dinner   4
 116   29.93  5.07    Male   No  Sun  Dinner   4
 155   29.85  5.14  Female   No  Sun  Dinner   5
 170   50.81 10.00    Male   Yes  Sat  Dinner   3
 172    7.25  5.15    Male   Yes  Sun  Dinner   2
 181   23.33  5.65    Male   Yes  Sun  Dinner   2
 183   23.17  6.50    Male   Yes  Sun  Dinner   4
 211   25.89  5.16    Male   Yes  Sat  Dinner   4
 212   48.33  9.00    Male   No  Sat  Dinner   4
 214   28.17  6.50  Female   Yes  Sat  Dinner   3
 239   29.03  5.92    Male   No  Sat  Dinner   3

-- tips by parties of at least 5 diners OR bill total was more than $45
SELECT *
FROM tips
WHERE size >= 5 OR total_bill > 45;
In [13]: tips[(tips['size'] >= 5) | (tips['total_bill'] > 45)]

Out[13]:

<table>
<thead>
<tr>
<th>total_bill</th>
<th>tip</th>
<th>sex</th>
<th>smoker</th>
<th>day</th>
<th>time</th>
<th>size</th>
</tr>
</thead>
<tbody>
<tr>
<td>59</td>
<td>48.27</td>
<td>6.73</td>
<td>Male</td>
<td>No</td>
<td>Sat</td>
<td>4</td>
</tr>
<tr>
<td>125</td>
<td>29.80</td>
<td>4.20</td>
<td>Female</td>
<td>No</td>
<td>Thur</td>
<td>6</td>
</tr>
<tr>
<td>141</td>
<td>34.30</td>
<td>6.70</td>
<td>Male</td>
<td>No</td>
<td>Thur</td>
<td>6</td>
</tr>
<tr>
<td>142</td>
<td>41.19</td>
<td>5.00</td>
<td>Male</td>
<td>No</td>
<td>Thur</td>
<td>5</td>
</tr>
<tr>
<td>143</td>
<td>27.05</td>
<td>5.00</td>
<td>Female</td>
<td>No</td>
<td>Thur</td>
<td>6</td>
</tr>
<tr>
<td>155</td>
<td>29.85</td>
<td>5.14</td>
<td>Female</td>
<td>No</td>
<td>Sun</td>
<td>5</td>
</tr>
<tr>
<td>156</td>
<td>48.17</td>
<td>5.00</td>
<td>Male</td>
<td>No</td>
<td>Sun</td>
<td>6</td>
</tr>
<tr>
<td>170</td>
<td>50.81</td>
<td>10.00</td>
<td>Male</td>
<td>Yes</td>
<td>Sat</td>
<td>3</td>
</tr>
<tr>
<td>182</td>
<td>45.35</td>
<td>3.50</td>
<td>Male</td>
<td>Yes</td>
<td>Sun</td>
<td>3</td>
</tr>
<tr>
<td>185</td>
<td>20.69</td>
<td>5.00</td>
<td>Male</td>
<td>No</td>
<td>Sun</td>
<td>5</td>
</tr>
<tr>
<td>187</td>
<td>30.46</td>
<td>2.00</td>
<td>Male</td>
<td>Yes</td>
<td>Sun</td>
<td>5</td>
</tr>
<tr>
<td>212</td>
<td>48.33</td>
<td>9.00</td>
<td>Male</td>
<td>No</td>
<td>Sat</td>
<td>4</td>
</tr>
<tr>
<td>216</td>
<td>28.15</td>
<td>3.00</td>
<td>Male</td>
<td>Yes</td>
<td>Sat</td>
<td>5</td>
</tr>
</tbody>
</table>

NULL checking is done using the `notna()` and `isna()` methods.

Assume we have a table of the same structure as our DataFrame above. We can see only the records where `col2` IS NULL with the following query:

```sql
SELECT * 
FROM frame 
WHERE col2 IS NULL;
```

In [16]: frame[frame['col2'].isna()]

Out[16]:

<table>
<thead>
<tr>
<th>col1</th>
<th>col2</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>F</td>
</tr>
<tr>
<td>B</td>
<td>NaN</td>
</tr>
<tr>
<td>C</td>
<td>H</td>
</tr>
<tr>
<td>D</td>
<td>I</td>
</tr>
</tbody>
</table>

Getting items where `col1` IS NOT NULL can be done with `notna()`.

```sql
SELECT * 
FROM frame 
WHERE col1 IS NOT NULL;
```

In [17]: frame[frame['col1'].notna()]

Out[17]:

<table>
<thead>
<tr>
<th>col1</th>
<th>col2</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>F</td>
</tr>
<tr>
<td>B</td>
<td>NaN</td>
</tr>
</tbody>
</table>
GROUP BY

In pandas, SQL’s GROUP BY operations are performed using the similarly named `groupby()` method. `groupby()` typically refers to a process where we’d like to split a dataset into groups, apply some function (typically aggregation), and then combine the groups together.

A common SQL operation would be getting the count of records in each group throughout a dataset. For instance, a query getting us the number of tips left by sex:

```
SELECT sex, count(*)
FROM tips
GROUP BY sex;
/*
Female 87
Male 157
*/
```

The pandas equivalent would be:

```
In [18]: tips.groupby('sex').size()
Out[18]:
   sex
Female 87
   Male 157
Name: size, dtype: int64
```

Notice that in the pandas code we used `size()` and not `count()`. This is because `count()` applies the function to each column, returning the number of not null records within each.

```
In [19]: tips.groupby('sex').count()
Out[19]:
      total_bill  tip  smoker  day  time  size
    sex
Female   87    87     87   87   87   87
Male     157   157    157  157  157  157
```

Alternatively, we could have applied the `count()` method to an individual column:

```
In [20]: tips.groupby('sex')['total_bill'].count()
Out[20]:
    sex
Female  87
Male    157
Name: total_bill, dtype: int64
```

Multiple functions can also be applied at once. For instance, say we’d like to see how tip amount differs by day of the week - `agg()` allows you to pass a dictionary to your grouped DataFrame, indicating which functions to apply to specific columns.

```
SELECT day, AVG(tip), COUNT(*)
FROM tips
(continues on next page)
```
GROUP BY day;
/*
Fri 2.734737 19
Sat 2.993103 87
Sun 3.255132 76
Thur 2.771452 62
*/

In [21]: tips.groupby('day').agg({'tip': np.mean, 'day': np.size})
Out[21]:

<table>
<thead>
<tr>
<th>tip</th>
<th>day</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.734737</td>
<td>19</td>
</tr>
<tr>
<td>2.993103</td>
<td>87</td>
</tr>
<tr>
<td>3.255132</td>
<td>76</td>
</tr>
<tr>
<td>2.771452</td>
<td>62</td>
</tr>
</tbody>
</table>

Grouping by more than one column is done by passing a list of columns to the `groupby()` method.

SELECT smoker, day, COUNT(*), AVG(tip)
FROM tips
GROUP BY smoker, day;
/*
smoker day
No  Fri 4 2.812500
    Sat 45 3.102889
    Sun 57 3.167895
    Thur 45 2.673778
Yes Fri 15 2.714000
     Sat 42 2.875476
     Sun 19 3.516842
      Thur 17 3.030000
*/

In [22]: tips.groupby(['smoker', 'day']).agg({'tip': [np.size, np.mean]})
Out[22]:

<table>
<thead>
<tr>
<th>tip</th>
<th>size</th>
<th>mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>No</td>
<td>4.0</td>
<td>2.812500</td>
</tr>
<tr>
<td></td>
<td>45.0</td>
<td>3.102889</td>
</tr>
<tr>
<td></td>
<td>57.0</td>
<td>3.167895</td>
</tr>
<tr>
<td></td>
<td>45.0</td>
<td>2.673778</td>
</tr>
<tr>
<td>Yes</td>
<td>15.0</td>
<td>2.714000</td>
</tr>
<tr>
<td></td>
<td>42.0</td>
<td>2.875476</td>
</tr>
<tr>
<td></td>
<td>19.0</td>
<td>3.516842</td>
</tr>
<tr>
<td></td>
<td>17.0</td>
<td>3.030000</td>
</tr>
</tbody>
</table>
JOIN

JOINs can be performed with \textit{join()} or \textit{merge()}. By default, \textit{join()} will join the DataFrames on their indices. Each method has parameters allowing you to specify the type of join to perform (LEFT, RIGHT, INNER, FULL) or the columns to join on (column names or indices).

Assume we have two database tables of the same name and structure as our DataFrames. Now let's go over the various types of JOINs.

\textbf{INNER JOIN}

\begin{verbatim}
SELECT *
FROM df1
INNER JOIN df2
    ON df1.key = df2.key;
\end{verbatim}

\begin{verbatim}
# merge performs an INNER JOIN by default
In [25]: pd.merge(df1, df2, on='key')
Out[25]:
   key  value_x  value_y
0  B    -0.282863  1.212112
1  D    -1.135632 -0.173215
2  D    -1.135632  0.119209
\end{verbatim}

\textit{merge()} also offers parameters for cases when you'd like to join one DataFrame's column with another DataFrame's index.

\begin{verbatim}
In [26]: indexed_df2 = df2.set_index('key')

In [27]: pd.merge(df1, indexed_df2, left_on='key', right_index=True)
Out[27]:
   key  value_x  value_y
0  B    -0.282863  1.212112
1  D    -1.135632 -0.173215
2  D    -1.135632  0.119209
\end{verbatim}
LEFT OUTER JOIN

-- show all records from df1
SELECT *
FROM df1
LEFT OUTER JOIN df2
  ON df1.key = df2.key;

# show all records from df1
In [28]: pd.merge(df1, df2, on='key', how='left')
Out[28]:
   key  value_x  value_y
0   A   0.469112   NaN
1   B -0.282863  1.212112
2   C  -1.509059   NaN
3   D -1.135632 -0.173215
4   D -1.135632  0.119209

RIGHT JOIN

-- show all records from df2
SELECT *
FROM df1
RIGHT OUTER JOIN df2
  ON df1.key = df2.key;

# show all records from df2
In [29]: pd.merge(df1, df2, on='key', how='right')
Out[29]:
   key  value_x  value_y
0   B  -0.282863  1.212112
1   D  -1.135632 -0.173215
2   D -1.135632  0.119209
3   E   NaN -1.044236

FULL JOIN

pandas also allows for FULL JOINs, which display both sides of the dataset, whether or not the joined columns find a match. As of writing, FULL JOINs are not supported in all RDBMS (MySQL).

-- show all records from both tables
SELECT *
FROM df1
FULL OUTER JOIN df2
  ON df1.key = df2.key;

# show all records from both frames
In [30]: pd.merge(df1, df2, on='key', how='outer')
Out[30]:
   key  value_x  value_y
0   A  0.469112   NaN
1   B -0.282863  1.212112
(continues on next page)
UNION

UNION ALL can be performed using `concat()`.

```python
In [31]: df1 = pd.DataFrame({'city': ['Chicago', 'San Francisco', 'New York City'], 'rank': range(1, 4)})
.....:
.....:

In [32]: df2 = pd.DataFrame({'city': ['Chicago', 'Boston', 'Los Angeles'], 'rank': [1, 4, 5]})
.....:
.....:
```

```sql
SELECT city, rank
FROM df1
UNION ALL
SELECT city, rank
FROM df2;
```

```sql
/*
city rank
Chicago 1
San Francisco 2
New York City 3
Chicago 1
Boston 4
Los Angeles 5
*/
```

```python
In [33]: pd.concat([df1, df2])
Out[33]:
city rank
0 Chicago 1
1 San Francisco 2
2 New York City 3
0 Chicago 1
1 Boston 4
2 Los Angeles 5
```

SQL's UNION is similar to UNION ALL, however UNION will remove duplicate rows.

```sql
SELECT city, rank
FROM df1
UNION
SELECT city, rank
FROM df2;
```

-- notice that there is only one Chicago record this time

```sql
/*
city rank
Chicago 1
San Francisco 2
*/
```
In pandas, you can use `concat()` in conjunction with `drop_duplicates()`.

```python
In [34]: pd.concat([df1, df2]).drop_duplicates()
Out[34]:
   city  rank
0  Chicago     1
1   San Francisco   2
2    New York City   3
1     Boston     4
2   Los Angeles   5
```

**pandas equivalents for some SQL analytic and aggregate functions**

**Top n rows with offset**

```sql
-- MySQL
SELECT * FROM tips
ORDER BY tip DESC
LIMIT 10 OFFSET 5;
```

```python
In [35]: tips.nlargest(10 + 5, columns='tip').tail(10)
Out[35]:
   total_bill  tip  sex  smoker  day  time  size
183     23.17  6.50  Male    Yes  Sun  Dinner   4
214     28.17  6.50 Female    Yes  Sat  Dinner   3
 47     32.40  6.00  Male     No  Sun  Dinner   4
239     29.03  5.92  Male     No  Sat  Dinner   3
 88     24.71  5.85  Male     No Thur  Lunch   2
181     23.33  5.65  Male    Yes  Sun  Dinner   2
 44     30.40  5.60  Male     No  Sun  Dinner   4
 52     34.81  5.20 Female    No  Sun  Dinner   4
 85     34.83  5.17 Female    No Thur  Lunch   4
211     25.89  5.16  Male    Yes  Sun  Dinner   4
```

**Top n rows per group**

```sql
-- Oracle's ROW_NUMBER() analytic function
SELECT * FROM (  SELECT *
               t.*,
               ROW_NUMBER() OVER(PARTITION BY day ORDER BY total_bill DESC) AS rn  FROM tips t
          )
WHERE rn < 3
ORDER BY day, rn;
```
In [36]: (tips.assign(rn=tips.sort_values(["total_bill"], ascending=False)
....: .groupby(["day"])
....: .cumcount() + 1)
....: .query('rn < 3')
....: .sort_values(["day", 'rn'])

Out[36]:
<table>
<thead>
<tr>
<th></th>
<th>total_bill</th>
<th>tip</th>
<th>sex</th>
<th>smoker</th>
<th>day</th>
<th>time</th>
<th>size</th>
<th>rn</th>
</tr>
</thead>
<tbody>
<tr>
<td>95</td>
<td>40.17</td>
<td>4.73</td>
<td>Male</td>
<td>Yes</td>
<td>Fri</td>
<td>Dinner</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>90</td>
<td>28.97</td>
<td>3.00</td>
<td>Male</td>
<td>Yes</td>
<td>Fri</td>
<td>Dinner</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>170</td>
<td>50.81</td>
<td>10.00</td>
<td>Male</td>
<td>Yes</td>
<td>Sat</td>
<td>Dinner</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>212</td>
<td>48.33</td>
<td>9.00</td>
<td>Male</td>
<td>No</td>
<td>Sat</td>
<td>Dinner</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>156</td>
<td>48.17</td>
<td>5.00</td>
<td>Male</td>
<td>No</td>
<td>Sun</td>
<td>Dinner</td>
<td>6</td>
<td>1</td>
</tr>
<tr>
<td>182</td>
<td>45.35</td>
<td>3.50</td>
<td>Male</td>
<td>Yes</td>
<td>Sun</td>
<td>Dinner</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>197</td>
<td>43.11</td>
<td>5.00</td>
<td>Female</td>
<td>Yes</td>
<td>Thur</td>
<td>Lunch</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>142</td>
<td>41.19</td>
<td>5.00</td>
<td>Male</td>
<td>No</td>
<td>Thur</td>
<td>Lunch</td>
<td>5</td>
<td>2</td>
</tr>
</tbody>
</table>

the same using rank(method='first') function

In [37]: (tips.assign(rnk=tips.groupby(["day"])["total_bill"]
....: .rank(method='first', ascending=False))
....: .query('rnk < 3')
....: .sort_values(["day", 'rnk'])

Out[37]:
<table>
<thead>
<tr>
<th></th>
<th>total_bill</th>
<th>tip</th>
<th>sex</th>
<th>smoker</th>
<th>day</th>
<th>time</th>
<th>size</th>
<th>rnk</th>
</tr>
</thead>
<tbody>
<tr>
<td>95</td>
<td>40.17</td>
<td>4.73</td>
<td>Male</td>
<td>Yes</td>
<td>Fri</td>
<td>Dinner</td>
<td>4</td>
<td>1.0</td>
</tr>
<tr>
<td>90</td>
<td>28.97</td>
<td>3.00</td>
<td>Male</td>
<td>Yes</td>
<td>Fri</td>
<td>Dinner</td>
<td>2</td>
<td>2.0</td>
</tr>
<tr>
<td>170</td>
<td>50.81</td>
<td>10.00</td>
<td>Male</td>
<td>Yes</td>
<td>Sat</td>
<td>Dinner</td>
<td>3</td>
<td>1.0</td>
</tr>
<tr>
<td>212</td>
<td>48.33</td>
<td>9.00</td>
<td>Male</td>
<td>No</td>
<td>Sat</td>
<td>Dinner</td>
<td>4</td>
<td>2.0</td>
</tr>
<tr>
<td>156</td>
<td>48.17</td>
<td>5.00</td>
<td>Male</td>
<td>No</td>
<td>Sun</td>
<td>Dinner</td>
<td>6</td>
<td>1.0</td>
</tr>
<tr>
<td>182</td>
<td>45.35</td>
<td>3.50</td>
<td>Male</td>
<td>Yes</td>
<td>Sun</td>
<td>Dinner</td>
<td>3</td>
<td>2.0</td>
</tr>
<tr>
<td>197</td>
<td>43.11</td>
<td>5.00</td>
<td>Female</td>
<td>Yes</td>
<td>Thur</td>
<td>Lunch</td>
<td>4</td>
<td>1.0</td>
</tr>
<tr>
<td>142</td>
<td>41.19</td>
<td>5.00</td>
<td>Male</td>
<td>No</td>
<td>Thur</td>
<td>Lunch</td>
<td>5</td>
<td>2.0</td>
</tr>
</tbody>
</table>

-- Oracle’s RANK() analytic function
SELECT * FROM (  
SELECT  
  t.*,  
  RANK() OVER(PARTITION BY sex ORDER BY tip) AS rnk  
FROM tips t  
WHERE tip < 2  
)  
WHERE rnk < 3  
ORDER BY sex, rnk;

Let’s find tips with (rank < 3) per gender group for (tips < 2). Notice that when using rank(method='min') function rnk_min remains the same for the same tip (as Oracle’s RANK() function)

In [38]: (tips[tips["tip"] < 2]
....: .assign(rnk_min=tips.groupby(["sex"])["tip"]
....: .rank(method='min'))
....: .query('rnk_min < 3')
....: .sort_values(["sex", 'rnk_min'])

Out[38]:
<table>
<thead>
<tr>
<th></th>
<th>total_bill</th>
<th>tip</th>
<th>sex</th>
<th>smoker</th>
<th>day</th>
<th>time</th>
<th>size</th>
<th>rnk_min</th>
</tr>
</thead>
<tbody>
<tr>
<td>95</td>
<td>40.17</td>
<td>4.73</td>
<td>Male</td>
<td>Yes</td>
<td>Fri</td>
<td>Dinner</td>
<td>4</td>
<td>1.0</td>
</tr>
<tr>
<td>90</td>
<td>28.97</td>
<td>3.00</td>
<td>Male</td>
<td>Yes</td>
<td>Fri</td>
<td>Dinner</td>
<td>2</td>
<td>2.0</td>
</tr>
<tr>
<td>170</td>
<td>50.81</td>
<td>10.00</td>
<td>Male</td>
<td>Yes</td>
<td>Sat</td>
<td>Dinner</td>
<td>3</td>
<td>1.0</td>
</tr>
<tr>
<td>212</td>
<td>48.33</td>
<td>9.00</td>
<td>Male</td>
<td>No</td>
<td>Sat</td>
<td>Dinner</td>
<td>4</td>
<td>2.0</td>
</tr>
<tr>
<td>156</td>
<td>48.17</td>
<td>5.00</td>
<td>Male</td>
<td>No</td>
<td>Sun</td>
<td>Dinner</td>
<td>6</td>
<td>1.0</td>
</tr>
<tr>
<td>182</td>
<td>45.35</td>
<td>3.50</td>
<td>Male</td>
<td>Yes</td>
<td>Sun</td>
<td>Dinner</td>
<td>3</td>
<td>2.0</td>
</tr>
<tr>
<td>197</td>
<td>43.11</td>
<td>5.00</td>
<td>Female</td>
<td>Yes</td>
<td>Thur</td>
<td>Lunch</td>
<td>4</td>
<td>1.0</td>
</tr>
<tr>
<td>142</td>
<td>41.19</td>
<td>5.00</td>
<td>Male</td>
<td>No</td>
<td>Thur</td>
<td>Lunch</td>
<td>5</td>
<td>2.0</td>
</tr>
</tbody>
</table>
UPDATE

UPDATE tips
SET tip = tip*2
WHERE tip < 2;

In [39]: tips.loc[tips['tip'] < 2, 'tip'] *= 2

DELETE

DELETE FROM tips
WHERE tip > 9;

In pandas we select the rows that should remain, instead of deleting them

In [40]: tips = tips.loc[tips['tip'] <= 9]

Comparison with SAS

For potential users coming from SAS this page is meant to demonstrate how different SAS operations would be performed in pandas.

If you’re new to pandas, you might want to first read through 10 Minutes to pandas to familiarize yourself with the library.

As is customary, we import pandas and NumPy as follows:

In [1]: import pandas as pd
In [2]: import numpy as np

Note: Throughout this tutorial, the pandas DataFrame will be displayed by calling df.head(), which displays the first N (default 5) rows of the DataFrame. This is often used in interactive work (e.g. Jupyter notebook or terminal) - the equivalent in SAS would be:

proc print data=df(obs=5);
run;
Data structures

General terminology translation

<table>
<thead>
<tr>
<th>pandas</th>
<th>SAS</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataFrame</td>
<td>data set</td>
</tr>
<tr>
<td>column</td>
<td>variable</td>
</tr>
<tr>
<td>row</td>
<td>observation</td>
</tr>
<tr>
<td>groupby</td>
<td>BY-group</td>
</tr>
<tr>
<td>NaN</td>
<td>.</td>
</tr>
</tbody>
</table>

DataFrame / Series

A DataFrame in pandas is analogous to a SAS data set - a two-dimensional data source with labeled columns that can be of different types. As will be shown in this document, almost any operation that can be applied to a data set using SAS’s DATA step, can also be accomplished in pandas.

A Series is the data structure that represents one column of a DataFrame. SAS doesn’t have a separate data structure for a single column, but in general, working with a Series is analogous to referencing a column in the DATA step.

Index

Every DataFrame and Series has an Index - which are labels on the rows of the data. SAS does not have an exactly analogous concept. A data set’s rows are essentially unlabeled, other than an implicit integer index that can be accessed during the DATA step (_N_).

In pandas, if no index is specified, an integer index is also used by default (first row = 0, second row = 1, and so on). While using a labeled Index or MultiIndex can enable sophisticated analyses and is ultimately an important part of pandas to understand, for this comparison we will essentially ignore the Index and just treat the DataFrame as a collection of columns. Please see the indexing documentation for much more on how to use an Index effectively.

Data input / output

Constructing a DataFrame from values

A SAS data set can be built from specified values by placing the data after a datalines statement and specifying the column names.

```plaintext
data df;
  input x y;
datalines;
  1 2
  3 4
  5 6
;
run;
```

A pandas DataFrame can be constructed in many different ways, but for a small number of values, it is often convenient to specify it as a Python dictionary, where the keys are the column names and the values are the data.
In [3]: df = pd.DataFrame({'x': [1, 3, 5], 'y': [2, 4, 6]})

In [4]: df
Out[4]:
   x  y
0  1  2
1  3  4
2  5  6

### Reading external data

Like SAS, pandas provides utilities for reading in data from many formats. The tips dataset, found within the pandas tests (csv) will be used in many of the following examples.

SAS provides PROC IMPORT to read csv data into a data set.

```plaintext
proc import datafile='tips.csv' dbms=csv out=tips replace;
   getnames=yes;
run;
```

The pandas method is `read_csv()`, which works similarly.

```plaintext
In [5]: url = ('https://raw.github.com/pandas-dev/
            ...:'
            ...:'pandas/master/pandas/tests/io/data/csv/tips.csv')

In [6]: tips = pd.read_csv(url)

In [7]: tips.head()
Out[7]:
      total_bill  tip  sex  smoker  day   time  size
0   16.990000  1.01 Female   No  Sun  Dinner   2
1   10.340000  1.66    Male    No  Sun  Dinner   3
2   21.010000  3.50    Male    No  Sun  Dinner   3
3   23.680000  3.31    Male    No  Sun  Dinner   2
4   24.590000  3.61 Female   No  Sun  Dinner   4
```

Like PROC IMPORT, `read_csv` can take a number of parameters to specify how the data should be parsed. For example, if the data was instead tab delimited, and did not have column names, the pandas command would be:

```plaintext
tips = pd.read_csv('tips.csv', sep='\t', header=None)
```

# alternatively, `read_table` is an alias to `read_csv` with tab delimiter
```
tips = pd.read_table('tips.csv', header=None)
```

In addition to text/csv, pandas supports a variety of other data formats such as Excel, HDF5, and SQL databases. These are all read via a `pd.read_*` function. See the [IO documentation](https://pandas.pydata.org/pandas-docs/stable/user_guide/io.html) for more details.
pandas: powerful Python data analysis toolkit, Release 1.1.1

Exporting data

The inverse of PROC IMPORT in SAS is PROC EXPORT

```python
proc export data=tips outfile='tips2.csv' dbms=csv;
run;
```

Similarly in pandas, the opposite of `read_csv` is `to_csv()`, and other data formats follow a similar api.

```python
tips.to_csv('tips2.csv')
```

Data operations

Operations on columns

In the DATA step, arbitrary math expressions can be used on new or existing columns.

```python
data tips;
set tips;
total_bill = total_bill - 2;
new_bill = total_bill / 2;
run;
```

pandas provides similar vectorized operations by specifying the individual `Series` in the DataFrame. New columns can be assigned in the same way.

```python
In [8]: tips['total_bill'] = tips['total_bill'] - 2
In [9]: tips['new_bill'] = tips['total_bill'] / 2.0
In [10]: tips.head()
```

<table>
<thead>
<tr>
<th></th>
<th>total_bill</th>
<th>tip</th>
<th>sex</th>
<th>smoker</th>
<th>day</th>
<th>time</th>
<th>size</th>
<th>new_bill</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>14.99</td>
<td>1.01</td>
<td>Female</td>
<td>No</td>
<td>Sun</td>
<td>Dinner</td>
<td>2</td>
<td>7.495</td>
</tr>
<tr>
<td>1</td>
<td>8.34</td>
<td>1.66</td>
<td>Male</td>
<td>No</td>
<td>Sun</td>
<td>Dinner</td>
<td>3</td>
<td>4.170</td>
</tr>
<tr>
<td>2</td>
<td>19.01</td>
<td>3.50</td>
<td>Male</td>
<td>No</td>
<td>Sun</td>
<td>Dinner</td>
<td>3</td>
<td>9.505</td>
</tr>
<tr>
<td>3</td>
<td>21.68</td>
<td>3.31</td>
<td>Male</td>
<td>No</td>
<td>Sun</td>
<td>Dinner</td>
<td>2</td>
<td>10.840</td>
</tr>
<tr>
<td>4</td>
<td>22.59</td>
<td>3.61</td>
<td>Female</td>
<td>No</td>
<td>Sun</td>
<td>Dinner</td>
<td>4</td>
<td>11.295</td>
</tr>
</tbody>
</table>

Filtering

Filtering in SAS is done with an `if` or `where` statement, on one or more columns.

```python
data tips;
set tips;
if total_bill > 10;
run;
```

```python
data tips;
set tips;
where total_bill > 10;
/* equivalent in this case - where happens before the DATA step begins and can also be used in PROC statements */
run;
```
DataFrames can be filtered in multiple ways; the most intuitive of which is using *boolean indexing*.

```
In [11]: tips[tips['total_bill'] > 10].head()
Out[11]:
   total_bill  tip     sex  smoker  day  time  size
0       14.99  1.01 Female   No  Sun  Dinner    2
2       19.01  3.50   Male    No  Sun  Dinner    3
3       21.68  3.31   Male    No  Sun  Dinner    2
4       22.59  3.61 Female   No  Sun  Dinner    4
5       23.29  4.71   Male    No  Sun  Dinner    4
```

**If/then logic**

In SAS, if/then logic can be used to create new columns.

```
data tips;
  set tips;
  format bucket $4.;;
  if total_bill < 10 then bucket = 'low';
  else bucket = 'high';
run;
```

The same operation in pandas can be accomplished using the `where` method from `numpy`.

```
In [12]: tips['bucket'] = np.where(tips['total_bill'] < 10, 'low', 'high')
In [13]: tips.head()
Out[13]:
   total_bill  tip     sex  smoker  day  time  size  bucket
0       14.99  1.01 Female   No  Sun  Dinner    2  high
1        8.34  1.66   Male    No  Sun  Dinner    3  low
2       19.01  3.50   Male    No  Sun  Dinner    3  high
3       21.68  3.31   Male    No  Sun  Dinner    2  high
4       22.59  3.61 Female   No  Sun  Dinner    4  high
```

**Date functionality**

SAS provides a variety of functions to do operations on date/datetime columns.

```
data tips;
  set tips;
  format date1 date2 date1_plusmonth mmdyyl10.;
  date1 = mdy(1, 15, 2013);
  date2 = mdy(2, 15, 2015);
  date1_year = year(date1);
  date2_month = month(date2);
  * shift date to beginning of next interval;
  date1_next = intnx('MONTH', date1, 1);
  * count intervals between dates;
  months_between = intck('MONTH', date1, date2);
run;
```

The equivalent pandas operations are shown below. In addition to these functions pandas supports other Time Series features not available in Base SAS (such as resampling and custom offsets) - see the `timeseries documentation` for

---

**1.4. Tutorials**
more details.

```python
In [14]: tips['date1'] = pd.Timestamp('2013-01-15')
In [15]: tips['date2'] = pd.Timestamp('2015-02-15')
In [16]: tips['date1_year'] = tips['date1'].dt.year
In [17]: tips['date2_month'] = tips['date2'].dt.month
In [18]: tips['date1_next'] = tips['date1'] + pd.offsets.MonthBegin()
In [19]: tips['months_between'] = (.....: tips['date2'].dt.to_period('M') - tips['date1'].dt.to_period('M'))
.....:
In [20]: tips[['date1', 'date2', 'date1_year', 'date2_month',
       ....: 'date1_next', 'months_between']].head()
.....:
Out[20]:
          date1     date2     date1_year  date2_month  date1_next  months_between
0 2013-01-15  2015-02-15        2013         2013-02-01 <25 * MonthEnds>
```

### Selection of columns

SAS provides keywords in the **DATA** step to select, drop, and rename columns.

```plaintext
data tips;
  set tips;
  keep sex total_bill tip;
run;

data tips;
  set tips;
  drop sex;
run;

data tips;
  set tips;
  rename total_bill=total_bill_2;
run;
```

The same operations are expressed in pandas below.

```python
# keep
In [21]: tips[['sex', 'total_bill', 'tip']].head()
Out[21]:
          sex    total_bill  tip
0  Female  14.990000   1.01
1    Male   8.340000   1.66
2    Male  19.010000   3.50
3    Male  21.680000   3.31
```

(continues on next page)
# drop
In [22]: tips.drop('sex', axis=1).head()
Out[22]:
<table>
<thead>
<tr>
<th>total_bill</th>
<th>tip</th>
<th>smoker</th>
<th>day</th>
<th>time</th>
<th>size</th>
</tr>
</thead>
<tbody>
<tr>
<td>14.99</td>
<td>1.01</td>
<td>No</td>
<td>Sun</td>
<td>Dinner</td>
<td>2</td>
</tr>
<tr>
<td>8.34</td>
<td>1.66</td>
<td>No</td>
<td>Sun</td>
<td>Dinner</td>
<td>3</td>
</tr>
<tr>
<td>19.01</td>
<td>3.50</td>
<td>No</td>
<td>Sun</td>
<td>Dinner</td>
<td>3</td>
</tr>
<tr>
<td>21.68</td>
<td>3.31</td>
<td>No</td>
<td>Sun</td>
<td>Dinner</td>
<td>2</td>
</tr>
<tr>
<td>22.59</td>
<td>3.61</td>
<td>No</td>
<td>Sun</td>
<td>Dinner</td>
<td>4</td>
</tr>
</tbody>
</table>

# rename
In [23]: tips.rename(columns={'total_bill': 'total_bill_2'}).head()
Out[23]:
<table>
<thead>
<tr>
<th>total_bill_2</th>
<th>tip</th>
<th>sex</th>
<th>smoker</th>
<th>day</th>
<th>time</th>
<th>size</th>
</tr>
</thead>
<tbody>
<tr>
<td>14.99</td>
<td>1.01</td>
<td>Female</td>
<td>No</td>
<td>Sun</td>
<td>Dinner</td>
<td>2</td>
</tr>
<tr>
<td>8.34</td>
<td>1.66</td>
<td>Male</td>
<td>No</td>
<td>Sun</td>
<td>Dinner</td>
<td>3</td>
</tr>
<tr>
<td>19.01</td>
<td>3.50</td>
<td>Male</td>
<td>No</td>
<td>Sun</td>
<td>Dinner</td>
<td>3</td>
</tr>
<tr>
<td>21.68</td>
<td>3.31</td>
<td>Male</td>
<td>No</td>
<td>Sun</td>
<td>Dinner</td>
<td>2</td>
</tr>
<tr>
<td>22.59</td>
<td>3.61</td>
<td>Female</td>
<td>No</td>
<td>Sun</td>
<td>Dinner</td>
<td>4</td>
</tr>
</tbody>
</table>

## Sorting by values

Sorting in SAS is accomplished via `PROC SORT`

```plaintext
proc sort data=tips;
    by sex total_bill;
run;
```

pandas objects have a `sort_values()` method, which takes a list of columns to sort by.

In [24]: tips = tips.sort_values(['sex', 'total_bill'])

In [25]: tips.head()
Out[25]:
<table>
<thead>
<tr>
<th>total_bill</th>
<th>tip</th>
<th>sex</th>
<th>smoker</th>
<th>day</th>
<th>time</th>
<th>size</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.07</td>
<td>1.00</td>
<td>Female</td>
<td>Yes</td>
<td>Sat</td>
<td>Dinner</td>
<td>1</td>
</tr>
<tr>
<td>3.75</td>
<td>1.00</td>
<td>Female</td>
<td>Yes</td>
<td>Fri</td>
<td>Dinner</td>
<td>2</td>
</tr>
<tr>
<td>5.25</td>
<td>1.00</td>
<td>Female</td>
<td>No</td>
<td>Sat</td>
<td>Dinner</td>
<td>1</td>
</tr>
<tr>
<td>6.35</td>
<td>1.50</td>
<td>Female</td>
<td>No</td>
<td>Thur</td>
<td>Lunch</td>
<td>2</td>
</tr>
<tr>
<td>6.51</td>
<td>1.25</td>
<td>Female</td>
<td>No</td>
<td>Thur</td>
<td>Lunch</td>
<td>2</td>
</tr>
</tbody>
</table>

## String processing

### Length

SAS determines the length of a character string with the `LENGTHN` and `LENGTHC` functions. `LENGTHN` excludes trailing blanks and `LENGTHC` includes trailing blanks.

```plaintext
data _null_; set tips;
```

(continues on next page)
Python determines the length of a character string with the `len` function. `len` includes trailing blanks. Use `len` and `rstrip` to exclude trailing blanks.

```plaintext
In [26]: tips['time'].str.len().head()
Out[26]:
   67   6
   92   6
  111   6
  145   5
  135   5
Name: time, dtype: int64

In [27]: tips['time'].str.rstrip().str.len().head()
Out[27]:
   67   6
   92   6
  111   6
  145   5
  135   5
Name: time, dtype: int64
```

### Find

SAS determines the position of a character in a string with the `FINDW` function. `FINDW` takes the string defined by the first argument and searches for the first position of the substring you supply as the second argument.

```plaintext
data _null_;  
set tips;  
put (FINDW(sex,'ale'));
run;
```

Python determines the position of a character in a string with the `find` function. `find` searches for the first position of the substring. If the substring is found, the function returns its position. Keep in mind that Python indexes are zero-based and the function will return -1 if it fails to find the substring.

```plaintext
In [28]: tips['sex'].str.find("ale").head()
Out[28]:
   67   3
   92   3
  111   3
  145   3
  135   3
Name: sex, dtype: int64
```
### Substring

SAS extracts a substring from a string based on its position with the `SUBSTR` function.

```sas
data _null_
set tips;
put (substr(sex,1,1));
run;
```

With pandas you can use `[]` notation to extract a substring from a string by position locations. Keep in mind that Python indexes are zero-based.

```python
In [29]: tips['sex'].str[0:1].head()
Out[29]:
   67    F
   92    F
  111    F
  145    F
  135    F
Name: sex, dtype: object
```

### Scan

The SAS `SCAN` function returns the nth word from a string. The first argument is the string you want to parse and the second argument specifies which word you want to extract.

```sas
data firstlast;
input String $60.;
First_Name = scan(string, 1);
Last_Name = scan(string, -1);
datalines2;
John Smith;
Jane Cook;
; ; ; ;
run;
```

Python extracts a substring from a string based on its text by using regular expressions. There are much more powerful approaches, but this just shows a simple approach.

```python
In [30]: firstlast = pd.DataFrame({'String': ['John Smith', 'Jane Cook']})
In [31]: firstlast['First_Name'] = firstlast['String'].str.split(" ", expand=True)[0]
In [32]: firstlast['Last_Name'] = firstlast['String'].str.rsplit(" ", expand=True)[0]
In [33]: firstlast
Out[33]:
   String First_Name Last_Name
0  John Smith    John    John
1  Jane Cook     Jane     Jane
```
Upcase, lowcase, and propcase

The SAS UPCASE LOWCASE and PROPCASE functions change the case of the argument.

```plaintext
data firstlast;
input String $60.;
string_up = UPCASE(string);
string_low = LOWCASE(string);
string_prop = PROPCASE(string);
datalines2;
John Smith;
Jane Cook;
;;
run;
```

The equivalent Python functions are upper, lower, and title.

```python
In [34]: firstlast = pd.DataFrame({'String': ['John Smith', 'Jane Cook']})
In [35]: firstlast['string_up'] = firstlast['String'].str.upper()
In [36]: firstlast['string_low'] = firstlast['String'].str.lower()
In [37]: firstlast['string_prop'] = firstlast['String'].str.title()
In [38]: firstlast
Out[38]:
   String      string_up    string_low    string_prop
0  John Smith     JOHN SMITH    john smith        John Smith
1    Jane Cook    JANE COOK     jane cook         Jane Cook
```

Merging

The following tables will be used in the merge examples

```python
In [39]: df1 = pd.DataFrame({'key': ['A', 'B', 'C', 'D'],
                      'value': np.random.randn(4)})
In [40]: df1
Out[40]:
   key  value
0  A  0.469112
1  B -0.282863
2  C -1.509059
3  D -1.135632
In [41]: df2 = pd.DataFrame({'key': ['B', 'D', 'D', 'E'],
                      'value': np.random.randn(4)})
In [42]: df2
Out[42]:
   key  value
0  B  1.212112
1  D -0.173215
```

(continues on next page)
In SAS, data must be explicitly sorted before merging. Different types of joins are accomplished using the **in=** dummy variables to track whether a match was found in one or both input frames.

```sas
proc sort data=df1;
  by key;
run;

proc sort data=df2;
  by key;
run;

data left_join inner_join right_join outer_join;
  merge df1(in=a) df2(in=b);
  if a and b then output inner_join;
  if a then output left_join;
  if b then output right_join;
  if a or b then output outer_join;
run;
```

Pandas DataFrames have a **merge()** method, which provides similar functionality. Note that the data does not have to be sorted ahead of time, and different join types are accomplished via the **how** keyword.

```python
In [43]: inner_join = df1.merge(df2, on=['key'], how='inner')

In [44]: inner_join
Out[44]:
   key  value_x  value_y
0  B   -0.282863  1.212112
1  D   -1.135632 -0.173215
2  D   -1.135632  0.119209

In [45]: left_join = df1.merge(df2, on=['key'], how='left')

In [46]: left_join
Out[46]:
   key  value_x  value_y
0  A    0.469112      NaN
1  B   -0.282863  1.212112
2  C  -1.509059      NaN
3  D  -1.135632  -0.173215
4  D  -1.135632  0.119209

In [47]: right_join = df1.merge(df2, on=['key'], how='right')

In [48]: right_join
Out[48]:
   key  value_x  value_y
0  B   -0.282863  1.212112
1  D   -1.135632 -0.173215
2  D   -1.135632  0.119209
3  E    NaN  -1.044236
```
In [49]: outer_join = df1.merge(df2, on=['key'], how='outer')

In [50]: outer_join
Out[50]:
   key  value_x  value_y
0   A  0.469112   NaN
1   B -0.282863  1.212112
2   C -1.509059   NaN
3   D -1.135632 -0.173215
4   D -1.135632  0.119209
5   E   NaN -1.044236

**Missing data**

Like SAS, pandas has a representation for missing data - which is the special float value NaN (not a number). Many of the semantics are the same, for example missing data propagates through numeric operations, and is ignored by default for aggregations.

In [51]: outer_join
Out[51]:
   key  value_x  value_y
0   A  0.469112   NaN
1   B -0.282863  1.212112
2   C -1.509059   NaN
3   D -1.135632 -0.173215
4   D -1.135632  0.119209
5   E   NaN -1.044236

In [52]: outer_join['value_x'] + outer_join['value_y']
Out[52]:
0   NaN
1  0.929249
2   NaN
3  0.173215
4  0.119209
5  0.044236

dtype: float64

In [53]: outer_join['value_x'].sum()
Out[53]: -3.5940742896293765

One difference is that missing data cannot be compared to its sentinel value. For example, in SAS you could do this to filter missing values.

data outer_join_nulls;
  set outer_join;
  if value_x = .;
run;

data outer_join_no_nulls;
  set outer_join;
  if value_x ^= .;
run;

Which doesn’t work in pandas. Instead, the pd.isna or pd.notna functions should be used for comparisons.
In [54]: outer_join[pd.isna(outer_join['value_x'])]
Out[54]:
   key  value_x  value_y
5    E       NaN  -1.044236

In [55]: outer_join[pd.notna(outer_join['value_x'])]
Out[55]:
   key  value_x  value_y
 0    A  0.469112   NaN
 1    B -0.282863  1.212112
 2    C -1.509059   NaN
 3    D -1.135632 -0.173215
 4    D -1.135632  0.119209

pandas also provides a variety of methods to work with missing data - some of which would be challenging to express in SAS. For example, there are methods to drop all rows with any missing values, replacing missing values with a specified value, like the mean, or forward filling from previous rows. See the missing data documentation for more.

In [56]: outer_join.dropna()
Out[56]:
   key  value_x  value_y
2    C -1.509059  1.212112
3    D -1.135632 -0.173215
4    D -1.135632  0.119209

In [57]: outer_joinfillna(method='ffill')
Out[57]:
   key  value_x  value_y
0    A  0.469112   NaN
1    B -0.282863  1.212112
2    C -1.509059  1.212112
3    D -1.135632 -0.173215
4    D -1.135632  0.119209
5    E -1.135632 -1.044236

In [58]: outer_join['value_x'].fillna(outer_join['value_x'].mean())
Out[58]:
   0    0.469112
   1   -0.282863
   2   -1.509059
   3   -1.135632
   4   -1.135632
   5   -0.718815
Name: value_x, dtype: float64

GroupBy

Aggregation

SAS’s PROC SUMMARY can be used to group by one or more key variables and compute aggregations on numeric columns.

```
proc summary data=tips nway;
   class sex smoker;
   var total_bill tip;
```

(continues on next page)
pandas provides a flexible `groupby` mechanism that allows similar aggregations. See the `groupby documentation` for more details and examples.

```python
In [59]: tips_summed = tips.groupby(['sex', 'smoker'])[['total_bill', 'tip']].sum()
In [60]: tips_summed.head()
Out[60]:
   total_bill  tip
sex   smoker
Female No       869.68  149.77
        Yes      527.27   96.74
Male   No       1725.75  302.00
        Yes     1217.07  183.07
```

### Transformation

In SAS, if the group aggregations need to be used with the original frame, it must be merged back together. For example, to subtract the mean for each observation by smoker group.

```sas
proc summary data=tips missing nway;
   class smoker;
   var total_bill;
   output out=smoker_means mean(total_bill)=group_bill;
run;
proc sort data=tips;
   by smoker;
run;
data tips;
   merge tips(in=a) smoker_means(in=b);
   by smoker;
   adj_total_bill = total_bill - group_bill;
   if a and b;
run;
```

pandas `groupby` provides a `transform` mechanism that allows these type of operations to be succinctly expressed in one operation.

```python
In [61]: gb = tips.groupby('smoker')['total_bill']
In [62]: tips['adj_total_bill'] = tips['total_bill'] - gb.transform('mean')
In [63]: tips.head()
Out[63]:
   total_bill  tip  sex   smoker  day  time  size  adj_total_bill
67  1.07  1.00  Female  Yes  Sat  Dinner  1  -17.686344
92  3.75  1.00  Female  Yes  Fri  Dinner  2  -15.006344
111 5.25  1.00  Female  No  Sat  Dinner  1  -11.938278
145 6.35  1.50  Female  No  Thur  Lunch  2  -10.838278
135 6.51  1.25  Female  No  Thur  Lunch  2  -10.678278
```

---

94 Chapter 1. Getting started
By group processing

In addition to aggregation, pandas `groupby` can be used to replicate most other by group processing from SAS. For example, this DATA step reads the data by sex/smoker group and filters to the first entry for each.

```plaintext
proc sort data=tips;
    by sex smoker;
run;

data tips_first;
    set tips;
    by sex smoker;
    if FIRST.sex or FIRST.smoker then output;
run;
```

In pandas this would be written as:

```plaintext
In [64]: tips.groupby(['sex', 'smoker']).first()
Out[64]:
   sex     smoker  total_bill  tip  day   time  size  adj_total_bill
0  Female  No  5.25     1.00  Sat  Dinner   1  -11.938278
  Yes  1.07     1.00  Sat  Dinner   1  -17.686344
1  Male  No  5.51     2.00  Thur  Lunch   2  -11.678278
  Yes  5.25     5.15  Sun  Dinner   2  -13.506344
```

Other considerations

Disk vs memory

pandas operates exclusively in memory, where a SAS data set exists on disk. This means that the size of data able to be loaded in pandas is limited by your machine’s memory, but also that the operations on that data may be faster.

If out of core processing is needed, one possibility is the `dask.dataframe` library (currently in development) which provides a subset of pandas functionality for an on-disk DataFrame

Data interop

pandas provides a `read_sas()` method that can read SAS data saved in the XPORT or SAS7BDAT binary format.

```plaintext
libname xportout xport 'transport-file.xpt';
data xportout.tips;
    set tips(rename=(total_bill=tbill));
    * xport variable names limited to 6 characters;
run;

df = pd.read_sas('transport-file.xpt')
df = pd.read_sas('binary-file.sas7bdat')
```

You can also specify the file format directly. By default, pandas will try to infer the file format based on its extension.

```plaintext
df = pd.read_sas('transport-file.xpt', format='xport')
df = pd.read_sas('binary-file.sas7bdat', format='sas7bdat')
```
XPORT is a relatively limited format and the parsing of it is not as optimized as some of the other pandas readers. An alternative way to interop data between SAS and pandas is to serialize to csv.

```python
In [8]: %time df = pd.read_sas('big.xpt')
Wall time: 14.6 s
In [9]: %time df = pd.read_csv('big.csv')
Wall time: 4.86 s
```

### Comparison with Stata

For potential users coming from Stata this page is meant to demonstrate how different Stata operations would be performed in pandas.

If you’re new to pandas, you might want to first read through 10 Minutes to pandas to familiarize yourself with the library.

As is customary, we import pandas and NumPy as follows. This means that we can refer to the libraries as `pd` and `np`, respectively, for the rest of the document.

```python
In [1]: import pandas as pd
In [2]: import numpy as np
```

#### Note:
Throughout this tutorial, the pandas DataFrame will be displayed by calling `df.head()`, which displays the first N (default 5) rows of the DataFrame. This is often used in interactive work (e.g. Jupyter notebook or terminal) – the equivalent in Stata would be:

```
list in 1/5
```

### Data structures

#### General terminology translation

<table>
<thead>
<tr>
<th>pandas</th>
<th>Stata</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataFrame</td>
<td>data set</td>
</tr>
<tr>
<td>column</td>
<td>variable</td>
</tr>
<tr>
<td>row</td>
<td>observation</td>
</tr>
<tr>
<td>groupby</td>
<td>bysort</td>
</tr>
<tr>
<td>NaN</td>
<td>.</td>
</tr>
</tbody>
</table>
**DataFrame / Series**

A DataFrame in pandas is analogous to a Stata data set – a two-dimensional data source with labeled columns that can be of different types. As will be shown in this document, almost any operation that can be applied to a data set in Stata can also be accomplished in pandas.

A Series is the data structure that represents one column of a DataFrame. Stata doesn’t have a separate data structure for a single column, but in general, working with a Series is analogous to referencing a column of a data set in Stata.

**Index**

Every DataFrame and Series has an Index – labels on the rows of the data. Stata does not have an exactly analogous concept. In Stata, a data set’s rows are essentially unlabeled, other than an implicit integer index that can be accessed with _n.

In pandas, if no index is specified, an integer index is also used by default (first row = 0, second row = 1, and so on). While using a labeled Index or MultiIndex can enable sophisticated analyses and is ultimately an important part of pandas to understand, for this comparison we will essentially ignore the Index and just treat the DataFrame as a collection of columns. Please see the indexing documentation for much more on how to use an Index effectively.

**Data input / output**

**Constructing a DataFrame from values**

A Stata data set can be built from specified values by placing the data after an input statement and specifying the column names.

```
input x y
1 2
3 4
5 6
end
```

A pandas DataFrame can be constructed in many different ways, but for a small number of values, it is often convenient to specify it as a Python dictionary, where the keys are the column names and the values are the data.

```
In [3]: df = pd.DataFrame({'x': [1, 3, 5], 'y': [2, 4, 6]})
```

```
In [4]: df
Out[4]:
   x  y
0  1  2
1  3  4
2  5  6
```
**Reading external data**

Like Stata, pandas provides utilities for reading in data from many formats. The tips data set, found within the pandas tests (csv) will be used in many of the following examples.

Stata provides `import delimited` to read csv data into a data set in memory. If the `tips.csv` file is in the current working directory, we can import it as follows.

```python
import delimited tips.csv
```

The pandas method is `read_csv()`, which works similarly. Additionally, it will automatically download the data set if presented with a url.

```python
In [5]: url = ('https://raw.github.com/pandas-dev/pandas/master/pandas/tests/io/data/csv/tips.csv')
...:
In [6]: tips = pd.read_csv(url)
```

```python
In [7]: tips.head()
```

```python
Out[7]:
total_bill  tip   sex  smoker day  time  size
0   16.99  1.01 Female No  Sun  Dinner  2
1   10.34  1.66 Male  No  Sun  Dinner  3
2   21.01  3.50 Male  No  Sun  Dinner  3
3   23.68  3.31 Male  No  Sun  Dinner  2
4   24.59  3.61 Female No  Sun  Dinner  4
```

Like `import delimited`, `read_csv()` can take a number of parameters to specify how the data should be parsed. For example, if the data were instead tab delimited, did not have column names, and existed in the current working directory, the pandas command would be:

```python
tips = pd.read_csv('tips.csv', sep='\t', header=None)
```

# alternatively, read_table is an alias to read_csv with tab delimiter
tips = pd.read_table('tips.csv', header=None)

Pandas can also read Stata data sets in `.dta` format with the `read_stata()` function.

```python
df = pd.read_stata('data.dta')
```

In addition to text/csv and Stata files, pandas supports a variety of other data formats such as Excel, SAS, HDF5, Parquet, and SQL databases. These are all read via a `pd.read_*` function. See the IO documentation for more details.

**Exporting data**

The inverse of `import delimited` in Stata is `export delimited`

```python
export delimited tips2.csv
```

Similarly in pandas, the opposite of `read_csv` is `DataFrame.to_csv()`.

```python
tips.to_csv('tips2.csv')
```

Pandas can also export to Stata file format with the `DataFrame.to_stata()` method.
Data operations

Operations on columns

In Stata, arbitrary math expressions can be used with the `generate` and `replace` commands on new or existing columns. The `drop` command drops the column from the data set.

```
replace total_bill = total_bill - 2
generate new_bill = total_bill / 2
drop new_bill
```

pandas provides similar vectorized operations by specifying the individual `Series` in the `DataFrame`. New columns can be assigned in the same way. The `DataFrame.drop()` method drops a column from the `DataFrame`.

```
In [8]: tips['total_bill'] = tips['total_bill'] - 2
In [9]: tips['new_bill'] = tips['total_bill'] / 2
In [10]: tips.head()
Out[10]:
   total_bill  tip    sex  smoker  day    time  size  new_bill
0      14.99  1.01  Female    No  Sun   Dinner   2    7.495
1       8.34  1.66     Male    No  Sun   Dinner   3    4.170
2      19.01  3.50     Male    No  Sun   Dinner   3    9.505
3      21.68  3.31     Male    No  Sun   Dinner   2  10.840
4      22.59  3.61  Female    No  Sun   Dinner   4  11.295
```

Filtering

Filtering in Stata is done with an `if` clause on one or more columns.

```
list if total_bill > 10
```

DataFrames can be filtered in multiple ways; the most intuitive of which is using *boolean indexing*.

```
In [12]: tips[tips['total_bill'] > 10].head()
Out[12]:
   total_bill  tip    sex  smoker  day    time  size
0      14.99  1.01  Female    No  Sun   Dinner   2
1      19.01  3.50     Male    No  Sun   Dinner   3
2      21.68  3.31     Male    No  Sun   Dinner   2
3      22.59  3.61  Female    No  Sun   Dinner   4
```
If/then logic

In Stata, an if clause can also be used to create new columns.

```plaintext
generate bucket = "low" if total_bill < 10
replace bucket = "high" if total_bill >= 10
```

The same operation in pandas can be accomplished using the where method from numpy.

```python
In [13]: tips['bucket'] = np.where(tips['total_bill'] < 10, 'low', 'high')
In [14]: tips.head()
Out[14]:
     total_bill  tip  sex   smoker  day   time  size  bucket
0       14.99  1.01 Female  No  Sun  Dinner    2  high
1        8.34  1.66    Male  No  Sun  Dinner    3  low
2       19.01  3.50    Male  No  Sun  Dinner    3  high
3       21.68  3.31    Male  No  Sun  Dinner    2  high
4       22.59  3.61 Female  No  Sun  Dinner    4  high
```

Date functionality

Stata provides a variety of functions to do operations on date/datetime columns.

```plaintext
generate date1 = mdy(1, 15, 2013)
generate date2 = date("Feb152015", "MDY")
generate date1_year = year(date1)
generate date2_month = month(date2)
* shift date to beginning of next month
generate date1_next = mdy(month(date1) + 1, 1, year(date1)) if month(date1) != 12
replace date1_next = mdy(1, 1, year(date1) + 1) if month(date1) == 12
generate months_between = mofd(date2) - mofd(date1)
list date1 date2 date1_year date2_month date1_next months_between
```

The equivalent pandas operations are shown below. In addition to these functions, pandas supports other Time Series features not available in Stata (such as time zone handling and custom offsets) – see the timeseries documentation for more details.

```python
In [15]: tips['date1'] = pd.Timestamp('2013-01-15')
In [16]: tips['date2'] = pd.Timestamp('2015-02-15')
In [17]: tips['date1_year'] = tips['date1'].dt.year
In [18]: tips['date2_month'] = tips['date2'].dt.month
In [19]: tips['date1_next'] = tips['date1'] + pd.offsets.MonthBegin()
In [20]: tips['months_between'] = (tips['date2'].dt.to_period('M')
.....:              - tips['date1'].dt.to_period('M'))
.....:
```

(continues on next page)
In [21]: tips[['date1', 'date2', 'date1_year', 'date2_month', 'date1_next', 'months_between']].head()

Out[21]:

<table>
<thead>
<tr>
<th>date1</th>
<th>date2</th>
<th>date1_year</th>
<th>date2_month</th>
<th>date1_next</th>
<th>months_between</th>
</tr>
</thead>
</table>

Selection of columns

Stata provides keywords to select, drop, and rename columns.

keep sex total_bill tip

drop sex

rename total_bill total_bill_2

The same operations are expressed in pandas below. Note that in contrast to Stata, these operations do not happen in place. To make these changes persist, assign the operation back to a variable.

# keep
In [22]: tips[['sex', 'total_bill', 'tip']].head()
Out[22]:

<table>
<thead>
<tr>
<th>sex</th>
<th>total_bill</th>
<th>tip</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>14.99</td>
<td>1.01</td>
</tr>
<tr>
<td>Male</td>
<td>8.34</td>
<td>1.66</td>
</tr>
<tr>
<td>Male</td>
<td>19.01</td>
<td>3.50</td>
</tr>
<tr>
<td>Male</td>
<td>21.68</td>
<td>3.31</td>
</tr>
<tr>
<td>Female</td>
<td>22.59</td>
<td>3.61</td>
</tr>
</tbody>
</table>

# drop
In [23]: tips.drop('sex', axis=1).head()
Out[23]:

<table>
<thead>
<tr>
<th>total_bill</th>
<th>tip</th>
<th>smoker</th>
<th>day</th>
<th>time</th>
<th>size</th>
</tr>
</thead>
<tbody>
<tr>
<td>14.99</td>
<td>1.01</td>
<td>No Sun</td>
<td>Dinner</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>8.34</td>
<td>1.66</td>
<td>No Sun</td>
<td>Dinner</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>19.01</td>
<td>3.50</td>
<td>No Sun</td>
<td>Dinner</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>21.68</td>
<td>3.31</td>
<td>No Sun</td>
<td>Dinner</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>22.59</td>
<td>3.61</td>
<td>No Sun</td>
<td>Dinner</td>
<td>4</td>
<td></td>
</tr>
</tbody>
</table>

# rename
In [24]: tips.rename(columns={'total_bill': 'total_bill_2'}).head()
Out[24]:

<table>
<thead>
<tr>
<th>total_bill_2</th>
<th>tip</th>
<th>sex</th>
<th>smoker</th>
<th>day</th>
<th>time</th>
<th>size</th>
</tr>
</thead>
<tbody>
<tr>
<td>14.99</td>
<td>1.01</td>
<td>Female</td>
<td>No Sun</td>
<td>Dinner</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>8.34</td>
<td>1.66</td>
<td>Male</td>
<td>No Sun</td>
<td>Dinner</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>19.01</td>
<td>3.50</td>
<td>Male</td>
<td>No Sun</td>
<td>Dinner</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>21.68</td>
<td>3.31</td>
<td>Male</td>
<td>No Sun</td>
<td>Dinner</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>22.59</td>
<td>3.61</td>
<td>Female</td>
<td>No Sun</td>
<td>Dinner</td>
<td>4</td>
<td></td>
</tr>
</tbody>
</table>
pandas: powerful Python data analysis toolkit, Release 1.1.1

**Sorting by values**

Sorting in Stata is accomplished via `sort`:

```
sort sex total_bill
```

pandas objects have a `DataFrame.sort_values()` method, which takes a list of columns to sort by.

```
In [25]: tips = tips.sort_values(["sex", "total_bill"])

In [26]: tips.head()
```

```
Out[26]:
   total_bill  tip  sex  smoker  day   time  size
0         67  1.07  Female  Yes    Sat  Dinner  1
1         92  3.75  Female  Yes     Fri  Dinner  2
2        111  5.25  Female   No    Sat  Dinner  1
3        145  6.35  Female  No   Thur  Lunch  2
4        135  6.51  Female  No   Thur  Lunch  2
```

**String processing**

**Finding length of string**

Stata determines the length of a character string with the `strlen()` and `ustrlen()` functions for ASCII and Unicode strings, respectively.

```
generate strlen_time = strlen(time)
generate ustrlen_time = ustrlen(time)
```

Python determines the length of a character string with the `len` function. In Python 3, all strings are Unicode strings. `len` includes trailing blanks. Use `len` and `rstrip` to exclude trailing blanks.

```
In [27]: tips['time'].str.len().head()
```

```
Out[27]:
0    6
1    6
2    6
3    6
4    5
Name: time, dtype: int64
```

```
In [28]: tips['time'].str.rstrip().str.len().head()
```

```
Out[28]:
0    6
1    6
2    6
3    6
4    5
Name: time, dtype: int64
```
Finding position of substring

Stata determines the position of a character in a string with the `strpos()` function. This takes the string defined by the first argument and searches for the first position of the substring you supply as the second argument.

```stata
generate str_position = strpos(sex, "ale")
```

Python determines the position of a character in a string with the `find()` function. `find` searches for the first position of the substring. If the substring is found, the function returns its position. Keep in mind that Python indexes are zero-based and the function will return -1 if it fails to find the substring.

```python
In [29]: tips['sex'].str.find("ale").head()
Out[29]:
   67 3
   92 3
  111 3
  145 3
  135 3
Name: sex, dtype: int64
```

Extracting substring by position

Stata extracts a substring from a string based on its position with the `substr()` function.

```stata
generate short_sex = substr(sex, 1, 1)
```

With pandas you can use `[]` notation to extract a substring from a string by position locations. Keep in mind that Python indexes are zero-based.

```python
In [30]: tips['sex'][0:1].head()
Out[30]:
   67 F
   92 F
  111 F
  145 F
  135 F
Name: sex, dtype: object
```

Extracting nth word

The Stata `word()` function returns the nth word from a string. The first argument is the string you want to parse and the second argument specifies which word you want to extract.

```stata
clear
input str20 string
"John Smith"
"Jane Cook"
end
generate first_name = word(name, 1)
generate last_name = word(name, -1)
```

Python extracts a substring from a string based on its text by using regular expressions. There are much more powerful approaches, but this just shows a simple approach.
In [31]: firstlast = pd.DataFrame({'string': ['John Smith', 'Jane Cook']})
In [32]: firstlast['First_Name'] = firstlast['string'].str.split(" ", expand=True)[0]
In [33]: firstlast['Last_Name'] = firstlast['string'].str.rsplit(" ", expand=True)[0]
In [34]: firstlast
Out[34]:
<table>
<thead>
<tr>
<th>string</th>
<th>First_Name</th>
<th>Last_Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>John</td>
<td>John</td>
</tr>
<tr>
<td>1</td>
<td>Jane</td>
<td>Jane</td>
</tr>
</tbody>
</table>

### Changing case

The Stata `strupper()`, `strlower()`, `strproper()`, `ustrupper()`, `ustrlower()`, and `ustrtitle()` functions change the case of ASCII and Unicode strings, respectively.

```
clear
input str20 string
"John Smith"
"Jane Cook"
end

generate upper = strupper(string)
generate lower = strlower(string)
generate title = strproper(string)
list
```

The equivalent Python functions are `upper`, `lower`, and `title`.

In [35]: firstlast = pd.DataFrame({'string': ['John Smith', 'Jane Cook']})
In [36]: firstlast['upper'] = firstlast['string'].str.upper()
In [37]: firstlast['lower'] = firstlast['string'].str.lower()
In [38]: firstlast['title'] = firstlast['string'].str.title()
In [39]: firstlast
Out[39]:
<table>
<thead>
<tr>
<th>string</th>
<th>upper</th>
<th>lower</th>
<th>title</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>JOHN SMITH</td>
<td>john smith</td>
<td>John Smith</td>
</tr>
<tr>
<td>1</td>
<td>JANE COOK</td>
<td>jane cook</td>
<td>Jane Cook</td>
</tr>
</tbody>
</table>

### Merging

The following tables will be used in the merge examples

In [40]: df1 = pd.DataFrame({'key': ['A', 'B', 'C', 'D'],
                         .....:     'value': np.random.randn(4))}
In [41]: df1
Out[41]:
       value
key         
A    0.512779
B  -0.682248
C    0.226985
D    0.663897

(continues on next page)
In Stata, to perform a merge, one data set must be in memory and the other must be referenced as a file name on disk. In contrast, Python must have both DataFrames already in memory.

By default, Stata performs an outer join, where all observations from both data sets are left in memory after the merge. One can keep only observations from the initial data set, the merged data set, or the intersection of the two by using the values created in the _merge variable.

```stata
* First create df2 and save to disk
clear
input str1 key
B
D
D
E
e nd
generate value = rnormal()
save df2.dta

* Now create df1 in memory
clear
input str1 key
A
B
C
D
d end
generate value = rnormal()

preserve

* Left join
merge 1:n key using df2.dta
keep if _merge == 1

* Right join
restore, preserve
merge 1:n key using df2.dta
keep if _merge == 2
```

(continues on next page)
pandas: powerful Python data analysis toolkit, Release 1.1.1

* Inner join
  restore, preserve
  merge 1:n key using df2.dta
  keep if _merge == 3

* Outer join
  restore
  merge 1:n key using df2.dta

pandas DataFrames have a `DataFrame.merge()` method, which provides similar functionality. Note that different join types are accomplished via the `how` keyword.

```
In [44]: inner_join = df1.merge(df2, on=['key'], how='inner')
In [45]: inner_join
Out[45]:
   key  value_x  value_y
0   B   -0.282863  1.212112
1   D   -1.135632 -0.173215
2   D   -1.135632  0.119209

In [46]: left_join = df1.merge(df2, on=['key'], how='left')
In [47]: left_join
Out[47]:
   key  value_x  value_y
0   A   0.469112   NaN
1   B   -0.282863  1.212112
2   C  -1.509059   NaN
3   D   -1.135632 -0.173215
4   D   -1.135632  0.119209
5   E   NaN   -1.044236

In [48]: right_join = df1.merge(df2, on=['key'], how='right')
In [49]: right_join
Out[49]:
   key  value_x  value_y
0   B   -0.282863  1.212112
1   D   -1.135632 -0.173215
2   D   -1.135632  0.119209
3   E   NaN   -1.044236

In [50]: outer_join = df1.merge(df2, on=['key'], how='outer')
In [51]: outer_join
Out[51]:
   key  value_x  value_y
0   A   0.469112   NaN
1   B   -0.282863  1.212112
2   C  -1.509059   NaN
3   D   -1.135632 -0.173215
4   D   -1.135632  0.119209
5   E   NaN   -1.044236
```
Missing data

Like Stata, pandas has a representation for missing data – the special float value `NaN` (not a number). Many of the semantics are the same; for example missing data propagates through numeric operations, and is ignored by default for aggregations.

```
In [52]: outer_join
Out[52]:
   key  value_x  value_y
0   A    0.469112     NaN
1   B   -0.282863    1.212112
2   C   -1.509059     NaN
3   D  -1.135632  -0.173215
4   D  -1.135632    0.119209
5   E     NaN    -1.044236
```

```
In [53]: outer_join['value_x'] + outer_join['value_y']
Out[53]:
   0      NaN
1  0.929249
2      NaN
3  1.308847
4 -1.016424
5      NaN
dtype: float64
```

```
In [54]: outer_join['value_x'].sum()
Out[54]: -3.5940742896293765
```

One difference is that missing data cannot be compared to its sentinel value. For example, in Stata you could do this to filter missing values.

```
* Keep missing values
list if value_x == .
* Keep non-missing values
list if value_x != .
```

This doesn’t work in pandas. Instead, the `pd.isna()` or `pd.notna()` functions should be used for comparisons.

```
In [55]: outer_join[pd.isna(outer_join['value_x'])]
Out[55]:
   key  value_x  value_y
5   E     NaN    -1.044236
```

```
In [56]: outer_join[pd.notna(outer_join['value_x'])]
Out[56]:
   key  value_x  value_y
0   A    0.469112     NaN
1   B   -0.282863    1.212112
2   C   -1.509059     NaN
3   D  -1.135632  -0.173215
4   D  -1.135632    0.119209
```

Pandas also provides a variety of methods to work with missing data – some of which would be challenging to express in Stata. For example, there are methods to drop all rows with any missing values, replacing missing values with a specified value, like the mean, or forward filling from previous rows. See the missing data documentation for more.
# Drop rows with any missing value
In [57]: outer_join.dropna()
Out[57]:
<table>
<thead>
<tr>
<th>key</th>
<th>value_x</th>
<th>value_y</th>
</tr>
</thead>
<tbody>
<tr>
<td>B</td>
<td>-0.282863</td>
<td>1.212112</td>
</tr>
<tr>
<td>D</td>
<td>-1.135632</td>
<td>-0.173215</td>
</tr>
<tr>
<td>D</td>
<td>-1.135632</td>
<td>0.119209</td>
</tr>
</tbody>
</table>

# Fill forwards
In [58]: outer_join.fillna(method='ffill')
Out[58]:
<table>
<thead>
<tr>
<th>key</th>
<th>value_x</th>
<th>value_y</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.469112</td>
<td>NaN</td>
</tr>
<tr>
<td>B</td>
<td>-0.282863</td>
<td>1.212112</td>
</tr>
<tr>
<td>C</td>
<td>-1.509059</td>
<td>1.212112</td>
</tr>
<tr>
<td>D</td>
<td>-1.135632</td>
<td>-0.173215</td>
</tr>
<tr>
<td>D</td>
<td>-1.135632</td>
<td>0.119209</td>
</tr>
<tr>
<td>E</td>
<td>-1.135632</td>
<td>-1.044236</td>
</tr>
</tbody>
</table>

# Impute missing values with the mean
In [59]: outer_join['value_x'].fillna(outer_join['value_x'].mean())
Out[59]:
<table>
<thead>
<tr>
<th>key</th>
<th>value_x</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.469112</td>
</tr>
<tr>
<td>1</td>
<td>-0.282863</td>
</tr>
<tr>
<td>2</td>
<td>-1.509059</td>
</tr>
<tr>
<td>3</td>
<td>-1.135632</td>
</tr>
<tr>
<td>4</td>
<td>-1.135632</td>
</tr>
<tr>
<td>5</td>
<td>-0.718815</td>
</tr>
</tbody>
</table>
Name: value_x, dtype: float64

GroupBy

Aggregation

Stata’s collapse can be used to group by one or more key variables and compute aggregations on numeric columns.

collapse (sum) total_bill tip, by(sex smoker)

pandas provides a flexible groupby mechanism that allows similar aggregations. See the groupby documentation for more details and examples.

In [60]: tips_summed = tips.groupby(['sex', 'smoker'])[['total_bill', 'tip']].sum()

In [61]: tips_summed.head()
Out[61]:
<table>
<thead>
<tr>
<th>sex</th>
<th>smoker</th>
<th>total_bill</th>
<th>tip</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>No</td>
<td>869.68</td>
<td>149.77</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>527.27</td>
<td>96.74</td>
</tr>
<tr>
<td>Male</td>
<td>No</td>
<td>1725.75</td>
<td>302.00</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>1217.07</td>
<td>183.07</td>
</tr>
</tbody>
</table>
Transformation

In Stata, if the group aggregations need to be used with the original data set, one would usually use `bysort` with `egen()`. For example, to subtract the mean for each observation by smoker group.

```
bysort sex smoker: egen group_bill = mean(total_bill)
generate adj_total_bill = total_bill - group_bill
```

Pandas `groupby` provides a `transform` mechanism that allows these type of operations to be succinctly expressed in one operation.

```
In [62]: gb = tips.groupby('smoker')['total_bill']
In [63]: tips['adj_total_bill'] = tips['total_bill'] - gb.transform('mean')
In [64]: tips.head()
Out[64]:
<table>
<thead>
<tr>
<th>total_bill</th>
<th>tip</th>
<th>sex</th>
<th>smoker</th>
<th>day</th>
<th>time</th>
<th>size</th>
<th>adj_total_bill</th>
</tr>
</thead>
<tbody>
<tr>
<td>67</td>
<td>1.07</td>
<td>1.00</td>
<td>Female</td>
<td>Yes</td>
<td>Sat</td>
<td>1</td>
<td>-17.686344</td>
</tr>
<tr>
<td>92</td>
<td>3.75</td>
<td>1.00</td>
<td>Female</td>
<td>Yes</td>
<td>Fri</td>
<td>2</td>
<td>-15.006344</td>
</tr>
<tr>
<td>111</td>
<td>5.25</td>
<td>1.00</td>
<td>Female</td>
<td>No</td>
<td>Sat</td>
<td>1</td>
<td>-11.938278</td>
</tr>
<tr>
<td>145</td>
<td>6.35</td>
<td>1.50</td>
<td>Female</td>
<td>No</td>
<td>Thur</td>
<td>2</td>
<td>-10.838278</td>
</tr>
<tr>
<td>135</td>
<td>6.51</td>
<td>1.25</td>
<td>Female</td>
<td>No</td>
<td>Thur</td>
<td>2</td>
<td>-10.678278</td>
</tr>
</tbody>
</table>
```

By group processing

In addition to aggregation, pandas `groupby` can be used to replicate most other `bysort` processing from Stata. For example, the following example lists the first observation in the current sort order by sex/smoker group.

```
bysort sex smoker: list if _n == 1
```

In pandas this would be written as:

```
In [65]: tips.groupby(['sex', 'smoker']).first()
Out[65]:
<table>
<thead>
<tr>
<th>total_bill</th>
<th>tip</th>
<th>sex</th>
<th>smoker</th>
<th>day</th>
<th>time</th>
<th>size</th>
<th>adj_total_bill</th>
</tr>
</thead>
<tbody>
<tr>
<td>67</td>
<td>1.07</td>
<td>1.00</td>
<td>Female</td>
<td>Yes</td>
<td>Sat</td>
<td>1</td>
<td>-17.686344</td>
</tr>
<tr>
<td>92</td>
<td>3.75</td>
<td>1.00</td>
<td>Female</td>
<td>Yes</td>
<td>Fri</td>
<td>2</td>
<td>-15.006344</td>
</tr>
<tr>
<td>111</td>
<td>5.25</td>
<td>1.00</td>
<td>Female</td>
<td>No</td>
<td>Sat</td>
<td>1</td>
<td>-11.938278</td>
</tr>
<tr>
<td>145</td>
<td>6.35</td>
<td>1.50</td>
<td>Female</td>
<td>No</td>
<td>Thur</td>
<td>2</td>
<td>-10.838278</td>
</tr>
<tr>
<td>135</td>
<td>6.51</td>
<td>1.25</td>
<td>Female</td>
<td>No</td>
<td>Thur</td>
<td>2</td>
<td>-10.678278</td>
</tr>
</tbody>
</table>
```

Other considerations

Disk vs memory

Pandas and Stata both operate exclusively in memory. This means that the size of data able to be loaded in pandas is limited by your machine’s memory. If out of core processing is needed, one possibility is the `dask.dataframe` library, which provides a subset of pandas functionality for an on-disk `DataFrame`.
1.4.5 Community tutorials

This is a guide to many pandas tutorials by the community, geared mainly for new users.

**pandas cookbook by Julia Evans**

The goal of this 2015 cookbook (by Julia Evans) is to give you some concrete examples for getting started with pandas. These are examples with real-world data, and all the bugs and weirdness that entails. For the table of contents, see the pandas-cookbook GitHub repository.

**Learn pandas by Hernan Rojas**

A set of lesson for new pandas users: https://bitbucket.org/hrojas/learn-pandas

**Practical data analysis with Python**

This guide is an introduction to the data analysis process using the Python data ecosystem and an interesting open dataset. There are four sections covering selected topics as munging data, aggregating data, visualizing data and time series.

**Exercises for new users**

Practice your skills with real data sets and exercises. For more resources, please visit the main repository.

**Modern pandas**

Tutorial series written in 2016 by Tom Augspurger. The source may be found in the GitHub repository TomAugspurger/effective-pandas.

- Modern Pandas
- Method Chaining
- Indexes
- Performance
- Tidy Data
- Visualization
- Timeseries

**Excel charts with pandas, vincent and xlsxwriter**

- Using Pandas and XlsxWriter to create Excel charts
Video tutorials

- Pandas: .head() to .tail() (2016) (1:26) GitHub repo
- Data analysis in Python with pandas (2016-2018) GitHub repo and Jupyter Notebook
- Best practices with pandas (2018) GitHub repo and Jupyter Notebook

Various tutorials

- Wes McKinney’s (pandas BDFL) blog
- Statistical analysis made easy in Python with SciPy and pandas DataFrames, by Randal Olson
- Statistical Data Analysis in Python, tutorial videos, by Christopher Fonnesbeck from SciPy 2013
- Financial analysis in Python, by Thomas Wiecki
- Intro to pandas data structures, by Greg Reda
- Pandas and Python: Top 10, by Manish Amde
- Pandas DataFrames Tutorial, by Karlijn Willems
- A concise tutorial with real life examples
The User Guide covers all of pandas by topic area. Each of the subsections introduces a topic (such as “working with missing data”), and discusses how pandas approaches the problem, with many examples throughout.

Users brand-new to pandas should start with 10min.

For a high level summary of the pandas fundamentals, see Intro to data structures and Essential basic functionality.

Further information on any specific method can be obtained in the API reference.

2.1 10 minutes to pandas

This is a short introduction to pandas, geared mainly for new users. You can see more complex recipes in the Cookbook.

Customarily, we import as follows:

```
In [1]: import numpy as np
In [2]: import pandas as pd
```

2.1.1 Object creation

See the Data Structure Intro section.

Creating a Series by passing a list of values, letting pandas create a default integer index:

```
In [3]: s = pd.Series([1, 3, 5, np.nan, 6, 8])
```

```
In [4]: s
Out[4]:
0    1.0
1    3.0
2    5.0
3  NaN
4    6.0
5    8.0
dtype: float64
```

Creating a DataFrame by passing a NumPy array, with a datetime index and labeled columns:

```
In [5]: dates = pd.date_range('20130101', periods=6)
In [6]: dates
```

(continues on next page)
Creating a DataFrame by passing a dict of objects that can be converted to series-like.

In [9]: df2 = pd.DataFrame({'A': 1.,
...:                       'B': pd.Timestamp('20130102'),
...:                       'C': pd.Series(1, index=list(range(4)),
...:                          dtype='float32'),
...:                       'D': np.array([3] * 4, dtype='int32'),
...:                       'E': pd.Categorical(['test', 'train', 'test', 'train']),
...:                       'F': 'foo'})

Out[10]:

    A     B
0  1.0 2013-01-02
1  1.0 2013-01-02
2  1.0 2013-01-02
3  1.0 2013-01-02
4  1.0 2013-01-02

The columns of the resulting DataFrame have different dtypes.

In [11]: df2.dtypes
Out[11]:

    A       B       C       D       E       F
dtype: float64, datetime64[ns], float32, int32, category, object

If you’re using IPython, tab completion for column names (as well as public attributes) is automatically enabled. Here’s a subset of the attributes that will be completed:

In [12]: df2.<TAB>  # noqa: E225, E999
    df2.A          df2.abs          df2.add
    df2.add_prefix df2.add_suffix  
    df2.oo
    df2.boxplot   df2.clip
    df2.bool      df2.columns

(continues on next page)
As you can see, the columns A, B, C, and D are automatically tab completed. E and F are there as well; the rest of the attributes have been truncated for brevity.

### 2.1.2 Viewing data

See the **Basics section**.

Here is how to view the top and bottom rows of the frame:

```python
In [13]: df.head()
Out[13]:
   A       B       C       D
2013-01-01 -0.626301 -0.639531  1.086514 -0.063857
2013-01-02  1.155598  1.016491 -0.772837  0.603099
2013-01-03 -0.631739 -0.918963  1.180634 -0.273130
2013-01-04  0.046220  0.103776 -0.283132 -1.926681
2013-01-05  0.698654  0.764023  0.474685 -0.481632
```

```python
In [14]: df.tail(3)
Out[14]:
   A       B       C       D
2013-01-04  0.046220  0.103776 -0.283132 -1.926681
2013-01-05  0.698654  0.764023  0.474685 -0.481632
2013-01-06 -0.490500 -0.747189  0.973844  0.760727
```

Display the index, columns:

```python
In [15]: df.index
Out[15]:
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05', '2013-01-06'],
               dtype='datetime64[ns]', freq='D')
```

```python
In [16]: df.columns
Out[16]:
Index(['A', 'B', 'C', 'D'], dtype='object')
```

`DataFrame.to_numpy()` gives a NumPy representation of the underlying data. Note that this can be an expensive operation when your DataFrame has columns with different data types, which comes down to a fundamental difference between pandas and NumPy: **NumPy arrays have one dtype for the entire array, while pandas DataFrames have one dtype per column.** When you call `DataFrame.to_numpy()`, pandas will find the NumPy dtype that can hold *all* of the dtypes in the DataFrame. This may end up being `object`, which requires casting every value to a Python object.

For `df`, our DataFrame of all floating-point values, `DataFrame.to_numpy()` is fast and doesn’t require copying data.
For \( df2 \), the DataFrame with multiple dtypes, \( DataFrame.to_numpy() \) is relatively expensive.

```python
In [18]: df2.to_numpy()
Out[18]:
array([[1.0, Timestamp('2013-01-02 00:00:00'), 1.0, 3, 'test', 'foo'],
      [1.0, Timestamp('2013-01-02 00:00:00'), 1.0, 3, 'train', 'foo'],
      [1.0, Timestamp('2013-01-02 00:00:00'), 1.0, 3, 'test', 'foo'],
      [1.0, Timestamp('2013-01-02 00:00:00'), 1.0, 3, 'train', 'foo']],
dtype=object)
```

**Note:** \( DataFrame.to_numpy() \) does *not* include the index or column labels in the output.

describe() shows a quick statistic summary of your data:

```python
In [19]: df.describe()
Out[19]:
   A    B    C    D
count 6.0000 6.0000 6.0000 6.0000
mean 0.0253 -0.0702 0.4433 -0.2302
std 0.7555 0.8258 0.8058 0.9641
min -0.6317 -0.9189 -0.7728 -1.9267
25% -0.5924 -0.7203 -0.0937 -0.4295
50% -0.2221 -0.2679 0.7243 -0.1685
75%  0.5355  0.5989  1.0583  0.4364
max  1.1556  1.0164  1.1806  0.7607
```

Transposing your data:

```python
In [20]: df.T
Out[20]:
A  -0.6263  1.1556 -0.6317  0.0462  0.6986 -0.4905
B  -0.6395  1.0164 -0.9189  0.1038  0.7640 -0.7472
C   1.0865 -0.7728  1.1806 -0.2831  0.4746  0.9738
D  -0.0638  0.6030 -0.2731 -1.9267 -0.4816  0.7607
```

Sorting by an axis:

```python
In [21]: df.sort_index(axis=1, ascending=False)
Out[21]:
   D    C    B    A
2013-01-01 -0.0638 1.0865 -0.6395 -0.6263
2013-01-02  0.6030 -0.7728  1.0164  1.1556
2013-01-03 -0.2731  1.1806 -0.9189 -0.6317
2013-01-04 -1.9267 -0.2831  0.1038  0.0462
2013-01-05 -0.4816  0.4746  0.7640  0.9738
2013-01-06  0.7607  0.9738 -0.7472 -0.4905
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

Sorting by values:

```python
In [22]: df.sort_values(by='B')
Out[22]:
     A       B       C       D
2013-01-03 -0.631739 -0.918963  1.180634 -0.273130
2013-01-06 -0.490500 -0.747189  0.973844  0.760727
2013-01-01 -0.626301 -0.639531  1.086514 -0.063857
2013-01-04  0.046220  0.103776 -0.283132 -1.926681
2013-01-05  0.698654  0.764023  0.474685 -0.481632
2013-01-02  1.155598  1.016491 -0.772837  0.603099
```

2.1.3 Selection

**Note:** While standard Python / Numpy expressions for selecting and setting are intuitive and come in handy for interactive work, for production code, we recommend the optimized pandas data access methods, `.at`, `.iat`, `.loc` and `.iloc`.

See the indexing documentation *Indexing and Selecting Data* and *MultiIndex / Advanced Indexing*.

Getting

Selecting a single column, which yields a `Series` equivalent to `df.A`:

```python
In [23]: df['A']
Out[23]:
2013-01-01    -0.626301
2013-01-02     1.155598
2013-01-03    -0.631739
2013-01-04     0.046220
2013-01-05     0.698654
Freq: D, Name: A, dtype: float64
```

Selecting via `[]`, which slices the rows.

```python
In [24]: df[0:3]
Out[24]:
     A       B       C       D
2013-01-01 -0.626301 -0.639531  1.086514 -0.063857
2013-01-02  1.155598  1.016491 -0.772837  0.603099
2013-01-03 -0.631739 -0.918963  1.180634 -0.273130

In [25]: df['20130102':'20130104']
Out[25]:
     A       B       C       D
2013-01-02  1.155598  1.016491 -0.772837  0.603099
2013-01-03 -0.631739 -0.918963  1.180634 -0.273130
2013-01-04  0.046220  0.103776 -0.283132 -1.926681
```
Selection by label

See more in Selection by Label.

For getting a cross section using a label:

```
In [26]: df.loc[dates[0]]
Out[26]:
A   -0.626301
B   -0.639531
C    1.086514
D   -0.063857
Name: 2013-01-01 00:00:00, dtype: float64
```

Selecting on a multi-axis by label:

```
In [27]: df.loc[:, ['A', 'B']]
Out[27]:
   A        B
2013-01-01 -0.626301 -0.639531
2013-01-02  1.155598  1.016491
2013-01-03 -0.631739 -0.918963
2013-01-04  0.046220  0.103776
2013-01-05  0.698654  0.764023
2013-01-06 -0.490500 -0.747189
```

Showing label slicing, both endpoints are included:

```
In [28]: df.loc['20130102':'20130104', ['A', 'B']]
Out[28]:
   A        B
2013-01-02  1.155598  1.016491
2013-01-03 -0.631739 -0.918963
2013-01-04  0.046220  0.103776
```

Reduction in the dimensions of the returned object:

```
In [29]: df.loc['20130102', ['A', 'B']]
Out[29]:
   A
2013-01-02  1.155598

   B
2013-01-02  1.016491

Name: 2013-01-02 00:00:00, dtype: float64
```

For getting a scalar value:

```
In [30]: df.loc[dates[0], 'A']
Out[30]:
-0.626301
```

For getting fast access to a scalar (equivalent to the prior method):

```
In [31]: df.at[dates[0], 'A']
Out[31]:
-0.626301
```
Selection by position

See more in Selection by Position.

Select via the position of the passed integers:

```python
In [32]: df.iloc[3]
Out[32]:
A  0.046220
B  0.103776
C -0.283132
D -1.926681
Name: 2013-01-04 00:00:00, dtype: float64
```

By integer slices, acting similar to numpy/python:

```python
In [33]: df.iloc[3:5, 0:2]
Out[33]:
   A    B
2013-01-04  0.046220  0.103776
2013-01-05  0.698654  0.764023
```

By lists of integer position locations, similar to the numpy/python style:

```python
In [34]: df.iloc[[1, 2, 4], [0, 2]]
Out[34]:
   A    C
2013-01-02  1.155598 -0.772837
2013-01-03 -0.631739  1.180634
2013-01-05  0.698654  0.474685
```

For slicing rows explicitly:

```python
In [35]: df.iloc[1:3, :]
Out[35]:
   A    B    C    D
2013-01-02  1.155598  1.016491 -0.772837  0.603099
2013-01-03 -0.631739 -0.918963  1.180634 -0.273130
```

For slicing columns explicitly:

```python
In [36]: df.iloc[:, 1:3]
Out[36]:
   B    C
2013-01-01 -0.639531  1.086514
2013-01-02  1.016491 -0.772837
2013-01-03 -0.918963  1.180634
2013-01-04  0.103776 -0.283132
2013-01-05  0.764023  0.474685
2013-01-06 -0.747189  0.973844
```

For getting a value explicitly:

```python
In [37]: df.iloc[1, 1]
Out[37]:
1.0164914726270666
```

For getting fast access to a scalar (equivalent to the prior method):

2.1. 10 minutes to pandas
In [38]: df.iat[1, 1]
Out[38]: 1.0164914726270666

Boolean indexing

Using a single column’s values to select data.

In [39]: df[df['A'] > 0]
Out[39]:
      A      B      C      D
2013-01-02  1.155598  1.016491 -0.772837  0.603099
2013-01-04  0.046220  0.103776 -0.283132 -1.926681
2013-01-05  0.698654  0.764023  0.474685 -0.481632

Selecting values from a DataFrame where a boolean condition is met.

In [40]: df[df > 0]
Out[40]:
      A      B      C      D
2013-01-01  NaN  NaN  1.086514  NaN
2013-01-02  1.155598  1.016491  NaN  0.603099
2013-01-03  NaN  NaN  1.180634  NaN
2013-01-04  0.046220  0.103776  NaN  NaN
2013-01-05  0.698654  0.764023  0.474685  NaN
2013-01-06  NaN  NaN  0.973844  0.760727

Using the `isin()` method for filtering:

In [41]: df2 = df.copy()

In [42]: df2['E'] = ['one', 'one', 'two', 'three', 'four', 'three']

In [43]: df2
Out[43]:
      A      B      C      D      E
2013-01-01 -0.626301 -0.639531  1.086514 -0.063857 one
2013-01-02  1.155598  1.016491 -0.772837  0.603099 one
2013-01-03 -0.631739 -0.918963  1.180634 -0.273130 two
2013-01-04  0.046220  0.103776 -0.283132 -1.926681 three
2013-01-05  0.698654  0.764023  0.474685 -0.481632 four
2013-01-06 -0.490500 -0.747189  0.973844  0.760727 three

In [44]: df2[df2['E'].isin(['two', 'four'])]
Out[44]:
      A      B      C      D      E
2013-01-03 -0.631739 -0.918963  1.180634 -0.273130 two
2013-01-05  0.698654  0.764023  0.474685 -0.481632 four
Setting

Setting a new column automatically aligns the data by the indexes.

```python
In [45]: s1 = pd.Series([1, 2, 3, 4, 5, 6], index=pd.date_range('20130102', periods=6))

In [46]: s1
Out[46]:
2013-01-02    1
2013-01-03    2
2013-01-04    3
2013-01-05    4
2013-01-06    5
2013-01-07    6
Freq: D, dtype: int64

In [47]: df['F'] = s1
```

Setting values by label:

```python
In [48]: df.at[dates[0], 'A'] = 0
```

Setting values by position:

```python
In [49]: df.iat[0, 1] = 0
```

Setting by assigning with a NumPy array:

```python
In [50]: df.loc[:, 'D'] = np.array([5] * len(df))
```

The result of the prior setting operations.

```python
In [51]: df
Out[51]:
     A       B       C       D       F
2013-01-01  0.000000  0.000000  1.086514  5.0  NaN
2013-01-02  1.155598  1.016491 -0.772837  5.0  1.0
2013-01-03 -0.631739 -0.918963  1.180634  5.0  2.0
2013-01-04  0.046220  0.103776 -0.283132  5.0  3.0
2013-01-05  0.698654  0.764023  0.474685  5.0  4.0
2013-01-06 -0.490500 -0.747189  0.973844  5.0  5.0
```

A `where` operation with setting.

```python
In [52]: df2 = df.copy()

In [53]: df2[df2 > 0] = -df2

In [54]: df2
Out[54]:
     A       B       C       D       F
2013-01-01  0.000000  0.000000   NaN      5  NaN
2013-01-02 -1.155598 -1.016491 -0.772837  5.0   -1.0
2013-01-03  0.631739  0.918963  1.180634  5.0   -2.0
2013-01-04 -0.046220 -0.103776 -0.283132  5.0   -3.0
2013-01-05 -0.698654 -0.764023 -0.474685  5.0   -4.0
2013-01-06  0.490500  0.747189  0.973844  5.0   -5.0
```

2.1. 10 minutes to pandas
2.1.4 Missing data

pandas primarily uses the value `np.nan` to represent missing data. It is by default not included in computations. See the Missing Data section.

Reindexing allows you to change/add/delete the index on a specified axis. This returns a copy of the data.

```
In [55]: df1 = df.reindex(index=dates[0:4], columns=list(df.columns) + ['E'])
In [56]: df1.loc[dates[0]:dates[1], 'E'] = 1
In [57]: df1
Out[57]:
          A         B         C         D         F    E
2013-01-01 0.000000 0.000000 1.086514 5.0  NaN    1
2013-01-02 1.155598 1.016491 -0.772837 5.0  1.0   1
2013-01-03 -0.631739 -0.918963 1.180634 5.0  2.0  NaN
2013-01-04 0.046220 0.103776 -0.283132 5.0  3.0  NaN
```

To drop any rows that have missing data.

```
In [58]: df1.dropna(how='any')
Out[58]:
          A         B         C         D         F
2013-01-02 1.155598 1.016491 -0.772837 5.0  1.0
```

Filling missing data.

```
In [59]: df1.fillna(value=5)
Out[59]:
          A         B         C         D         F    E
2013-01-01 0.000000 0.000000 1.086514 5.0  5.0    1
2013-01-02 1.155598 1.016491 -0.772837 5.0  1.0   1
2013-01-03 -0.631739 -0.918963 1.180634 5.0  2.0  5.0
2013-01-04 0.046220 0.103776 -0.283132 5.0  3.0  5.0
```

To get the boolean mask where values are `nan`.

```
In [60]: pd.isna(df1)
Out[60]:
          A        B        C        D        F    E
2013-01-01 False   False   False   False    True False
2013-01-02 False   False   False   False    False False
2013-01-03 False   False   False   False    False False
2013-01-04 False   False   False   False    False False
```

2.1.5 Operations

See the Basic section on Binary Ops.
Stats

Operations in general exclude missing data.

Performing a descriptive statistic:

```
In [61]: df.mean()
Out[61]:
A    0.129705
B    0.036356
C    0.443285
D    5.000000
F    3.000000
dtype: float64
```

Same operation on the other axis:

```
In [62]: df.mean(1)
Out[62]:
2013-01-01  1.521629
2013-01-02  1.479850
2013-01-03  1.325986
2013-01-04  1.573373
2013-01-05  2.187472
2013-01-06  1.947231
Freq: D, dtype: float64
```

Operating with objects that have different dimensionality and need alignment. In addition, pandas automatically broadcasts along the specified dimension.

```
In [63]: s = pd.Series([1, 3, 5, np.nan, 6, 8], index=dates).shift(2)
In [64]: s
Out[64]:
2013-01-01    NaN
2013-01-02    NaN
2013-01-03    1.0
2013-01-04    3.0
2013-01-05    5.0
2013-01-06    NaN
Freq: D, dtype: float64
```

```
In [65]: df.sub(s, axis='index')
Out[65]:
      A     B     C     D     F
2013-01-01 NaN NaN NaN NaN NaN
2013-01-02 NaN NaN NaN NaN NaN
2013-01-03 -1.631739 -1.918963 0.180634 4.0 1.0
2013-01-04 -2.953780 -2.896224 -3.283132 2.0 0.0
2013-01-05 -4.301346 -4.235977 -4.525315 0.0 -1.0
2013-01-06 NaN NaN NaN NaN NaN
```

2.1. 10 minutes to pandas
Apply

Applying functions to the data:

```
In [66]: df.apply(np.cumsum)
Out[66]:
          A         B         C         D        F
2013-01-01 0.000000 0.000000 1.086514   5 NaN
2013-01-02 1.155598 1.016491 0.313677  10  1.0
2013-01-03 0.523858 0.097528 1.494312  15  3.0
2013-01-04 0.570078 0.201304 1.211180  20  6.0
2013-01-05 1.268733 0.965327 1.685864  25 10.0
2013-01-06 0.778233 0.218139 2.659708  30 15.0
```

```
In [67]: df.apply(lambda x: x.max() - x.min())
Out[67]:
          A         B         C         D        F
        1.787337  1.935455  1.953471   0.000000  4.000000
dtype: float64
```

Histogramming

See more at Histogramming and Discretization.

```
In [68]: s = pd.Series(np.random.randint(0, 7, size=10))
In [69]: s
Out[69]:
0   0
1   3
2   3
3   3
4   0
5   1
6   2
7   6
8   1
9   3
dtype: int64
```

```
In [70]: s.value_counts()
Out[70]:
3   4
1   2
6   1
2   1
dtype: int64
```
String Methods

Series is equipped with a set of string processing methods in the \texttt{str} attribute that make it easy to operate on each element of the array, as in the code snippet below. Note that pattern-matching in \texttt{str} generally uses regular expressions by default (and in some cases always uses them). See more at \texttt{Vectorized String Methods}.

```
In [71]: s = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog', 'cat'])

In [72]: s.str.lower()
Out[72]:
0 a
1 b
2 c
3 aaba
4 baca
5 NaN
6 caba
7 dog
8 cat
dtype: object
```

### 2.1.6 Merge

**Concat**

pandas provides various facilities for easily combining together Series and DataFrame objects with various kinds of set logic for the indexes and relational algebra functionality in the case of join / merge-type operations.

See the \texttt{Merging section}.

Concatenating pandas objects together with \texttt{concat()}:

```
In [73]: df = pd.DataFrame(np.random.randn(10, 4))

In [74]: df
Out[74]:
     0        1        2        3
0 -0.137146  0.150048 -1.682346  0.182075
1  0.418058 -1.842945 -1.013824 -1.235850
2 -0.566820  2.087129  0.004033  0.181691
3  1.354161  0.748732 -1.294254 -0.448831
4 -0.113542 -0.263825  0.947580  0.395036
5 -0.234090  1.297769  0.013069  0.736962
6  0.113542  0.721999 -0.886004  0.314778
7 -1.346004  0.110371 -0.275713  0.736962
8 -3.051659  1.297769  1.021689  0.314660
9 -1.060402 -0.013069  0.298383  1.338698

# break it into pieces
In [75]: pieces = [df[:3], df[3:7], df[7:]]

In [76]: pd.concat(pieces)
Out[76]:
     0        1        2        3
0 -0.137146  0.150048 -1.682346  0.182075
1  0.418058 -1.842945 -1.013824 -1.235850
2 -0.566820  2.087129  0.004033  0.181691
3  1.354161  0.748732 -1.294254 -0.448831
4 -0.113542 -0.263825  0.947580  0.395036
5  0.756199 -0.886004  0.314778
   NaN  0.298383  1.338698
   NaN  0.314660
   NaN
(continues on next page)
Note: Adding a column to a DataFrame is relatively fast. However, adding a row requires a copy, and may be expensive. We recommend passing a pre-built list of records to the DataFrame constructor instead of building a DataFrame by iteratively appending records to it. See Appending to dataframe for more.

Join

SQL style merges. See the Database style joining section.

In [77]: left = pd.DataFrame({'key': ['foo', 'foo'], 'lval': [1, 2]})

In [78]: right = pd.DataFrame({'key': ['foo', 'foo'], 'rval': [4, 5]})

In [79]: left
Out[79]:
key  lval
0   foo   1
1   foo   2

In [80]: right
Out[80]:
key  rval
0   foo   4
1   foo   5

In [81]: pd.merge(left, right, on='key')
Out[81]:
key  lval  rval
0   foo   1   4
1   foo   1   5
2   foo   2   4
3   foo   2   5

Another example that can be given is:

In [82]: left = pd.DataFrame({'key': ['foo', 'bar'], 'lval': [1, 2]})

In [83]: right = pd.DataFrame({'key': ['foo', 'bar'], 'rval': [4, 5]})

In [84]: left
Out[84]:
key  lval
0   foo   1
1   bar   2

(continues on next page)
2.1.7 Grouping

By “group by” we are referring to a process involving one or more of the following steps:

- **Splitting** the data into groups based on some criteria
- **Applying** a function to each group independently
- **Combining** the results into a data structure

See the Grouping section.

Grouping and then applying the `sum()` function to the resulting groups.

Grouping by multiple columns forms a hierarchical index, and again we can apply the `sum()` function.
In [90]: df.groupby(['A', 'B']).sum()
Out[90]:
   C   D
A  B
bar one  -1.732558  0.687876
       three  2.124274  0.393483
       two   -1.148064 -1.103515
foo one  -0.355964  2.879986
       three  0.880324 -0.572834
       two   2.865719 -1.257225

2.1.8 Reshaping

See the sections on Hierarchical Indexing and Reshaping.

Stack

In [91]: tuples = list(zip(*[['bar', 'bar', 'baz', 'baz',
                           'foo', 'foo', 'qux', 'qux'],
                           ['one', 'two', 'one', 'two',
                           'one', 'two', 'one', 'two']]))

In [92]: index = pd.MultiIndex.from_tuples(tuples, names=['first', 'second'])

In [93]: df = pd.DataFrame(np.random.randn(8, 2), index=index, columns=['A', 'B'])

In [94]: df2 = df[:4]

In [95]: df2
Out[95]:
   A   B
first second
bar one  -1.368126  1.106592
       two  -1.871179 -0.410771
baz one  -1.510566 -1.081931
       two   0.706517  0.606471

The stack() method “compresses” a level in the DataFrame’s columns.

In [96]: stacked = df2.stack()

In [97]: stacked
Out[97]:
   first second
bar one  A -1.368126
        B  1.106592
       two A -1.871179
           B -0.410771
baz one  A -1.510566
        B -1.081931
       two A  0.706517
           B  0.606471
dtype: float64
With a “stacked” DataFrame or Series (having a MultiIndex as the index), the inverse operation of `stack()` is `unstack()`, which by default unstacks the last level:

```
In [98]: stacked.unstack()
Out[98]:
   A     B
first second
bar one  -1.368126  1.106592
   two   -1.871179  -0.410771
baz one  -1.510566  -1.081931
   two    0.706517   0.606471

In [99]: stacked.unstack(1)
Out[99]:
   second one two
first
bar    A  -1.368126 -1.871179
      B   1.106592  -0.410771
baz    A  -1.510566   0.706517
      B  -1.081931   0.606471

In [100]: stacked.unstack(0)
Out[100]:
   first bar  baz
second
one    A  -1.368126 -1.510566
      B   1.106592  -1.081931
two    A  -1.871179  0.706517
      B  -0.410771   0.606471
```

### Pivot tables

See the section on Pivot Tables.

```
In [101]: df = pd.DataFrame({'A': ['one', 'one', 'two', 'three'] * 3,
                    'B': ['A', 'B', 'C'] * 4,
                    'C': ['foo', 'foo', 'foo', 'bar', 'bar', 'bar'] * 2,
                    'D': np.random.randn(12),
                    'E': np.random.randn(12)})

In [102]: df
Out[102]:
   A     B     C     D     E
  0 one  foo  -1.122841  0.520795
  1 one  foo  -0.538861  0.702732
  2 two  C    -0.024471  0.789857
  3 three A    -0.164726  0.953948
  4 one  B    0.527952  1.756980
  5 one  C    1.245248  0.650431
  6 two  A    -0.046761  1.422809
  7 three B    0.651777  0.528106
  8 one  C    0.651177  2.180666
  9 one  A    0.275987  0.441037
 10 two  B   -0.996414  0.730188
 11 three C    1.188593  0.227205
```
We can produce pivot tables from this data very easily:

```
In [103]: pd.pivot_table(df, values='D', index=['A', 'B'], columns=['C'])
Out[103]:
   C    bar    foo
A  B
one A  0.275987 -1.122841
     B  0.527952 -0.538861
     C  1.245248  0.651177
three A -0.164726    NaN
       B    NaN  0.651777
       C  1.188593    NaN
two A   NaN  -0.046761
       B -0.996414    NaN
       C   NaN  -0.024471
```

### 2.1.9 Time series

pandas has simple, powerful, and efficient functionality for performing resampling operations during frequency conversion (e.g., converting secondly data into 5-minutely data). This is extremely common in, but not limited to, financial applications. See the Time Series section.

```
In [104]: rng = pd.date_range('1/1/2012', periods=100, freq='S')
In [105]: ts = pd.Series(np.random.randint(0, 500, len(rng)), index=rng)
In [106]: ts.resample('5Min').sum()
Out[106]:
2012-01-01     26340
Freq: 5T, dtype: int64
```

Time zone representation:

```
In [107]: rng = pd.date_range('3/6/2012 00:00', periods=5, freq='D')
In [108]: ts = pd.Series(np.random.randn(len(rng)), rng)
In [109]: ts
Out[109]:
2012-03-06 -0.531408
2012-03-07  0.517261
2012-03-08  0.412497
2012-03-09  0.982989
2012-03-10  0.249870
Freq: D, dtype: float64
In [110]: ts_utc = ts.tz_localize('UTC')
In [111]: ts_utc
Out[111]:
2012-03-06 00:00:00+00:00  -0.531408
2012-03-07 00:00:00+00:00   0.517261
2012-03-08 00:00:00+00:00   0.412497
2012-03-09 00:00:00+00:00   0.982989
2012-03-10 00:00:00+00:00   0.249870
Freq: D, dtype: float64
```
Converting to another time zone:

```python
In [112]: ts_utc.tz_convert('US/Eastern')
Out[112]:
2012-03-05 19:00:00-05:00   -0.531408
2012-03-06 19:00:00-05:00    0.517261
2012-03-07 19:00:00-05:00    0.412497
2012-03-08 19:00:00-05:00    0.982989
2012-03-09 19:00:00-05:00    0.249870
Freq: D, dtype: float64
```

Converting between time span representations:

```python
In [113]: rng = pd.date_range('1/1/2012', periods=5, freq='M')
In [114]: ts = pd.Series(np.random.randn(len(rng)), index=rng)
In [115]: ts
Out[115]:
2012-01-31 -0.482863
2012-02-29  0.654788
2012-03-31  1.533429
2012-04-30 -0.170084
2012-05-31  0.812274
Freq: M, dtype: float64

In [116]: ps = ts.to_period()
In [117]: ps
Out[117]:
2012-01  -0.482863
2012-02   0.654788
2012-03   1.533429
2012-04  -0.170084
2012-05   0.812274
Freq: M, dtype: float64

In [118]: ps.to_timestamp()
Out[118]:
2012-01-01 -0.482863
2012-02-01  0.654788
2012-03-01  1.533429
2012-04-01 -0.170084
2012-05-01  0.812274
Freq: MS, dtype: float64
```

Converting between period and timestamp enables some convenient arithmetic functions to be used. In the following example, we convert a quarterly frequency with year ending in November to 9am of the end of the month following the quarter end:

```python
In [119]: prng = pd.period_range('1990Q1', '2000Q4', freq='Q-NOV')
In [120]: ts = pd.Series(np.random.randn(len(prng)), prng)
In [121]: ts.index = (prng.asfreq('M', 'e') + 1).asfreq('H', 's') + 9
In [122]: ts.head()
Out[122]:
```

(continues on next page)
2.1.10 Categoricals

Pandas can include categorical data in a DataFrame. For full docs, see the categorical introduction and the API documentation.

```python
In [123]: df = pd.DataFrame({"id": [1, 2, 3, 4, 5, 6],
                      "raw_grade": ['a', 'b', 'b', 'a', 'a', 'e']})

In [124]: df["grade"] = df["raw_grade"].astype("category")

In [125]: df["grade"]
Out[125]:
0  a
1  b
2  b
3  a
4  a
5  e
Name: grade, dtype: category
Categories (3, object): ['a', 'b', 'e']
```

Convert the raw grades to a categorical data type.

```python
In [126]: df["grade"].cat.categories = ["very good", "good", "very bad"]

Rename the categories to more meaningful names (assigning to Series.cat.categories() is in place!).

```python
In [127]: df["grade"] = df["grade"].cat.set_categories(["very bad", "bad", "medium",
                                           "good", "very good")

Reorder the categories and simultaneously add the missing categories (methods under Series.cat() return a new Series by default).

```python
In [128]: df["grade"]
Out[128]:
0  very good
1    good
2    good
3  very good
4  very good
5    very bad
Name: grade, dtype: category
Categories (5, object): ['very bad', 'bad', 'medium', 'good', 'very good']
```

Sorting is per order in the categories, not lexical order.
In [129]: df.sort_values(by="grade")
Out[129]:
    id  raw_grade  grade
  5   6          e  very bad
  1   2          b  good
  2   3          b  good
  0   1          a  very good
  3   4          a  very good
  4   5          a  very good

Grouping by a categorical column also shows empty categories.

In [130]: df.groupby("grade").size()
Out[130]:
     grade
very bad     1
bad          0
medium       0
good         2
very good    3
dtype: int64

2.1.11 Plotting

See the Plotting docs.

We use the standard convention for referencing the matplotlib API:

In [131]: import matplotlib.pyplot as plt

In [132]: plt.close('all')

In [133]: ts = pd.Series(np.random.randn(1000),
                   index=pd.date_range('1/1/2000', periods=1000))

In [134]: ts = ts.cumsum()

In [135]: ts.plot()
Out[135]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6702668490>
On a DataFrame, the `plot()` method is a convenience to plot all of the columns with labels:

```python
In [136]: df = pd.DataFrame(np.random.randn(1000, 4), index=ts.index,
                      columns=['A', 'B', 'C', 'D'])

In [137]: df = df.cumsum()

In [138]: plt.figure()
Out[138]: <Figure size 640x480 with 0 Axes>

In [139]: df.plot()
Out[139]: <matplotlib.axes._subplots.AxesSubplot at 0x7f66ff076160>

In [140]: plt.legend(loc='best')
Out[140]: <matplotlib.legend.Legend at 0x7f66fefd4580>
```
2.1.12 Getting data in/out

CSV

Writing to a csv file.

```
In [141]: df.to_csv('foo.csv')
```

Reading from a csv file.

```
In [142]: pd.read_csv('foo.csv')
Out[142]:
     Unnamed: 0      A       B       C       D
0  2000-01-01  0.604544  1.635682  1.669485  0.107401
1  2000-01-02  1.927633 -0.232688  2.791595  0.968931
2  2000-01-03  1.664463 -0.443586  1.029513 -1.178716
3  2000-01-04  1.254743  0.400169  0.776625 -1.551537
4  2000-01-05  1.420427 -0.147175  1.729271 -0.341097
...        ...     ...     ...     ...     ...
995  2002-09-22  38.003210  37.093673 -32.411919  12.682904
996  2002-09-23  36.653262  38.162818 -32.998640  12.645621
997  2002-09-24  36.430422  37.455353 -32.941709  12.316965
998  2002-09-25  35.973367  37.269644 -32.604973  11.829633
```

(continues on next page)
HDF5

Reading and writing to HDFStores.

Writing to a HDF5 Store.

```python
In [143]: df.to_hdf('foo.h5', 'df')
```

Reading from a HDF5 Store.

```python
In [144]: pd.read_hdf('foo.h5', 'df')
Out[144]:
```

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01</td>
<td>0.604544</td>
<td>1.635682</td>
<td>1.669485</td>
<td>0.107401</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>1.927633</td>
<td>-0.232688</td>
<td>2.791595</td>
<td>0.968931</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>1.664463</td>
<td>-0.443586</td>
<td>1.029513</td>
<td>-1.178716</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>1.254743</td>
<td>0.400169</td>
<td>0.776625</td>
<td>-1.551537</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>1.420427</td>
<td>-0.147175</td>
<td>1.729271</td>
<td>-0.341097</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>2002-09-22</td>
<td>38.003210</td>
<td>37.093673</td>
<td>-32.411919</td>
<td>12.682904</td>
</tr>
<tr>
<td>2002-09-23</td>
<td>36.653262</td>
<td>38.162818</td>
<td>-32.998640</td>
<td>12.645621</td>
</tr>
<tr>
<td>2002-09-24</td>
<td>36.430422</td>
<td>37.455353</td>
<td>-32.941709</td>
<td>12.316965</td>
</tr>
<tr>
<td>2002-09-25</td>
<td>35.973367</td>
<td>37.269644</td>
<td>-32.604973</td>
<td>11.829633</td>
</tr>
<tr>
<td>2002-09-26</td>
<td>35.231306</td>
<td>37.436543</td>
<td>-32.560902</td>
<td>13.020537</td>
</tr>
</tbody>
</table>

[1000 rows x 4 columns]

Excel

Reading and writing to MS Excel.

Writing to an excel file.

```python
In [145]: df.to_excel('foo.xlsx', sheet_name='Sheet1')
```

Reading from an excel file.

```python
In [146]: pd.read_excel('foo.xlsx', 'Sheet1', index_col=None, na_values=['NA'])
Out[146]:
```

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01</td>
<td>0.604544</td>
<td>1.635682</td>
<td>1.669485</td>
<td>0.107401</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>1.927633</td>
<td>-0.232688</td>
<td>2.791595</td>
<td>0.968931</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>1.664463</td>
<td>-0.443586</td>
<td>1.029513</td>
<td>-1.178716</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>1.254743</td>
<td>0.400169</td>
<td>0.776625</td>
<td>-1.551537</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>1.420427</td>
<td>-0.147175</td>
<td>1.729271</td>
<td>-0.341097</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>2002-09-22</td>
<td>38.003210</td>
<td>37.093673</td>
<td>-32.411919</td>
<td>12.682904</td>
</tr>
<tr>
<td>2002-09-23</td>
<td>36.653262</td>
<td>38.162818</td>
<td>-32.998640</td>
<td>12.645621</td>
</tr>
<tr>
<td>2002-09-24</td>
<td>36.430422</td>
<td>37.455353</td>
<td>-32.941709</td>
<td>12.316965</td>
</tr>
<tr>
<td>2002-09-25</td>
<td>35.973367</td>
<td>37.269644</td>
<td>-32.604973</td>
<td>11.829633</td>
</tr>
</tbody>
</table>

(continues on next page)
2.1.13 Gotchas

If you are attempting to perform an operation you might see an exception like:

```python
>>> if pd.Series([False, True, False]):
...     print("I was true")
Traceback
...
ValueError: The truth value of an array is ambiguous. Use a.empty, a.any() or a.all().
```

See *Comparisons* for an explanation and what to do.

See *Gotchas* as well.

2.2 Intro to data structures

We’ll start with a quick, non-comprehensive overview of the fundamental data structures in pandas to get you started. The fundamental behavior about data types, indexing, and axis labeling / alignment apply across all of the objects. To get started, import NumPy and load pandas into your namespace:

```python
In [1]: import numpy as np
In [2]: import pandas as pd
```

Here is a basic tenet to keep in mind: *data alignment is intrinsic*. The link between labels and data will not be broken unless done so explicitly by you.

We’ll give a brief intro to the data structures, then consider all of the broad categories of functionality and methods in separate sections.

2.2.1 Series

*Series* is a one-dimensional labeled array capable of holding any data type (integers, strings, floating point numbers, Python objects, etc.). The axis labels are collectively referred to as the *index*. The basic method to create a Series is to call:

```python
>>> s = pd.Series(data, index=index)
```

Here, *data* can be many different things:

- a Python dict
- an ndarray
- a scalar value (like 5)

The passed *index* is a list of axis labels. Thus, this separates into a few cases depending on what *data* is:

**From ndarray**

2.2. Intro to data structures
If `data` is an `ndarray`, `index` must be the same length as `data`. If no index is passed, one will be created having values `[0, ..., len(data) - 1]`.

```python
In [3]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [4]: s
Out[4]:
   a    0.469112
   b   -0.282863
   c   -1.509059
   d   -1.135632
   e    1.212112
dtype: float64

In [5]: s.index
Out[5]: Index(['a', 'b', 'c', 'd', 'e'], dtype='object')

In [6]: pd.Series(np.random.randn(5))
Out[6]:
0   -0.173215
1    0.119209
2   -1.044236
3   -0.861849
4   -2.104569
dtype: float64
```

**Note:** pandas supports non-unique index values. If an operation that does not support duplicate index values is attempted, an exception will be raised at that time. The reason for being lazy is nearly all performance-based (there are many instances in computations, like parts of GroupBy, where the index is not used).

**From dict**

Series can be instantiated from dicts:

```python
In [7]: d = {'b': 1, 'a': 0, 'c': 2}

In [8]: pd.Series(d)
Out[8]:
   b   1
   a   0
   c   2
dtype: int64
```

**Note:** When the data is a dict, and an index is not passed, the `Series` index will be ordered by the dict’s insertion order, if you’re using Python version >= 3.6 and Pandas version >= 0.23.

If you’re using Python < 3.6 or Pandas < 0.23, and an index is not passed, the `Series` index will be the lexically ordered list of dict keys.

In the example above, if you were on a Python version lower than 3.6 or a Pandas version lower than 0.23, the `Series` would be ordered by the lexical order of the dict keys (i.e. ['a', 'b', 'c'] rather than ['b', 'a', 'c']).

If an index is passed, the values in data corresponding to the labels in the index will be pulled out.
In [9]: d = {'a': 0., 'b': 1., 'c': 2.}
In [10]: pd.Series(d)
Out[10]:
a 0.0
b 1.0
c 2.0
dtype: float64
In [11]: pd.Series(d, index=['b', 'c', 'd', 'a'])
Out[11]:
b 1.0
c 2.0
d  NaN
a  0.0
dtype: float64

Note: NaN (not a number) is the standard missing data marker used in pandas.

From scalar value

If data is a scalar value, an index must be provided. The value will be repeated to match the length of index.

In [12]: pd.Series(5., index=['a', 'b', 'c', 'd', 'e'])
Out[12]:
a  5.0
b  5.0
c  5.0
d  5.0
e  5.0
dtype: float64

Series is ndarray-like

Series acts very similarly to an ndarray, and is a valid argument to most NumPy functions. However, operations such as slicing will also slice the index.

In [13]: s[0]
Out[13]: 0.4691122999071863
In [14]: s[:3]
Out[14]:
a  0.469112
b -0.282863
c -1.509059
dtype: float64
In [15]: s[s > s.median()]
Out[15]:
a  0.469112
e  1.212112
dtype: float64
In [16]: s[[4, 3, 1]]
Like a NumPy array, a pandas Series has a `dtype`.

```python
In [18]: s.dtype
Out[18]: dtype('float64')
```

This is often a NumPy dtype. However, pandas and 3rd-party libraries extend NumPy’s type system in a few places, in which case the dtype would be an `ExtensionDtype`. Some examples within pandas are `Categorical data` and `Nullable integer data type`. See `dtypes` for more.

If you need the actual array backing a Series, use `Series.array`.

```python
In [19]: s.array
Out[19]: <PandasArray>
[ 0.4691122999071863, -0.2828633443286633, -1.5090585031735124, -1.1356323710171934, 1.2121120250208506]
Length: 5, dtype: float64
```

Accessing the array can be useful when you need to do some operation without the index (to disable automatic alignment, for example).

`Series.array` will always be an `ExtensionArray`. Briefly, an ExtensionArray is a thin wrapper around one or more `concrete` arrays like a `numpy.ndarray`. Pandas knows how to take an ExtensionArray and store it in a Series or a column of a DataFrame. See `dtypes` for more.

While Series is ndarray-like, if you need an `actual` ndarray, then use `Series.to_numpy()`.

```python
In [20]: s.to_numpy()
Out[20]: array([ 0.4691, -0.2829, -1.5091, -1.1356,  1.2121])
```

Even if the Series is backed by a `ExtensionArray`, `Series.to_numpy()` will return a NumPy ndarray.
Series is dict-like

A Series is like a fixed-size dict in that you can get and set values by index label:

```python
In [21]: s['a']
Out[21]: 0.4691122999071863

In [22]: s['e'] = 12.

In [23]: s
Out[23]:
        a   0.469112
        b  -0.282863
        c  -1.509059
        d  -1.135632
        e   12.000000
        dtype: float64

In [24]: 'e' in s
Out[24]: True

In [25]: 'f' in s
Out[25]: False
```

If a label is not contained, an exception is raised:

```python
>>> s['f']
KeyError: 'f'
```

Using the `get` method, a missing label will return None or specified default:

```python
In [26]: s.get('f')
Out[26]:

In [27]: s.get('f', np.nan)
Out[27]: nan
```

See also the section on attribute access.

Vectorized operations and label alignment with Series

When working with raw NumPy arrays, looping through value-by-value is usually not necessary. The same is true when working with Series in pandas. Series can also be passed into most NumPy methods expecting an ndarray.

```python
In [28]: s + s
Out[28]:
        a   0.938225
        b  -0.565727
        c  -3.018117
        d  -2.271265
        e   24.000000
        dtype: float64

In [29]: s * 2
Out[29]:
        a   0.938225
        b  -0.565727
```

(continues on next page)
c -3.018117
d -2.271265
e 24.000000
dtype: float64

In [30]: np.exp(s)
Out[30]:
a 1.598575
b 0.753623
c 0.221118
d 0.321219
e 162754.791419
dtype: float64

A key difference between Series and ndarray is that operations between Series automatically align the data based on label. Thus, you can write computations without giving consideration to whether the Series involved have the same labels.

In [31]: s[1:] + s[:-1]
Out[31]:
a NaN
b -0.565727
c -3.018117
d -2.271265
e NaN
dtype: float64

The result of an operation between unaligned Series will have the union of the indexes involved. If a label is not found in one Series or the other, the result will be marked as missing NaN. Being able to write code without doing any explicit data alignment grants immense freedom and flexibility in interactive data analysis and research. The integrated data alignment features of the pandas data structures set pandas apart from the majority of related tools for working with labeled data.

Note: In general, we chose to make the default result of operations between differently indexed objects yield the union of the indexes in order to avoid loss of information. Having an index label, though the data is missing, is typically important information as part of a computation. You of course have the option of dropping labels with missing data via the dropna function.

**Name attribute**

Series can also have a name attribute:

In [32]: s = pd.Series(np.random.randn(5), name='something')

In [33]: s
Out[33]:
0 -0.494929
1 1.071804
2 0.721555
3 -0.706771
4 -1.039575
Name: something, dtype: float64
In [34]: s.name
Out[34]: 'something'

The Series name will be assigned automatically in many cases, in particular when taking 1D slices of DataFrame as you will see below.

You can rename a Series with the pandas.Series.rename() method.

In [35]: s2 = s.rename("different")
In [36]: s2.name
Out[36]: 'different'

Note that s and s2 refer to different objects.

### 2.2.2 DataFrame

**DataFrame** is a 2-dimensional labeled data structure with columns of potentially different types. You can think of it like a spreadsheet or SQL table, or a dict of Series objects. It is generally the most commonly used pandas object. Like Series, DataFrame accepts many different kinds of input:

- Dict of 1D ndarrays, lists, dicts, or Series
- 2-D numpy.ndarray
- Structured or record ndarray
- A Series
- Another DataFrame

Along with the data, you can optionally pass *index* (row labels) and *columns* (column labels) arguments. If you pass an index and / or columns, you are guaranteeing the index and / or columns of the resulting DataFrame. Thus, a dict of Series plus a specific index will discard all data not matching up to the passed index.

If axis labels are not passed, they will be constructed from the input data based on common sense rules.

**Note:** When the data is a dict, and *columns* is not specified, the DataFrame columns will be ordered by the dict's insertion order, if you are using Python version >= 3.6 and Pandas >= 0.23.

If you are using Python < 3.6 or Pandas < 0.23, and *columns* is not specified, the DataFrame columns will be the lexically ordered list of dict keys.

**From dict of Series or dicts**

The resulting index will be the **union** of the indexes of the various Series. If there are any nested dicts, these will first be converted to Series. If no columns are passed, the columns will be the ordered list of dict keys.

In [37]: d = {'one': pd.Series([1., 2., 3.], index=['a', 'b', 'c']),'two': pd.Series([1., 2., 3., 4.], index=['a', 'b', 'c', 'd'])}

In [38]: df = pd.DataFrame(d)
In [39]: df

(continues on next page)
Out[39]:
   one two
a  1.0  1.0
b  2.0  2.0
c  3.0  3.0
d  NaN 4.0

In[40]: pd.DataFrame(d, index=['d', 'b', 'a'])
Out[40]:
   one two
  d NaN 4.0
  b  2.0  2.0
  a  1.0  1.0

In[41]: pd.DataFrame(d, index=['d', 'b', 'a'], columns=['two', 'three'])
Out[41]:
  two three
  d  4.0    NaN
  b  2.0    NaN
  a  1.0    NaN

The row and column labels can be accessed respectively by accessing the **index** and **columns** attributes:

**Note:** When a particular set of columns is passed along with a dict of data, the passed columns override the keys in the dict.

In[42]: df.index
Out[42]: Index(['a', 'b', 'c', 'd'], dtype='object')

In[43]: df.columns
Out[43]: Index(['one', 'two'], dtype='object')

**From dict of ndarrays / lists**

The ndarrays must all be the same length. If an index is passed, it must clearly also be the same length as the arrays. If no index is passed, the result will be `range(n)`, where `n` is the array length.

In[44]: d = {'one': [1., 2., 3., 4.],
           'two': [4., 3., 2., 1.],
       }

In[45]: pd.DataFrame(d)
Out[45]:
   one  two
0  1.0  4.0
1  2.0  3.0
2  3.0  2.0
3  4.0  1.0

In[46]: pd.DataFrame(d, index=['a', 'b', 'c', 'd'])
Out[46]:
   one  two
a  1.0  4.0
From structured or record array

This case is handled identically to a dict of arrays.

```
In [47]: data = np.zeros((2, ), dtype=[('A', 'i4'), ('B', 'f4'), ('C', 'a10')])

In [48]: data[:] = [(1, 2., 'Hello'), (2, 3., 'World')]

In [49]: pd.DataFrame(data)
Out[49]:
     A    B          C
0    1  2.0     b'Hello'
1    2  3.0     b'World'

In [50]: pd.DataFrame(data, index=['first', 'second'])
Out[50]:
     A    B          C
first    1  2.0     b'Hello'
second   2  3.0     b'World'

In [51]: pd.DataFrame(data, columns=['C', 'A', 'B'])
Out[51]:
     C  A    B
0  b'Hello'  1  2.0
1  b'World'  2  3.0
```

**Note:** DataFrame is not intended to work exactly like a 2-dimensional NumPy ndarray.

From a list of dicts

```
In [52]: data2 = [{'a': 1, 'b': 2}, {'a': 5, 'b': 10, 'c': 20}]

In [53]: pd.DataFrame(data2)
Out[53]:
   a    b    c
0  1  2.0  NaN
1  5  10  20.0

In [54]: pd.DataFrame(data2, index=['first', 'second'])
Out[54]:
   a    b    c
first  1  2.0  NaN
second 5  10  20.0

In [55]: pd.DataFrame(data2, columns=['a', 'b'])
Out[55]:
   a    b
0  1  2.0
1  5  10
```

---

2.2. Intro to data structures
From a dict of tuples

You can automatically create a MultiIndexed frame by passing a tuples dictionary.

```
0 1 2
1 5 10
```

```
In [56]: pd.DataFrame({('a', 'b'): {('A', 'B'): 1, ('A', 'C'): 2},
                         ('a', 'a'): {('A', 'C'): 3, ('A', 'B'): 4},
                         ('a', 'c'): {('A', 'B'): 5, ('A', 'C'): 6},
                         ('b', 'a'): {('A', 'C'): 7, ('A', 'B'): 8},
                         ('b', 'b'): {('A', 'D'): 9, ('A', 'B'): 10}})
```

```
Out[56]:
      a  b
b a  c  a  b
A  B  1.0 4.0 5.0 8.0 10.0
C  NaN NaN NaN NaN
D  NaN NaN NaN NaN 9.0
```

From a Series

The result will be a DataFrame with the same index as the input Series, and with one column whose name is the original name of the Series (only if no other column name provided).

From a list of dataclasses

New in version 1.1.0.

Data Classes as introduced in PEP557, can be passed into the DataFrame constructor. Passing a list of dataclasses is equivalent to passing a list of dictionaries.

Please be aware, that that all values in the list should be dataclasses, mixing types in the list would result in a TypeError.

```
In [57]: from dataclasses import make_dataclass
In [58]: Point = make_dataclass("Point", [("x", int), ("y", int)])
In [59]: pd.DataFrame([Point(0, 0), Point(0, 3), Point(2, 3))]
```

```
Out[59]:
x  y
0  0  0
1  0  3
2  2  3
```

Missing data

Much more will be said on this topic in the Missing data section. To construct a DataFrame with missing data, we use np.nan to represent missing values. Alternatively, you may pass a numpy.MaskedArray as the data argument to the DataFrame constructor, and its masked entries will be considered missing.
Alternate constructors

**DataFrame.from_dict**

`DataFrame.from_dict` takes a dict of dicts or a dict of array-like sequences and returns a DataFrame. It operates like the `DataFrame` constructor except for the `orient` parameter which is 'columns' by default, but which can be set to 'index' in order to use the dict keys as row labels.

```python
In [60]: pd.DataFrame.from_dict(dict([('A', [1, 2, 3]), ('B', [4, 5, 6])]))
Out[60]:
     A  B
0   1  4
1   2  5
2   3  6
```

If you pass `orient='index'`, the keys will be the row labels. In this case, you can also pass the desired column names:

```python
In [61]: pd.DataFrame.from_dict(dict([('A', [1, 2, 3]), ('B', [4, 5, 6])]),
                           orient='index', columns=['one', 'two', 'three'])
```

**DataFrame.from_records**

`DataFrame.from_records` takes a list of tuples or an ndarray with structured dtype. It works analogously to the normal `DataFrame` constructor, except that the resulting DataFrame index may be a specific field of the structured dtype. For example:

```python
In [62]: data
Out[62]:
array([(1, 2., b'Hello'), (2, 3., b'World')],
      dtype=[('A', '<i4'), ('B', '<f4'), ('C', 'S10')])

In [63]: pd.DataFrame.from_records(data, index='C')
Out[63]:
     A  B
C b'Hello' 1  2.0
    b'World' 2  3.0
```

Column selection, addition, deletion

You can treat a DataFrame semantically like a dict of like-indexed Series objects. Getting, setting, and deleting columns works with the same syntax as the analogous dict operations:

```python
In [64]: df['one']
Out[64]:
   a    1.0
   b    2.0
   c    3.0
d    NaN
Name: one, dtype: float64
```
In [65]: df['three'] = df['one'] * df['two']

In [66]: df['flag'] = df['one'] > 2

In [67]: df
Out[67]:
   one  two  three  flag
  a  1.0  1.0   1.0  False
  b  2.0  2.0   4.0  False
  c  3.0  3.0   9.0   True
  d  NaN  4.0  NaN  False

Columns can be deleted or popped like with a dict:

In [68]: del df['two']

In [69]: three = df.pop('three')

In [70]: df
Out[70]:
   one  flag
  a  1.0  False
  b  2.0  False
  c  3.0   True
  d  NaN  False

When inserting a scalar value, it will naturally be propagated to fill the column:

In [71]: df['foo'] = 'bar'

In [72]: df
Out[72]:
   one  flag  foo
  a  1.0  False  bar
  b  2.0  False  bar
  c  3.0   True  bar
  d  NaN  False  bar

When inserting a Series that does not have the same index as the DataFrame, it will be conformed to the DataFrame’s index:

In [73]: df['one_trunc'] = df['one'][:2]

In [74]: df
Out[74]:
   one  flag  foo  one_trunc
  a  1.0  False  bar   1.0
  b  2.0  False  bar   2.0
  c  3.0   True  bar  NaN
  d  NaN  False  bar  NaN

You can insert raw ndarrays but their length must match the length of the DataFrame’s index.

By default, columns get inserted at the end. The insert function is available to insert at a particular location in the columns:
Assigning new columns in method chains

Inspired by dplyr's `mutate` verb, DataFrame has an `assign()` method that allows you to easily create new columns that are potentially derived from existing columns.

In the example above, we inserted a precomputed value. We can also pass in a function of one argument to be evaluated on the DataFrame being assigned to.

assign always returns a copy of the data, leaving the original DataFrame untouched.

Passing a callable, as opposed to an actual value to be inserted, is useful when you don’t have a reference to the DataFrame at hand. This is common when using assign in a chain of operations. For example, we can limit the DataFrame to just those observations with a Sepal Length greater than 5, calculate the ratio, and plot:
Since a function is passed in, the function is computed on the DataFrame being assigned to. Importantly, this is the DataFrame that’s been filtered to those rows with sepal length greater than 5. The filtering happens first, and then the ratio calculations. This is an example where we didn’t have a reference to the filtered DataFrame available.

The function signature for `assign` is simply `**kwargs`. The keys are the column names for the new fields, and the values are either a value to be inserted (for example, a `Series` or NumPy array), or a function of one argument to be called on the `DataFrame`. A copy of the original DataFrame is returned, with the new values inserted.

Changed in version 0.23.0.

Starting with Python 3.6 the order of `**kwargs` is preserved. This allows for `dependent` assignment, where an expression later in `**kwargs` can refer to a column created earlier in the same `assign()`.

```python
In [82]: dfa = pd.DataFrame({"A": [1, 2, 3],
                        "B": [4, 5, 6]})
...:

In [83]: dfa.assign(C=lambda x: x['A'] + x['B'],
```
In the second expression, `x['C']` will refer to the newly created column, that's equal to `dfa['A'] + dfa['B']`.

### Indexing / selection

The basics of indexing are as follows:

<table>
<thead>
<tr>
<th>Operation</th>
<th>Syntax</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Select column</td>
<td><code>df[col]</code></td>
<td>Series</td>
</tr>
<tr>
<td>Select row by label</td>
<td><code>df.loc[label]</code></td>
<td>Series</td>
</tr>
<tr>
<td>Select row by integer location</td>
<td><code>df.iloc[loc]</code></td>
<td>Series</td>
</tr>
<tr>
<td>Slice rows</td>
<td><code>df[5:10]</code></td>
<td>DataFrame</td>
</tr>
<tr>
<td>Select rows by boolean vector</td>
<td><code>df[bool_vec]</code></td>
<td>DataFrame</td>
</tr>
</tbody>
</table>

Row selection, for example, returns a Series whose index is the columns of the DataFrame:

```python
In [84]: df.loc['b']
Out[84]:
   one  2
   bar  2
   flag False
   foo  bar
   one_trunc  2
Name: b, dtype: object
```

```python
In [85]: df.iloc[2]
Out[85]:
   one  3
   bar  3
   flag  True
   foo  bar
   one_trunc  NaN
Name: c, dtype: object
```

For a more exhaustive treatment of sophisticated label-based indexing and slicing, see the section on indexing. We will address the fundamentals of reindexing / conforming to new sets of labels in the section on reindexing.
**Data alignment and arithmetic**

Data alignment between DataFrame objects automatically align on both the columns and the index (row labels). Again, the resulting object will have the union of the column and row labels.

| In [86]: df = pd.DataFrame(np.random.randn(10, 4), columns=['A', 'B', 'C', 'D']) |
| In [87]: df2 = pd.DataFrame(np.random.randn(7, 3), columns=['A', 'B', 'C']) |
| In [88]: df + df2 |
| **Out [88]:** |
| | A | B | C | D |
| 0 0.045691 -0.014138 1.380871 NaN |
| 1 -0.955398 -1.501007 0.037181 NaN |
| 2 -0.662690 1.534833 -0.859691 NaN |
| 3 -2.452949 1.237274 -0.133712 NaN |
| 4 1.414490 1.951676 -2.320422 NaN |
| 5 -0.494922 -1.649727 -1.084601 NaN |
| 6 -1.047551 -0.748572 -0.805479 NaN |
| 7 NaN NaN NaN NaN |
| 8 NaN NaN NaN NaN |
| 9 NaN NaN NaN NaN |

When doing an operation between DataFrame and Series, the default behavior is to align the Series index on the DataFrame columns, thus broadcasting row-wise. For example:

| In [89]: df - df.iloc[0] |
| **Out [89]:** |
| | A | B | C | D |
| 0 0.000000 0.000000 0.000000 0.000000 |
| 1 -1.359261 -0.248717 -0.453372 -1.754659 |
| 2 0.253128 0.829678 0.010026 -1.991234 |
| 3 -1.311128 0.054325 -1.724913 -1.620544 |
| 4 0.573025 1.500742 -0.676070 1.367331 |
| 5 -1.741248 0.781993 -1.241620 -2.053136 |
| 6 -1.240774 -0.869551 -0.153282 0.000430 |
| 7 -0.743894 0.411013 -0.929563 -0.282386 |
| 8 -1.194921 1.320690 0.238224 -1.482644 |
| 9 2.293786 1.856228 0.773289 -1.446531 |

In the special case of working with time series data, if the DataFrame index contains dates, the broadcasting will be column-wise:

| In [90]: index = pd.date_range('1/1/2000', periods=8) |
| In [91]: df = pd.DataFrame(np.random.randn(8, 3), index=index, columns=list('ABC')) |
| In [92]: df |
| **Out [92]:** |
| | A | B | C |
| 2000-01-01 -1.226825 0.769804 -1.281247 |
| 2000-01-02 -0.727707 -0.121306 -0.097883 |
| 2000-01-03 0.695775 0.341734 0.959726 |
| 2000-01-04 -1.110336 -0.619976 0.149748 |
| 2000-01-05 -0.732339 0.687738 0.176444 |
| 2000-01-06 0.403310 -0.154951 0.301624 |
| 2000-01-07 -2.179861 -1.369849 -0.954208 |

(continues on next page)
In [93]: type(df['A'])
Out[93]: pandas.core.series.Series

In [94]: df - df['A']
Out[94]:
   2000-01-01 00:00:00 2000-01-02 00:00:00 2000-01-03 00:00:00 2000-01-04 00:00:00 ...
2000-01-01    NaN    NaN    NaN    NaN    NaN ...
2000-01-02    NaN    NaN    NaN    NaN    NaN ...
2000-01-03    NaN    NaN    NaN    NaN    NaN ...
2000-01-04    NaN    NaN    NaN    NaN    NaN ...
2000-01-05    NaN    NaN    NaN    NaN    NaN ...
2000-01-06    NaN    NaN    NaN    NaN    NaN ...
2000-01-07    NaN    NaN    NaN    NaN    NaN ...
2000-01-08    NaN    NaN    NaN    NaN    NaN ...

[8 rows x 11 columns]

Warning:

df - df['A']

is now deprecated and will be removed in a future release. The preferred way to replicate this behavior is

df.sub(df['A'], axis=0)

For explicit control over the matching and broadcasting behavior, see the section on flexible binary operations.

Operations with scalars are just as you would expect:

In [95]: df * 5 + 2
Out[95]:
   A       B       C
2000-01-01 -4.134126  5.849018 -4.406237
2000-01-02 -1.638535  1.393469  1.510587
2000-01-03  5.478873  3.708672  6.798628
2000-01-04 -3.551681 -1.099880  2.748742
2000-01-05 -1.661697  5.438692  2.882222
2000-01-06  4.016548  1.225246  3.508122
2000-01-07 -8.899303 -4.849247 -2.771039
2000-01-08  9.313480 -6.715805 -2.132955

In [96]: 1 / df
Out[96]:
   A        B        C
2000-01-01 -2.254098 -0.200642 -0.221381
2000-01-02  0.607248  0.752795  0.710593
2000-01-03 -0.374354  0.219307  0.285714
2000-01-04  0.282857  0.219307  0.285714
2000-01-05  0.182830  1.000000  0.285714
2000-01-06 -0.247706  0.196078  0.285714
2000-01-07 -0.114354  1.000000  0.285714
2000-01-08 -0.114354  1.000000  0.285714

(continues on next page)
In [97]: df ** 4
Out[97]:

<table>
<thead>
<tr>
<th>Date</th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01</td>
<td>2.265327</td>
<td>0.351172</td>
<td>2.694833</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>0.280431</td>
<td>0.000217</td>
<td>0.000092</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>0.234355</td>
<td>0.013638</td>
<td>0.848376</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>1.519910</td>
<td>0.147740</td>
<td>0.000503</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>0.287640</td>
<td>0.223714</td>
<td>0.000969</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>0.026458</td>
<td>0.000576</td>
<td>0.008277</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>22.579530</td>
<td>3.521204</td>
<td>0.829033</td>
</tr>
<tr>
<td>2000-01-08</td>
<td>4.577374</td>
<td>9.233151</td>
<td>0.466834</td>
</tr>
</tbody>
</table>

Boolean operators work as well:

In [98]: df1 = pd.DataFrame({'a': [1, 0, 1], 'b': [0, 1, 1]}, dtype=bool)
In [99]: df2 = pd.DataFrame({'a': [0, 1, 1], 'b': [1, 1, 0]}, dtype=bool)
In [100]: df1 & df2
Out[100]:

<table>
<thead>
<tr>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>False False</td>
</tr>
<tr>
<td>1</td>
<td>False True</td>
</tr>
<tr>
<td>2</td>
<td>True False</td>
</tr>
</tbody>
</table>

In [101]: df1 | df2
Out[101]:

<table>
<thead>
<tr>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>True True</td>
</tr>
<tr>
<td>1</td>
<td>True True</td>
</tr>
<tr>
<td>2</td>
<td>True True</td>
</tr>
</tbody>
</table>

In [102]: df1 ^ df2
Out[102]:

<table>
<thead>
<tr>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>True True</td>
</tr>
<tr>
<td>1</td>
<td>True False</td>
</tr>
<tr>
<td>2</td>
<td>False True</td>
</tr>
</tbody>
</table>

In [103]: -df1
Out[103]:

<table>
<thead>
<tr>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>False True</td>
</tr>
<tr>
<td>1</td>
<td>True False</td>
</tr>
<tr>
<td>2</td>
<td>False False</td>
</tr>
</tbody>
</table>
Transposing

To transpose, access the T attribute (also the `transpose` function), similar to an ndarray:

```python
# only show the first 5 rows
In [104]: df[:5].T
Out[104]:
A     -1.226825   -0.727707    0.695775  -1.110336   -0.732339
B      0.769804   -0.121306    0.341734  -0.619976    0.687738
C     -1.281247   -0.097883    0.959726    0.149748    0.176444
```

Dataframe interoperability with NumPy functions

Elementwise NumPy ufuncs (log, exp, sqrt, ...) and various other NumPy functions can be used with no issues on Series and DataFrame, assuming the data within are numeric:

```python
In [105]: np.exp(df)
Out[105]:
         A         B         C
2000-01-01 0.293222 2.159342 0.277691
2000-01-02 0.483015 0.885763 0.906755
2000-01-03 2.005262 1.407386 2.610980
2000-01-04 0.329448 0.537957 1.161542
2000-01-05 0.480783 1.989212 1.192968
2000-01-06 1.496770 0.856457 1.352053
2000-01-07 0.113057 0.254145 0.385117
2000-01-08 4.317584 0.174966 0.437538

In [106]: np.asarray(df)
Out[106]:
array([[ -1.2268,   0.7698,  -1.2812],
       [ -0.7277,  -0.1213,  -0.0979],
       [  0.6958,   0.3417,   0.9597],
       [ -1.1103,   -0.62   ,   0.1497],
       [ -0.7323,   0.6877,   0.1764],
       [  0.4033,  -0.155   ,   0.3016],
       [ -2.1799,  -1.3698,  -0.9542],
       [  1.4627,  -1.7432,  -0.8266]])
```

DataFrame is not intended to be a drop-in replacement for ndarray as its indexing semantics and data model are quite different in places from an n-dimensional array.

*Series* implements __array_ufunc__, which allows it to work with NumPy’s universal functions.

The ufunc is applied to the underlying array in a Series.

```python
In [107]: ser = pd.Series([1, 2, 3, 4])

In [108]: np.exp(ser)
Out[108]:
       0    2.718282
       1    7.389056
       2   20.085537
       3   54.598150
dtype: float64
```
Changed in version 0.25.0: When multiple `Series` are passed to a ufunc, they are aligned before performing the operation.

Like other parts of the library, pandas will automatically align labeled inputs as part of a ufunc with multiple inputs. For example, using `numpy.remainder()` on two `Series` with differently ordered labels will align before the operation.

```
In [109]: ser1 = pd.Series([1, 2, 3], index=['a', 'b', 'c'])

In [110]: ser2 = pd.Series([1, 3, 5], index=['b', 'a', 'c'])

In [111]: ser1
Out[111]:
a 1
b 2
c 3
dtype: int64

In [112]: ser2
Out[112]:
b 1
a 3
c 5
dtype: int64

In [113]: np.remainder(ser1, ser2)
Out[113]:
a 1
b 0
c 3
```

As usual, the union of the two indices is taken, and non-overlapping values are filled with missing values.

```
In [114]: ser3 = pd.Series([2, 4, 6], index=['b', 'c', 'd'])

In [115]: ser3
Out[115]:
b 2
c 4
d 6
dtype: int64

In [116]: np.remainder(ser1, ser3)
Out[116]:
a NaN
b 0.0
c 3.0
d NaN
dtype: float64
```

When a binary ufunc is applied to a `Series` and `Index`, the Series implementation takes precedence and a Series is returned.

```
In [117]: ser = pd.Series([1, 2, 3])

In [118]: idx = pd.Index([4, 5, 6])
```
NumPy ufuncs are safe to apply to *Series* backed by non-ndarray arrays, for example *arrays.SparseArray* (see *Sparse calculation*). If possible, the ufunc is applied without converting the underlying data to an ndarray.

### Console display

Very large DataFrames will be truncated to display them in the console. You can also get a summary using *info()*.

(Here I am reading a CSV version of the *baseball* dataset from the *plyr* R package):

```
In [120]: baseball = pd.read_csv('data/baseball.csv')

In [121]: print(baseball)
   id player year stint team lg g ab r h X2b X3b hr rbi sb…
  cs bb so ibb hbp sh sf gidp
0 88641 womacto01 2006 2 CHN NL 19 50 6 14 1 0 1 2.0 1.0
1.0 4 4.0 0.0 0.0 3.0 0.0 0.0
1 88643 schilcu01 2006 1 BOS AL 31 2 0 1 0 0 0 0.0 0.0
2.0 0 1.0 0.0 0.0 0.0 0.0 0.0
... ... ... ... ... ... ... ... ... ... ... ... ...
98 89533 aloumo01 2007 1 NYN NL 87 328 51 112 19 1 13 49.0 3.0
3.0 0.0 27 30.0 5.0 2.0 0.0 3.0 13.0
99 89534 alomasa02 2007 1 NYN NL 8 22 1 3 1 0 0 0.0 0.0
0.0 0.0 3.0 0.0 0.0 0.0 0.0 0.0
[100 rows x 23 columns]
```

```
In [122]: baseball.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 23 columns):
# Column Non-Null Count Dtype
--- ----- -------------- ----- 0 id 100 non-null int64
1 player 100 non-null object
2 year 100 non-null int64
3 stint 100 non-null int64
4 team 100 non-null object
5 lg 100 non-null object
6 g 100 non-null int64
7 ab 100 non-null int64
8 r 100 non-null int64
9 h 100 non-null int64
10 X2b 100 non-null int64
11 X3b 100 non-null int64
12 hr 100 non-null int64
13 rbi 100 non-null float64
14 sb 100 non-null float64
15 cs 100 non-null float64
```
However, using to_string will return a string representation of the DataFrame in tabular form, though it won't always fit the console width:

```python
In [123]: print(baseball.iloc[-20:, :12].to_string())
```

<table>
<thead>
<tr>
<th>id</th>
<th>player</th>
<th>year</th>
<th>stint</th>
<th>team</th>
<th>lg</th>
<th>g</th>
<th>ab</th>
<th>r</th>
<th>h</th>
<th>X2b</th>
<th>X3b</th>
</tr>
</thead>
<tbody>
<tr>
<td>80</td>
<td>finlest01</td>
<td>2007</td>
<td>1</td>
<td>COL</td>
<td>NL</td>
<td>43</td>
<td>94</td>
<td>9</td>
<td>17</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>81</td>
<td>embreal01</td>
<td>2007</td>
<td>1</td>
<td>OAK</td>
<td>AL</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>82</td>
<td>edmonji01</td>
<td>2007</td>
<td>1</td>
<td>SLN</td>
<td>NL</td>
<td>117</td>
<td>365</td>
<td>39</td>
<td>92</td>
<td>15</td>
<td>2</td>
</tr>
<tr>
<td>83</td>
<td>easleda01</td>
<td>2007</td>
<td>1</td>
<td>NYN</td>
<td>NL</td>
<td>76</td>
<td>193</td>
<td>24</td>
<td>54</td>
<td>6</td>
<td>0</td>
</tr>
<tr>
<td>84</td>
<td>delgaca01</td>
<td>2007</td>
<td>1</td>
<td>NYN</td>
<td>NL</td>
<td>139</td>
<td>538</td>
<td>71</td>
<td>139</td>
<td>30</td>
<td>0</td>
</tr>
<tr>
<td>85</td>
<td>cormirh01</td>
<td>2007</td>
<td>1</td>
<td>CIN</td>
<td>NL</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>86</td>
<td>coninje01</td>
<td>2007</td>
<td>2</td>
<td>NYN</td>
<td>NL</td>
<td>21</td>
<td>41</td>
<td>2</td>
<td>8</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>87</td>
<td>coninje01</td>
<td>2007</td>
<td>1</td>
<td>CIN</td>
<td>NL</td>
<td>80</td>
<td>215</td>
<td>23</td>
<td>57</td>
<td>11</td>
<td>1</td>
</tr>
<tr>
<td>88</td>
<td>coninje01</td>
<td>2007</td>
<td>1</td>
<td>NYA</td>
<td>AL</td>
<td>2</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>89</td>
<td>claytro01</td>
<td>2007</td>
<td>2</td>
<td>BOS</td>
<td>AL</td>
<td>8</td>
<td>6</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>90</td>
<td>claytro01</td>
<td>2007</td>
<td>1</td>
<td>TOR</td>
<td>AL</td>
<td>69</td>
<td>189</td>
<td>23</td>
<td>48</td>
<td>14</td>
<td>0</td>
</tr>
<tr>
<td>91</td>
<td>cirilje01</td>
<td>2007</td>
<td>2</td>
<td>ARI</td>
<td>NL</td>
<td>28</td>
<td>40</td>
<td>6</td>
<td>8</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>92</td>
<td>cirilje01</td>
<td>2007</td>
<td>1</td>
<td>MIN</td>
<td>AL</td>
<td>50</td>
<td>153</td>
<td>18</td>
<td>40</td>
<td>9</td>
<td>2</td>
</tr>
<tr>
<td>93</td>
<td>bondsba01</td>
<td>2007</td>
<td>1</td>
<td>SFN</td>
<td>NL</td>
<td>126</td>
<td>340</td>
<td>75</td>
<td>94</td>
<td>14</td>
<td>0</td>
</tr>
<tr>
<td>94</td>
<td>biggicr01</td>
<td>2007</td>
<td>1</td>
<td>HOU</td>
<td>NL</td>
<td>141</td>
<td>517</td>
<td>68</td>
<td>130</td>
<td>31</td>
<td>3</td>
</tr>
<tr>
<td>95</td>
<td>benitar01</td>
<td>2007</td>
<td>2</td>
<td>FLO</td>
<td>NL</td>
<td>34</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>96</td>
<td>benitar01</td>
<td>2007</td>
<td>1</td>
<td>SFN</td>
<td>NL</td>
<td>19</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>97</td>
<td>ausmubr01</td>
<td>2007</td>
<td>1</td>
<td>HOU</td>
<td>NL</td>
<td>117</td>
<td>349</td>
<td>38</td>
<td>82</td>
<td>16</td>
<td>3</td>
</tr>
<tr>
<td>98</td>
<td>alomasa02</td>
<td>2007</td>
<td>1</td>
<td>NYN</td>
<td>NL</td>
<td>87</td>
<td>328</td>
<td>51</td>
<td>112</td>
<td>19</td>
<td>1</td>
</tr>
<tr>
<td>99</td>
<td>alomasa02</td>
<td>2007</td>
<td>1</td>
<td>NYN</td>
<td>NL</td>
<td>8</td>
<td>22</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

Wide DataFrames will be printed across multiple rows by default:

```python
In [124]: pd.DataFrame(np.random.randn(3, 12))
```

```
 0  1  2  3  4  5  6  7  8  9  10  11
-0.345352 1.314232 0.690579 0.995761 2.396780 0.014871 3.357427 -0.317441 -1.236269 0.896171 -0.487602 -0.082240 1.182937 0.380396 0.084844 0.432390 1.519970 -0.493851 0.600178 0.274230 0.132885 -0.023688 2.410179 1.450520 2.020653 -0.251905 -2.213588 1.063327 1.266143 0.299368 -0.863838 0.408204 -1.048089 -0.025747 -0.988387 0.094055
```

You can change how much to print on a single row by setting the display.width option:

```python
In [125]: pd.set_option('display.width', 40) # default is 80

In [126]: pd.DataFrame(np.random.randn(3, 12))
```
You can adjust the max width of the individual columns by setting `display.max_colwidth`

```python
In [127]: datafile = {'filename': ['filename_01', 'filename_02'],
               'path': ['media/user_name/storage/folder_01/filename_01',
                        'media/user_name/storage/folder_02/filename_02']}

In [128]: pd.set_option('display.max_colwidth', 30)

In [129]: pd.DataFrame(datafile)
Out[129]:
    filename       path
0  filename_01  media/user_name/storage/folder_01/filename_01
1  filename_02  media/user_name/storage/folder_02/filename_02

In [130]: pd.set_option('display.max_colwidth', 100)

In [131]: pd.DataFrame(datafile)
Out[131]:
    filename       path
0  filename_01  media/user_name/storage/folder_01/filename_01
1  filename_02  media/user_name/storage/folder_02/filename_02
```

You can also disable this feature via the `expand_frame_repr` option. This will print the table in one block.

**DataFrame column attribute access and IPython completion**

If a DataFrame column label is a valid Python variable name, the column can be accessed like an attribute:

```python
In [132]: df = pd.DataFrame({'foo1': np.random.randn(5),
                        'foo2': np.random.randn(5)})

In [133]: df
Out[133]:
   foo1   foo2
0  1.171   -0.858
1  0.520   0.307
2 -1.197  -0.029
3 -1.067   0.384
4 -0.303   1.574

In [134]: df.foo1
Out[134]:
0  1.171
1  0.520
2 -1.197
3 -1.067
```

(continues on next page)
The columns are also connected to the IPython completion mechanism so they can be tab-completed:

```python
In [5]: df.fo<TAB>  # noqa: E225, E999
df.foo1 df.foo2
```

## 2.3 Essential basic functionality

Here we discuss a lot of the essential functionality common to the pandas data structures. To begin, let's create some example objects like we did in the 10 minutes to pandas section:

```python
In [1]: index = pd.date_range('1/1/2000', periods=8)
In [2]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])
In [3]: df = pd.DataFrame(np.random.randn(8, 3), index=index,
                      columns=['A', 'B', 'C'])
```

### 2.3.1 Head and tail

To view a small sample of a Series or DataFrame object, use the `head()` and `tail()` methods. The default number of elements to display is five, but you may pass a custom number.

```python
In [4]: long_series = pd.Series(np.random.randn(1000))
In [5]: long_series.head()
Out[5]:
0   -1.157892
1   -1.344312
2    0.844885
3    1.075770
4   -0.109050
dtype: float64
In [6]: long_series.tail(3)
Out[6]:
997  -0.289388
998  -1.020544
999   0.589993
dtype: float64
```
2.3.2 Attributes and underlying data

Pandas objects have a number of attributes enabling you to access the metadata

- **shape**: gives the axis dimensions of the object, consistent with ndarray
- **Axis labels**
  - **Series**: `index` (only axis)
  - **DataFrame**: `index` (rows) and `columns`

Note, these attributes can be safely assigned to!

```python
In [7]: df[:2]
Out[7]:
   A    B    C
2000-01-01 -0.173215 0.119209 -1.044236
2000-01-02 -0.861849 -2.104569 -0.494929

In [8]: df.columns = [x.lower() for x in df.columns]

In [9]: df
Out[9]:
   a    b    c
2000-01-01 -0.173215 0.119209 -1.044236
2000-01-02 -0.861849 -2.104569 -0.494929
2000-01-03  1.071804  0.721555  -0.706771
2000-01-04 -1.039575  0.271860  -0.429724
2000-01-05  0.567020  0.276232  -1.087401
2000-01-06 -0.673690  0.113648  -1.478427
2000-01-07  0.524988  0.404705   0.577046
2000-01-08 -1.715002 -1.039268  -0.370647
```

Pandas objects (`Index`, `Series`, `DataFrame`) can be thought of as containers for arrays, which hold the actual data and do the actual computation. For many types, the underlying array is a `numpy.ndarray`. However, pandas and 3rd party libraries may extend NumPy’s type system to add support for custom arrays (see `dtypes`).

To get the actual data inside a `Index` or `Series`, use the `.array` property

```python
In [10]: s.array
Out[10]:
<PandasArray>
[ 0.4691122999071863, -0.2828633443286633, -1.5090585031735124,
 -1.1356323710171934, 1.2121120250208506]
Length: 5, dtype: float64

In [11]: s.index.array
Out[11]:
<PandasArray>
['a', 'b', 'c', 'd', 'e']
Length: 5, dtype: object
```

`array` will always be an `ExtensionArray`. The exact details of what an `ExtensionArray` is and why pandas uses them are a bit beyond the scope of this introduction. See `dtypes` for more.

If you know you need a NumPy array, use `to_numpy()` or `numpy.asarray()`.

```python
In [12]: s.to_numpy()
Out[12]: array([ 0.4691, -0.2829, -1.5091, -1.1356, 1.2121])
```

(continues on next page)
In [13]: np.asarray(s)
Out[13]: array([ 0.4691, -0.2829, -1.5091, -1.1356, 1.2121])

When the Series or Index is backed by an ExtensionArray, to_numpy() may involve copying data and coercing values. See dtypes for more.

to_numpy() gives some control over the dtype of the resulting numpy.ndarray. For example, consider datetimes with timezones. NumPy doesn’t have a dtype to represent timezone-aware datetimes, so there are two possibly useful representations:

1. An object-dtype numpy.ndarray with Timestamp objects, each with the correct tz
2. A datetime64[ns] -dtype numpy.ndarray, where the values have been converted to UTC and the timezone discarded

Timezones may be preserved with dtype=object

In [14]: ser = pd.Series(pd.date_range('2000', periods=2, tz="CET"))
In [15]: ser.to_numpy(dtype=object)
Out[15]: array([Timestamp('2000-01-01 00:00:00+0100', tz='CET', freq='D'),
                     Timestamp('2000-01-02 00:00:00+0100', tz='CET', freq='D')],
                   dtype=object)

Or thrown away with dtype='datetime64[ns]'

In [16]: ser.to_numpy(dtype="datetime64[ns]"")
Out[16]: array(['1999-12-31T23:00:00.000000000', '2000-01-01T23:00:00.000000000'],
                       dtype='datetime64[ns]')

Getting the “raw data” inside a DataFrame is possibly a bit more complex. When your DataFrame only has a single data type for all the columns, DataFrame.to_numpy() will return the underlying data:

In [17]: df.to_numpy()
Out[17]: array([[-0.1732, 0.1192, -1.0442],
                   [-0.8618, -2.1046, -0.4949],
                   [ 1.0718, 0.7216, -0.7068],
                   [-1.0396, 0.2719, -0.425 ],
                   [ 0.567 , 0.2762, -1.0874],
                   [-0.6737, 0.1136, -1.4784],
                   [ 0.525 , 0.4047, 0.577 ],
                   [-1.715 , -1.0393, -0.3706]])

If a DataFrame contains homogeneously-typed data, the ndarray can actually be modified in-place, and the changes will be reflected in the data structure. For heterogeneous data (e.g. some of the DataFrame’s columns are not all the same dtype), this will not be the case. The values attribute itself, unlike the axis labels, cannot be assigned to.

Note: When working with heterogeneous data, the dtype of the resulting ndarray will be chosen to accommodate all of the data involved. For example, if strings are involved, the result will be of object dtype. If there are only floats and integers, the resulting array will be of float dtype.

In the past, pandas recommended Series.values or DataFrame.values for extracting the data from a Series
or DataFrame. You'll still find references to these in old code bases and online. Going forward, we recommend avoiding `.values` and using `.array` or `.to_numpy()`. `.values` has the following drawbacks:

1. When your Series contains an extension type, it's unclear whether `Series.values` returns a NumPy array or the extension array. `Series.array` will always return an ExtensionArray, and will never copy data. `Series.to_numpy()` will always return a NumPy array, potentially at the cost of copying / coercing values.

2. When your DataFrame contains a mixture of data types, `DataFrame.values` may involve copying data and coercing values to a common dtype, a relatively expensive operation. `DataFrame.to_numpy()`, being a method, makes it clearer that the returned NumPy array may not be a view on the same data in the DataFrame.

### 2.3.3 Accelerated operations

pandas has support for accelerating certain types of binary numerical and boolean operations using the `numexpr` library and the `bottleneck` libraries.

These libraries are especially useful when dealing with large data sets, and provide large speedups. `numexpr` uses smart chunking, caching, and multiple cores. `bottleneck` is a set of specialized cython routines that are especially fast when dealing with arrays that have `nans`.

Here is a sample (using 100 column x 100,000 row DataFrames):

<table>
<thead>
<tr>
<th>Operation</th>
<th>0.11.0 (ms)</th>
<th>Prior Version (ms)</th>
<th>Ratio to Prior</th>
</tr>
</thead>
<tbody>
<tr>
<td>df1 &gt; df2</td>
<td>13.32</td>
<td>125.35</td>
<td>0.1063</td>
</tr>
<tr>
<td>df1 * df2</td>
<td>21.71</td>
<td>36.63</td>
<td>0.5928</td>
</tr>
<tr>
<td>df1 + df2</td>
<td>22.04</td>
<td>36.50</td>
<td>0.6039</td>
</tr>
</tbody>
</table>

You are highly encouraged to install both libraries. See the section `Recommended Dependencies` for more installation info.

These are both enabled to be used by default, you can control this by setting the options:

```python
pd.set_option('compute.use_bottleneck', False)
pd.set_option('compute.use_numexpr', False)
```

### 2.3.4 Flexible binary operations

With binary operations between pandas data structures, there are two key points of interest:

- Broadcasting behavior between higher- (e.g. DataFrame) and lower-dimensional (e.g. Series) objects.
- Missing data in computations.

We will demonstrate how to manage these issues independently, though they can be handled simultaneously.

#### Matching / broadcasting behavior

DataFrame has the methods `add()`, `sub()`, `mul()`, `div()` and related functions `radd()`, `rsub()`, ... for carrying out binary operations. For broadcasting behavior, Series input is of primary interest. Using these functions, you can use to either match on the `index` or `columns` via the `axis` keyword:

```python
In [18]: df = pd.DataFrame({
    ....:     'one': pd.Series(np.random.randn(3), index=['a', 'b', 'c'])),
    ....:     'two': pd.Series(np.random.randn(4), index=['a', 'b', 'c', 'd'])},
```

(continues on next page)
Furthermore you can align a level of a MultiIndexed DataFrame with a Series.

```python
In [26]: dfmi = df.copy()
In [27]: dfmi.index = pd.MultiIndex.from_tuples([(1, 'a'), (1, 'b'),
                                             (1, 'c'), (2, 'a')],
                                             names=['first', 'second'])
In [28]: dfmi.sub(column, axis=0, level='second')
```

(continues on next page)
Series and Index also support the `divmod()` built-in. This function takes the floor division and modulo operation at the same time returning a two-tuple of the same type as the left hand side. For example:

```
In [29]: s = pd.Series(np.arange(10))
In [30]: s
Out[30]:
     0  1  2  3  4  5  6  7  8  9
0  0  1  2  3  4  5  6  7  8  9
dtype: int64
In [31]: div, rem = divmod(s, 3)
In [32]: div
Out[32]:
     0  1  2  3  4  5  6  7  8  9
0  0  0  0  1  1  1  2  2  2
dtype: int64
In [33]: rem
Out[33]:
     0  1  2  3  4  5  6  7  8  9
0  0  1  2  0  1  2  0  1  2
dtype: int64
```
In [34]: idx = pd.Index(np.arange(10))

In [35]: idx
Out[35]: Int64Index([0, 1, 2, 3, 4, 5, 6, 7, 8, 9], dtype='int64')

In [36]: div, rem = divmod(idx, 3)

In [37]: div
Out[37]: Int64Index([0, 0, 0, 1, 1, 1, 2, 2, 2, 3], dtype='int64')

In [38]: rem
Out[38]: Int64Index([0, 1, 2, 0, 1, 2, 0, 1, 2, 0], dtype='int64')

We can also do elementwise \texttt{divmod}:

In [39]: div, rem = divmod(s, [2, 2, 3, 3, 4, 4, 5, 5, 6, 6])

In [40]: div
Out[40]:
   0  0
   1  0
   2  0
   3  1
   4  1
   5  1
   6  1
   7  1
   8  1
   9  1
dtype: int64

In [41]: rem
Out[41]:
   0  0
   1  1
   2  2
   3  0
   4  0
   5  1
   6  1
   7  2
   8  2
   9  3
dtype: int64
Missing data / operations with fill values

In Series and DataFrame, the arithmetic functions have the option of inputting a fill_value, namely a value to substitute when at most one of the values at a location are missing. For example, when adding two DataFrame objects, you may wish to treat NaN as 0 unless both DataFrames are missing that value, in which case the result will be NaN (you can later replace NaN with some other value using fillna if you wish).

```
In [42]: df
Out[42]:
   one   two   three
a  1.394981  1.772517  NaN
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435
d   NaN      0.279344 -0.613172

In [43]: df2
Out[43]:
   one   two   three
a  1.394981  1.772517  1.000000
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435
d   NaN      0.279344 -0.613172

In [44]: df + df2
Out[44]:
   one   two   three
a  2.789963  3.545034  NaN
b  0.686107  3.824246 -0.100780
c  1.390491  2.956737  2.454870
d   NaN      0.558688 -1.226343

In [45]: df.add(df2, fill_value=0)
Out[45]:
   one   two   three
a  2.789963  3.545034  1.000000
b  0.686107  3.824246 -0.100780
c  1.390491  2.956737  2.454870
d   NaN      0.558688 -1.226343
```

Flexible comparisons

Series and DataFrame have the binary comparison methods eq, ne, lt, gt, le, and ge whose behavior is analogous to the binary arithmetic operations described above:

```
In [46]: df.gt(df2)
Out[46]:
   one  two  three
a  False False False
b  False False False
c  False False False
d  False False False

In [47]: df2.ne(df)
Out[47]:
   one  two  three
a  False False True
(continues on next page)
```
These operations produce a pandas object of the same type as the left-hand-side input that is of dtype \texttt{bool}. These boolean objects can be used in indexing operations, see the section on \textit{Boolean indexing}.

### Boolean reductions

You can apply the reductions: \texttt{empty}, \texttt{any()}, \texttt{all()}, and \texttt{bool()} to provide a way to summarize a boolean result.

```
In [48]: (df > 0).all()
Out[48]:
one   False
two   True
three  False
dtype: bool

In [49]: (df > 0).any()
Out[49]:
one   True
two   True
three   True
dtype: bool
```

You can reduce to a final boolean value.

```
In [50]: (df > 0).any().any()
Out[50]: True
```

You can test if a pandas object is empty, via the \texttt{empty} property.

```
In [51]: df.empty
Out[51]: False

In [52]: pd.DataFrame(columns=list('ABC')).empty
Out[52]: True
```

To evaluate single-element pandas objects in a boolean context, use the method \texttt{bool()}:

```
In [53]: pd.Series([True]).bool()
Out[53]: True

In [54]: pd.Series([False]).bool()
Out[54]: False

In [55]: pd.DataFrame([[True]]).bool()
Out[55]: True

In [56]: pd.DataFrame([[False]]).bool()
Out[56]: False
```

**Warning:** You might be tempted to do the following:
See gotchas for a more detailed discussion.

### Comparing if objects are equivalent

Often you may find that there is more than one way to compute the same result. As a simple example, consider $\text{df + df}$ and $\text{df * 2}$. To test that these two computations produce the same result, given the tools shown above, you might imagine using $(\text{df + df == df * 2}).\text{all()}$. But in fact, this expression is False:

```
In [57]: df + df == df * 2
Out[57]:
   one  two  three
a  True  True  False
b  True  True  True
c  True  True  True
d  False  True  True

In [58]: (df + df == df * 2).all()
Out[58]:
   one  False
two  True
three  False
dtype: bool
```

Notice that the boolean DataFrame $\text{df + df == df * 2}$ contains some False values! This is because NaNs do not compare as equals:

```
In [59]: np.nan == np.nan
Out[59]: False
```

So, NDFrames (such as Series and DataFrames) have an `equals()` method for testing equality, with NaNs in corresponding locations treated as equal.

```
In [60]: (df + df).equals(df * 2)
Out[60]: True
```

Note that the Series or DataFrame index needs to be in the same order for equality to be True:

```
In [61]: df1 = pd.DataFrame({'col': ['foo', 0, np.nan]})
In [62]: df2 = pd.DataFrame({'col': [np.nan, 0, 'foo']}, index=[2, 1, 0])
In [63]: df1.equals(df2)
Out[63]: False
```
Comparing array-like objects

You can conveniently perform element-wise comparisons when comparing a pandas data structure with a scalar value:

```python
In [65]: pd.Series(['foo', 'bar', 'baz']) == 'foo
Out[65]:
0    True
1    False
2    False
dtype: bool
```

```python
In [66]: pd.Index(['foo', 'bar', 'baz']) == 'foo
Out[66]: array([True, False, False])
```

Pandas also handles element-wise comparisons between different array-like objects of the same length:

```python
In [67]: pd.Series(['foo', 'bar', 'baz']) == pd.Index(['foo', 'bar', 'qux'])
Out[67]:
0    True
1    True
2    False
dtype: bool
```

```python
In [68]: pd.Series(['foo', 'bar', 'baz']) == np.array(['foo', 'bar', 'qux'])
Out[68]:
0    True
1    True
2    False
dtype: bool
```

Trying to compare `Index` or `Series` objects of different lengths will raise a `ValueError`:

```python
In [55]: pd.Series(['foo', 'bar', 'baz']) == pd.Series(['foo', 'bar'])
ValueError: Series lengths must match to compare
```

```python
In [56]: pd.Series(['foo', 'bar', 'baz']) == pd.Series(['foo'])
ValueError: Series lengths must match to compare
```

Note that this is different from the NumPy behavior where a comparison can be broadcast:

```python
In [69]: np.array([1, 2, 3]) == np.array([2])
Out[69]: array([False, True, False])
```

or it can return `False` if broadcasting can not be done:

```python
In [70]: np.array([1, 2, 3]) == np.array([1, 2])
Out[70]: False
```
Combining overlapping data sets

A problem occasionally arising is the combination of two similar data sets where values in one are preferred over the other. An example would be two data series representing a particular economic indicator where one is considered to be of “higher quality”. However, the lower quality series might extend further back in history or have more complete data coverage. As such, we would like to combine two DataFrame objects where missing values in one DataFrame are conditionally filled with like-labeled values from the other DataFrame. The function implementing this operation is `combine_first()`, which we illustrate:

```
In [71]: df1 = pd.DataFrame({'A': [1., np.nan, 3., 5., np.nan],
                         'B': [np.nan, 2., 3., np.nan, 6.]})
In [72]: df2 = pd.DataFrame({'A': [5., 2., 4., np.nan, 3., 7.],
                         'B': [np.nan, np.nan, 3., 4., 6., 8.]})
...
In [73]: df1
Out[73]:
      A  B
0   1.0 NaN
1   NaN 2.0
2   3.0 3.0
3   5.0 NaN
4   NaN 6.0
In [74]: df2
Out[74]:
      A  B
0   5.0 NaN
1   2.0 NaN
2   4.0 3.0
3   NaN 4.0
4   3.0 6.0
5   7.0 8.0
In [75]: df1.combine_first(df2)
Out[75]:
      A  B
0   1.0 NaN
1   2.0 2.0
2   3.0 3.0
3   5.0 4.0
4   3.0 6.0
5   7.0 8.0
```

General DataFrame combine

The `combine_first()` method above calls the more general `DataFrame.combine()`. This method takes another DataFrame and a combiner function, aligns the input DataFrame and then passes the combiner function pairs of Series (i.e., columns whose names are the same).

So, for instance, to reproduce `combine_first()` as above:

```
In [76]: def combiner(x, y):
             ....:     return np.where(pd.isna(x), y, x)
```
2.3.5 Descriptive statistics

There exists a large number of methods for computing descriptive statistics and other related operations on `Series`, `DataFrame`. Most of these are aggregations (hence producing a lower-dimensional result) like `sum()`, `mean()`, and `quantile()`, but some of them, like `cumsum()` and `cumprod()`, produce an object of the same size. Generally speaking, these methods take an `axis` argument, just like `ndarray.{sum, std, ...}`, but the axis can be specified by name or integer:

- **Series**: no axis argument needed
- **DataFrame**: “index” (axis=0, default), “columns” (axis=1)

For example:

```python
In [77]: df
Out[77]:
    one   two   three
   a  1.394981  1.772517    NaN
   b  0.343054  1.912123 -0.050390
   c  0.695246  1.478369  1.227435
   d    NaN    0.279344 -0.613172

In [78]: df.mean(0)
Out[78]:
    one   0.811094
    two   1.360588
   three  0.187958
dtype: float64

In [79]: df.mean(1)
Out[79]:
   a   1.583749
   b   0.734929
   c   1.133683
   d  -0.166914
dtype: float64

In [80]: df.sum(0, skipna=False)
Out[80]:
    one    NaN
    two   5.442353
   three    NaN
dtype: float64

In [81]: df.sum(axis=1, skipna=True)
Out[81]:
   a   3.167498
   b   2.204786
   c   3.401050
   d  -0.333828
dtype: float64
```

All such methods have a `skipna` option signaling whether to exclude missing data (True by default):
Combined with the broadcasting / arithmetic behavior, one can describe various statistical procedures, like standardization (rendering data zero mean and standard deviation of 1), very concisely:

```python
In [82]: ts_stand = (df - df.mean()) / df.std()
In [83]: ts_stand.std()
```

```
Out[83]:
one    1.0
two    1.0
two    1.0
dtype: float64
```

```python
In [84]: xs_stand = df.sub(df.mean(1), axis=0).div(df.std(1), axis=0)
In [85]: xs_stand.std(1)
```

```
Out[85]:
a    1.0
b    1.0
c    1.0
d    1.0
dtype: float64
```

Note that methods like `cumsum()` and `cumprod()` preserve the location of NaN values. This is somewhat different from `expanding()` and `rolling()`. For more details please see this note.

```python
In [86]: df.cumsum()
```

```
Out[86]:
          one         two         three
a   1.394981   1.772517             NaN
b   1.738035   3.684640  -0.05039047
 c   2.433281   5.163008   1.17704509
d   NaN        5.442353   0.56387299
```

Here is a quick reference summary table of common functions. Each also takes an optional `level` parameter which applies only if the object has a `hierarchical index`. 

2.3. Essential basic functionality

173
### Table of Summary Functions

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>count</td>
<td>Number of non-NA observations</td>
</tr>
<tr>
<td>sum</td>
<td>Sum of values</td>
</tr>
<tr>
<td>mean</td>
<td>Mean of values</td>
</tr>
<tr>
<td>mad</td>
<td>Mean absolute deviation</td>
</tr>
<tr>
<td>median</td>
<td>Arithmetic median of values</td>
</tr>
<tr>
<td>min</td>
<td>Minimum</td>
</tr>
<tr>
<td>max</td>
<td>Maximum</td>
</tr>
<tr>
<td>mode</td>
<td>Mode</td>
</tr>
<tr>
<td>abs</td>
<td>Absolute Value</td>
</tr>
<tr>
<td>prod</td>
<td>Product of values</td>
</tr>
<tr>
<td>std</td>
<td>Bessel-corrected sample standard deviation</td>
</tr>
<tr>
<td>var</td>
<td>Unbiased variance</td>
</tr>
<tr>
<td>sem</td>
<td>Standard error of the mean</td>
</tr>
<tr>
<td>skew</td>
<td>Sample skewness (3rd moment)</td>
</tr>
<tr>
<td>kurt</td>
<td>Sample kurtosis (4th moment)</td>
</tr>
<tr>
<td>quantile</td>
<td>Sample quantile (value at %)</td>
</tr>
<tr>
<td>cumsum</td>
<td>Cumulative sum</td>
</tr>
<tr>
<td>cumprod</td>
<td>Cumulative product</td>
</tr>
<tr>
<td>cummax</td>
<td>Cumulative maximum</td>
</tr>
<tr>
<td>cummin</td>
<td>Cumulative minimum</td>
</tr>
</tbody>
</table>

Note that by chance some NumPy methods, like `mean`, `std`, and `sum`, will exclude NAs on Series input by default:

```python
In [87]: np.mean(df['one'])
Out[87]: 0.8110935116651192
In [88]: np.mean(df['one'].to_numpy())
Out[88]: nan
```

`Series.nunique()` will return the number of unique non-NA values in a Series:

```python
In [89]: series = pd.Series(np.random.randn(500))
In [90]: series[20:500] = np.nan
In [91]: series[10:20] = 5
In [92]: series.nunique()
Out[92]: 11
```

### Summarizing data: `describe`

There is a convenient `describe()` function which computes a variety of summary statistics about a Series or the columns of a DataFrame (excluding NAs of course):

```python
In [93]: series = pd.Series(np.random.randn(1000))
In [94]: series[:2] = np.nan
In [95]: series.describe()
Out[95]:
   count       500.000000
```

(continues on next page)
mean  -0.021292
std   1.015906
min  -2.683763
25%  -0.699070
50%  -0.069718
75%   0.714483
max   3.160915
dtype: float64

In [96]: frame = pd.DataFrame(np.random.randn(1000, 5),
                           columns=['a', 'b', 'c', 'd', 'e'])

In [97]: frame.iloc[::2] = np.nan

In [98]: frame.describe()
Out[98]:

    a            b            c            d            e
count 500.000000 500.000000 500.000000 500.000000 500.000000
mean   0.033387  0.030045  -0.043719  -0.051686   0.005979
std    1.017152  0.978743   1.025270  1.015888   1.006695
25%  -0.647623 -0.576449  -0.712369  -0.691338  -0.691115
50%   0.047578 -0.021499  -0.023888  -0.032652  -0.025363
75%   0.729907  0.775880   0.618896   0.670047   0.649748
max   2.740139  2.752332   3.004229   2.728702   3.240991

dtype: float64

You can select specific percentiles to include in the output:

In [99]: series.describe(percentiles=[.05, .25, .75, .95])
Out[99]:

    count    mean     std      min     5%      25%      75%     95%       max
a         500.000000 0.033387 1.017152 -3.000951 -1.645423  0.729907  1.711409  3.240991
b         500.000000 0.030045 0.978743 -2.637901 -0.576449 -0.021499  0.775880  2.752332
c         500.000000-0.043719 1.025270 -3.303099 -0.712369 -0.023888  0.618896  3.004229
d         500.000000-0.051686 1.015888 -3.159200 -0.691338 -0.032652  0.670047  2.728702
e         500.000000  0.005979 1.006695 -3.188821 -0.691115 -0.025363  0.649748  3.240991
dtype: float64

By default, the median is always included.

For a non-numerical Series object, describe() will give a simple summary of the number of unique values and most frequently occurring values:

In [100]: s = pd.Series(['a', 'a', 'b', 'b', 'a', 'a', np.nan, 'c', 'd', 'a'])

In [101]: s.describe()
Out[101]:

    count    unique     top     freq
dtype: object

  count 9
unique 4
top    a
freq   5
Note that on a mixed-type DataFrame object, `describe()` will restrict the summary to include only numerical columns or, if none are, only categorical columns:

```python
In [102]: frame = pd.DataFrame({'a': ['Yes', 'Yes', 'No', 'No'], 'b': range(4)})

In [103]: frame.describe()
Out[103]:
              b
        count  4.000000
        mean   1.500000
        std    1.290994
        min    0.000000
       25%    0.750000
       50%    1.500000
       75%    2.250000
        max   3.000000
```

This behavior can be controlled by providing a list of types as `include/exclude` arguments. The special value `all` can also be used:

```python
In [104]: frame.describe(include=['object'])
Out[104]:

<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>count</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>unique</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>top</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>freq</td>
<td>2</td>
<td></td>
</tr>
</tbody>
</table>

In [105]: frame.describe(include=['number'])
Out[105]:

<table>
<thead>
<tr>
<th></th>
<th>b</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>count</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>mean</td>
<td>1.500000</td>
<td></td>
</tr>
<tr>
<td>std</td>
<td>1.290994</td>
<td></td>
</tr>
<tr>
<td>min</td>
<td>0.000000</td>
<td></td>
</tr>
<tr>
<td>25%</td>
<td>0.750000</td>
<td></td>
</tr>
<tr>
<td>50%</td>
<td>1.500000</td>
<td></td>
</tr>
<tr>
<td>75%</td>
<td>2.250000</td>
<td></td>
</tr>
<tr>
<td>max</td>
<td>3.000000</td>
<td></td>
</tr>
</tbody>
</table>

In [106]: frame.describe(include='all')
Out[106]:

<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td>count</td>
<td>4</td>
<td>4.000000</td>
</tr>
<tr>
<td>unique</td>
<td>2</td>
<td>NaN</td>
</tr>
<tr>
<td>top</td>
<td>Yes</td>
<td>NaN</td>
</tr>
<tr>
<td>freq</td>
<td>2</td>
<td>NaN</td>
</tr>
<tr>
<td>mean</td>
<td>NaN</td>
<td>1.500000</td>
</tr>
<tr>
<td>std</td>
<td>NaN</td>
<td>1.290994</td>
</tr>
<tr>
<td>min</td>
<td>NaN</td>
<td>0.000000</td>
</tr>
<tr>
<td>25%</td>
<td>NaN</td>
<td>0.750000</td>
</tr>
<tr>
<td>50%</td>
<td>NaN</td>
<td>1.500000</td>
</tr>
<tr>
<td>75%</td>
<td>NaN</td>
<td>2.250000</td>
</tr>
<tr>
<td>max</td>
<td>NaN</td>
<td>3.000000</td>
</tr>
</tbody>
</table>
```

That feature relies on `select_dtypes`. Refer to there for details about accepted inputs.
Index of min/max values

The `idxmin()` and `idxmax()` functions on Series and DataFrame compute the index labels with the minimum and maximum corresponding values:

```
In [107]: s1 = pd.Series(np.random.randn(5))

In [108]: s1
Out[108]:
0    1.118076
1   -0.352051
2   -1.242883
3   -1.277155
4   -0.641184
dtype: float64

In [109]: s1.idxmin(), s1.idxmax()
Out[109]: (3, 0)

In [110]: df1 = pd.DataFrame(np.random.randn(5, 3), columns=['A', 'B', 'C'])

In [111]: df1
Out[111]:
   A       B       C
0 -0.327863 -0.946180 -0.137570
1 -0.186235 -0.257213 -0.486567
2 -0.507027 -0.871259 -0.111110
3  2.000339 -2.430505  0.089759
4 -0.321434 -0.033695  0.096271

In [112]: df1.idxmin(axis=0)
Out[112]:
A    2
B    3
C    1
dtype: int64

In [113]: df1.idxmax(axis=1)
Out[113]:
   0  1  2
A  C  A  C
B  C  A  C
C
```

When there are multiple rows (or columns) matching the minimum or maximum value, `idxmin()` and `idxmax()` return the first matching index:

```
In [114]: df3 = pd.DataFrame([2, 1, 1, 3, np.nan], columns=['A'], index=list('edcba'))

In [115]: df3
Out[115]:
     A
e  2.0
d  1.0
c  1.0
b  3.0
```

(continues on next page)
Value counts (histogramming) / mode

The `value_counts()` Series method and top-level function computes a histogram of a 1D array of values. It can also be used as a function on regular arrays:

```python
In [117]: data = np.random.randint(0, 7, size=50)
In [118]: data
Out[118]: array([6, 6, 2, 3, 5, 3, 2, 5, 4, 5, 4, 3, 4, 5, 0, 2, 0, 4, 2, 0, 3, 2,
                2, 5, 6, 5, 3, 4, 6, 4, 3, 5, 6, 4, 3, 6, 2, 6, 2, 3, 4, 2, 1,
                6, 2, 6, 1, 5, 4])
In [119]: s = pd.Series(data)
In [120]: s.value_counts()
Out[120]:
   6    10
   2    10
   4     9
   5     8
   3     8
   0     3
   1     2
dtype: int64
In [121]: pd.value_counts(data)
Out[121]:
   6    10
   2    10
   4     9
   5     8
   3     8
   0     3
   1     2
dtype: int64
```

New in version 1.1.0.

The `value_counts()` method can be used to count combinations across multiple columns. By default all columns are used but a subset can be selected using the `subset` argument.

```python
In [122]: data = {"a": [1, 2, 3, 4], "b": ["x", "x", "y", "y"]}
In [123]: frame = pd.DataFrame(data)
```
Similarly, you can get the most frequently occurring value(s), i.e. the mode, of the values in a Series or DataFrame:

\[
\text{In [125]: } \text{s5 = pd.Series([1, 1, 3, 3, 5, 5, 7, 7, 7])}
\]
\[
\text{In [126]: } \text{s5.mode()}
\]
\[
\text{Out[126]:}
\]
\[
0 3
1 7
\]
\[
dtype: int64
\]

\[
\text{In [127]: } \text{df5 = pd.DataFrame({"A": np.random.randint(0, 7, size=50),}
\]
\[
\text{......:}
\]
\[
\text{"B": np.random.randint(-10, 15, size=50)})}
\]
\[
\text{In [128]: } \text{df5.mode()}
\]
\[
\text{Out[128]:}
\]
\[
\begin{array}{cc}
A & B \\
0 & 1.0 -9 \\
1 & NaN 10 \\
2 & NaN 13 \\
\end{array}
\]

**Discretization and quantiling**

Continuous values can be discretized using the `cut()` (bins based on values) and `qcut()` (bins based on sample quantiles) functions:

\[
\text{In [129]: } \text{arr = np.random.randn(20)}
\]
\[
\text{In [130]: } \text{factor = pd.cut(arr, 4)}
\]
\[
\text{In [131]: } \text{factor}
\]
\[
\text{Out[131]:}
\]
\[
\begin{array}{c}
\text{(-0.251, 0.464]}, (-0.968, -0.251]}, (0.464, 1.179]}, (-0.251, 0.464]}, (-0.968, -0.251]}, (-0.968, -0.251]}, (-0.251, 0.464]}, (-0.968, -0.251]}, (-0.968, -0.251]}, (-0.251, 0.464]}
\end{array}
\]
\[
\text{Length: 20}
\]
\[
\text{Categories (4, interval[float64]):} \{-0.968, -0.251\} < \{-0.251, 0.464\} < \{0.464, 1.179\} < (1.179, 1.893)]
\]

\[
\text{In [132]: } \text{factor = pd.cut(arr, [-5, -1, 0, 1, 5])}
\]
\[
\text{In [133]: } \text{factor}
\]
\[
\text{Out[133]:}
\]
\[
\begin{array}{c}
\{0, 1\}, (-1, 0]}, (0, 1], (0, 1], (-1, 0]}, \ldots, (-1, 0], (-1, 0], (-1, 0], (-1, 0]}
\end{array}
\]
qcut() computes sample quantiles. For example, we could slice up some normally distributed data into equal-size quartiles like so:

```python
In [134]: arr = np.random.randn(30)
In [135]: factor = pd.qcut(arr, [0, .25, .5, .75, 1])
In [136]: factor
Out[136]:
[(0.569, 1.184], (-2.278, -0.301], (-2.278, -0.301], (0.569, 1.184], (0.569, 1.184], ...
...
(-0.301, 0.569], (1.184, 2.346], (1.184, 2.346], (-0.301, 0.569], (-2.278, -0.301)
Length: 30
Categories (4, interval[float64]): [(-2.278, -0.301] < (-0.301, 0.569] < (0.569, 1.184] <
...
(1.184, 2.346])
```

```python
In [137]: pd.value_counts(factor)
Out[137]:
(1.184, 2.346] 8
(-2.278, -0.301] 8
(0.569, 1.184] 7
(-0.301, 0.569] 7
dtype: int64
```

We can also pass infinite values to define the bins:

```python
In [138]: arr = np.random.randn(20)
In [139]: factor = pd.cut(arr, [-np.inf, 0, np.inf])
In [140]: factor
Out[140]:
[(-inf, 0.0], (0.0, inf], (0.0, inf], (-inf, 0.0], (-inf, 0.0], ...
...
(-inf, 0.0], (-inf, 0.0], (0.0, inf], (0.0, inf]
Length: 20
Categories (2, interval[float64]): [(-inf, 0.0] < (0.0, inf]]
```

### 2.3.6 Function application

To apply your own or another library’s functions to pandas objects, you should be aware of the three methods below. The appropriate method to use depends on whether your function expects to operate on an entire DataFrame or Series, row- or column-wise, or elementwise.

1. **Tablewise Function Application**: `pipe()`
2. **Row or Column-wise Function Application**: `apply()`
3. **Aggregation API**: `agg()` and `transform()`
4. **Applying Elementwise Functions**: `applymap()`
Tablewise function application

DataFrames and Series can be passed into functions. However, if the function needs to be called in a chain, consider using the pipe() method.

First some setup:

```python
In [141]: def extract_city_name(df):
   ...:     """
   ...:     Chicago, IL -> Chicago for city_name column
   ...:     """
   ...:     df["city_name"] = df["city_and_code"].str.split(",").str.get(0)
   ...:     return df
   ...

In [142]: def add_country_name(df, country_name=None):
   ...:     """
   ...:     Chicago -> Chicago-US for city_name column
   ...:     """
   ...:     col = 'city_name'
   ...:     df['city_and_country'] = df[col] + country_name
   ...:     return df
   ...

In [143]: df_p = pd.DataFrame({'city_and_code': ['Chicago, IL']})
```

extract_city_name and add_country_name are functions taking and returning DataFrames.

Now compare the following:

```python
In [144]: add_country_name(extract_city_name(df_p), country_name='US')
Out[144]:
   city_and_code  city_name  city_and_country
0    Chicago, IL    Chicago      ChicagoUS
```

Is equivalent to:

```python
In [145]: (df_p.pipe(extract_city_name)
   ...:     .pipe(add_country_name, country_name="US"))
Out[145]:
   city_and_code  city_name  city_and_country
0    Chicago, IL    Chicago      ChicagoUS
```

Pandas encourages the second style, which is known as method chaining. pipe makes it easy to use your own or another library’s functions in method chains, alongside pandas’ methods.

In the example above, the functions extract_city_name and add_country_name each expected a DataFrame as the first positional argument. What if the function you wish to apply takes its data as, say, the second argument? In this case, provide pipe with a tuple of (callable, data_keyword). pipe will route the DataFrame to the argument specified in the tuple.

For example, we can fit a regression using statsmodels. Their API expects a formula first and a DataFrame as the second argument, data. We pass in the function, keyword pair (sm.ols, 'data') to pipe:

```python
In [146]: import statsmodels.formula.api as sm
In [147]: bb = pd.read_csv('data/baseball.csv', index_col='id')
```

(continues on next page)
In [148]: (bb.query('h > 0')
.....:     .assign(ln_h=lambda df: np.log(df.h))
.....:     .pipe((sm.ols, 'data'), 'hr ~ ln_h + year + g + C(lg)')
.....:     .fit()
.....:     .summary()
.....:
Out[148]:
<class 'statsmodels.iolib.summary.Summary'>

OLS Regression Results
==============================================================================
Dep. Variable: hr R-squared: 0.685
Model: OLS Adj. R-squared: 0.665
Method: Least Squares F-statistic: 34.28
Date: Thu, 20 Aug 2020 Prob (F-statistic): 3.48e-15
Time: 19:37:10 Log-Likelihood: -205.92
No. Observations: 68 AIC: 421.8
Df Residuals: 63 BIC: 432.9
Df Model: 4
Covariance Type: nonrobust
===============================================================================
              coef     std err          t      P>|t|     [0.025  0.975]
-------------------------------------------------------------------------------
Intercept   -8484.7720   4664.146      -1.819   0.074    -1.78e+04 835.780
C(lg)[T.NL]  -2.2736     1.325      -1.716   0.091     -4.922  0.375
ln_h        -1.3542     0.875      -1.547   0.127     -3.103  0.395
year         4.2277     2.324      1.819    0.074      -0.417 8.872
 g           0.1841     0.029      6.258    0.000       0.125 0.243
===============================================================================
Omnibus: 10.875 Durbin-Watson: 1.999
Prob(Omnibus): 0.004 Jarque-Bera (JB): 17.298
Skew: 0.537 Prob(JB): 0.000175
Kurtosis: 5.225 Cond. No. 1.49e+07
===============================================================================
Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
    specified.
[2] The condition number is large, 1.49e+07. This might indicate that there are
    strong multicollinearity or other numerical problems.

The pipe method is inspired by unix pipes and more recently dplyr and magrittr, which have introduced the popular (%>% (read pipe) operator for R. The implementation of pipe here is quite clean and feels right at home in python. We encourage you to view the source code of pipe().
Row or column-wise function application

Arbitrary functions can be applied along the axes of a DataFrame using the `apply()` method, which, like the descriptive statistics methods, takes an optional `axis` argument:

```python
In [149]: df.apply(np.mean)
Out[149]:
one    0.811094
two    1.360588
three  0.187958
dtype: float64

In [150]: df.apply(np.mean, axis=1)
Out[150]:
a    1.583749
b    0.734929
c    1.133683
d  -0.166914
dtype: float64

In [151]: df.apply(lambda x: x.max() - x.min())
Out[151]:
one    1.051928
two    1.632779
three  1.840607
dtype: float64

In [152]: df.apply(np.cumsum)
Out[152]:
   one  two  three
a  1.394981 1.772517  NaN
b  1.738035 3.684640 -0.050390
c  2.433281 5.163008  1.177045
d   NaN   5.442353  0.563873

In [153]: df.apply(np.exp)
Out[153]:
   one  two  three
a  4.034899 5.885648  NaN
b  1.409244 6.767440  0.950858
c  2.004201 4.385785  3.412466
d   NaN   1.322262  0.541630
```

The `apply()` method will also dispatch on a string method name.

```python
In [154]: df.apply('mean')
Out[154]:
   one    0.811094
   two    1.360588
  three    0.187958
dtype: float64

In [155]: df.apply('mean', axis=1)
Out[155]:
a    1.583749
b    0.734929
c    1.133683
d  -0.166914
```
The return type of the function passed to `apply()` affects the type of the final output from `DataFrame.apply` for the default behaviour:

- If the applied function returns a `Series`, the final output is a `DataFrame`. The columns match the index of the `Series` returned by the applied function.
- If the applied function returns any other type, the final output is a `Series`.

This default behaviour can be overridden using the `result_type`, which accepts three options: `reduce`, `broadcast`, and `expand`. These will determine how list-likes return values expand (or not) to a `DataFrame`.

`apply()` combined with some cleverness can be used to answer many questions about a data set. For example, suppose we wanted to extract the date where the maximum value for each column occurred:

```python
In [156]: tsdf = pd.DataFrame(np.random.randn(1000, 3), columns=['A', 'B', 'C'], index=pd.date_range('1/1/2000', periods=1000))
In [157]: tsdf.apply(lambda x: x.idxmax())
```

```
Out[157]:
A  2000-08-06
B  2001-01-18
C  2001-07-18
dtype: datetime64[ns]
```

You may also pass additional arguments and keyword arguments to the `apply()` method. For instance, consider the following function you would like to apply:

```python
def subtract_and_divide(x, sub, divide=1):
    return (x - sub) / divide
```

You may then apply this function as follows:

```python
df.apply(subtract_and_divide, args=(5,), divide=3)
```

Another useful feature is the ability to pass `Series` methods to carry out some `Series` operation on each column or row:

```python
In [158]: tsdf
Out[158]:
          A         B         C
2000-01-01 -0.158131 -0.232466  0.321604
2000-01-02 -1.810340 -3.105758  0.433834
2000-01-03 -1.209847 -1.156793 -0.136794
2000-01-04    NaN       NaN       NaN
2000-01-05    NaN       NaN       NaN
2000-01-06    NaN       NaN       NaN
2000-01-07    NaN       NaN       NaN
2000-01-08 -0.653602  0.178875  1.008298
2000-01-09  1.007996  0.462824  0.254472
2000-01-10  0.307473  0.600337  1.643950
In [159]: tsdf.apply(pd.Series.interpolate)
Out[159]:
          A         B         C
2000-01-01 -0.158131 -0.232466  0.321604
```

(continues on next page)
Finally, `apply()` takes an argument `raw` which is False by default, which converts each row or column into a Series before applying the function. When set to True, the passed function will instead receive an ndarray object, which has positive performance implications if you do not need the indexing functionality.

### Aggregation API

The aggregation API allows one to express possibly multiple aggregation operations in a single concise way. This API is similar across pandas objects, see groupby API, the window functions API, and the resample API. The entry point for aggregation is `DataFrame.aggregate()`, or the alias `DataFrame.agg()`.

We will use a similar starting frame from above:

```
In [160]: tsdf = pd.DataFrame(np.random.randn(10, 3), columns=['A', 'B', 'C'],
                       index=pd.date_range('1/1/2000', periods=10))
   .....:
   .....:
In [161]: tsdf.iloc[3:7] = np.nan
In [162]: tsdf
Out[162]:
   A         B         C
2000-01-01  1.257606  1.004194  0.167574
2000-01-02 -0.749892  0.288112 -0.757304
2000-01-03 -0.207550 -0.298599  0.116018
2000-01-04  nan        nan        nan
2000-01-05  nan        nan        nan
2000-01-06  nan        nan        nan
2000-01-07  nan        nan        nan
2000-01-08  0.814347 -0.257623  0.869226
2000-01-09 -0.250663 -1.206601  0.896839
2000-01-10  2.169758 -1.333363  0.283157
```

Using a single function is equivalent to `apply()`. You can also pass named methods as strings. These will return a Series of the aggregated output:

```
In [163]: tsdf.agg(np.sum)
Out[163]:
   A     B     C
2000-01-01  3.033606  1.040194  0.167574
2000-01-02  0.749892  0.288112 -0.757304
2000-01-03  0.207550 -0.298599  0.116018
2000-01-04  nan      nan      nan
2000-01-05  nan      nan      nan
2000-01-06  nan      nan      nan
2000-01-07  nan      nan      nan
2000-01-08  0.814347 -0.257623  0.869226
2000-01-09 -0.250663 -1.206601  0.896839
2000-01-10  2.169758 -1.333363  0.283157
```

```
In [164]: tsdf.agg('sum')
Out[164]:
   A
2000-01-01  3.033606
```

(continues on next page)
# Aggregating with multiple functions

You can pass multiple aggregation arguments as a list. The results of each of the passed functions will be a row in the resulting DataFrame. These are naturally named from the aggregation function.

```
In [167]: tsdf.agg(['sum'])
Out[167]:
A    3.033606
B   -1.803879
C    1.575510
dtype: float64
```

Multiple functions yield multiple rows:

```
In [168]: tsdf.agg(['sum', 'mean'])
Out[168]:
   A     B     C
sum 3.033606 -1.803879  1.575510
mean 0.505601 -0.300647  0.262585
```

On a Series, multiple functions return a Series, indexed by the function names:

```
In [169]: tsdf['A'].agg(['sum', 'mean'])
Out[169]:
sum    3.033606
mean   0.505601
Name: A, dtype: float64
```

Passing a lambda function will yield a `<lambda>` named row:

```
In [170]: tsdf['A'].agg(['sum', lambda x: x.mean()])
Out[170]:
   sum 3.033606
<lambda> 0.505601
Name: A, dtype: float64
```

Passing a named function will yield that name for the row:
In [171]: def mymean(x):
    .....:     return x.mean()
    .....:

In [172]: tsdf['A'].agg(['sum', mymean])
Out[172]:
          sum  mymean
Name: A, dtype: float64

Aggregating with a dict

Passing a dictionary of column names to a scalar or a list of scalars, to `DataFrame.agg` allows you to customize which functions are applied to which columns. Note that the results are not in any particular order, you can use an `OrderedDict` instead to guarantee ordering.

In [173]: tsdf.agg({'A': 'mean', 'B': 'sum'})
Out[173]:
          A     B
Name: , dtype: float64

Passing a list-like will generate a DataFrame output. You will get a matrix-like output of all of the aggregators. The output will consist of all unique functions. Those that are not noted for a particular column will be NaN:

In [174]: tsdf.agg({'A': ['mean', 'min'], 'B': 'sum'})
Out[174]:
       A     B
       mean 0.505601 NaN
       min -0.749892 NaN
       sum NaN -1.803879

Mixed dtypes

When presented with mixed dtypes that cannot aggregate, `.agg` will only take the valid aggregations. This is similar to how `.groupby.agg` works.

In [175]: mdf = pd.DataFrame({'A': [1, 2, 3],
       .....:     'B': [1., 2., 3.],
       .....:     'C': ['foo', 'bar', 'baz'],
       .....:     'D': pd.date_range('20130101', periods=3)})

In [176]: mdf.dtypes
Out[176]:
          A     B     C     D
dtype: int64, float64, object, datetime64[ns]

In [177]: mdf.agg(['min', 'sum'])
Out[177]:
Custom describe

With `.agg()` it is possible to easily create a custom describe function, similar to the built in `describe` function.

```
In [178]: from functools import partial

In [179]: q_25 = partial(pd.Series.quantile, q=0.25)

In [180]: q_25.__name__ = '25%'

In [181]: q_75 = partial(pd.Series.quantile, q=0.75)

In [182]: q_75.__name__ = '75%'

In [183]: tsdf.agg(['count', 'mean', 'std', 'min', q_25, 'median', q_75, 'max'])
```

```
Out[183]:
          A         B         C
count  6.000000  6.000000  6.000000
mean  0.505601 -0.300647  0.262585
std   1.103362  0.887508  0.606860
min  -0.749892 -1.333363 -0.757304
25%   -0.239885 -0.979600  0.128907
median  0.303398 -0.278111  0.225365
75%   1.146791  0.151678  0.722709
max   2.169758  1.004194  0.896839
```

Transform API

The `transform()` method returns an object that is indexed the same (same size) as the original. This API allows you to provide multiple operations at the same time rather than one-by-one. Its API is quite similar to the `.agg` API.

We create a frame similar to the one used in the above sections.

```
In [184]: tsdf = pd.DataFrame(np.random.randn(10, 3), columns=[ 'A', 'B', 'C'],
                   index=pd.date_range('1/1/2000', periods=10))

In [185]: tsdf.iloc[3:7] = np.nan

In [186]: tsdf
```

```
Out[186]:
          A         B         C
2000-01-01 -0.428759 -0.864890 -0.675341
2000-01-02 -0.168731  1.338144 -1.279321
2000-01-03 -1.621034  0.438107  0.903794
2000-01-04  NaN      NaN      NaN
2000-01-05  NaN      NaN      NaN
2000-01-06  NaN      NaN      NaN
2000-01-07  NaN      NaN      NaN
```

(continues on next page)
Transform the entire frame. `.transform()` allows input functions as: a NumPy function, a string function name or a user defined function.

```python
In [187]: tsdf.transform(np.abs)
Out[187]:
   A      B      C
2000-01-01 0.428759 0.864890 0.675341
2000-01-02 0.168731 1.338144 1.279321
2000-01-03 1.621034 0.438107 0.903794
2000-01-04  NaN    NaN    NaN
2000-01-05  NaN    NaN    NaN
2000-01-06  NaN    NaN    NaN
2000-01-07  NaN    NaN    NaN
2000-01-08 0.254374 1.240447 0.201052
2000-01-09 0.157795 0.791197 1.144209
2000-01-10 0.030876 0.371900 0.061932
```

```python
In [188]: tsdf.transform('abs')
Out[188]:
   A      B      C
2000-01-01 0.428759 0.864890 0.675341
2000-01-02 0.168731 1.338144 1.279321
2000-01-03 1.621034 0.438107 0.903794
2000-01-04  NaN    NaN    NaN
2000-01-05  NaN    NaN    NaN
2000-01-06  NaN    NaN    NaN
2000-01-07  NaN    NaN    NaN
2000-01-08 0.254374 1.240447 0.201052
2000-01-09 0.157795 0.791197 1.144209
2000-01-10 0.030876 0.371900 0.061932
```

```python
In [189]: tsdf.transform(lambda x: x.abs())
Out[189]:
   A      B      C
2000-01-01 0.428759 0.864890 0.675341
2000-01-02 0.168731 1.338144 1.279321
2000-01-03 1.621034 0.438107 0.903794
2000-01-04  NaN    NaN    NaN
2000-01-05  NaN    NaN    NaN
2000-01-06  NaN    NaN    NaN
2000-01-07  NaN    NaN    NaN
2000-01-08 0.254374 1.240447 0.201052
2000-01-09 0.157795 0.791197 1.144209
2000-01-10 0.030876 0.371900 0.061932
```

Here `.transform()` received a single function; this is equivalent to a ufunc application.

```python
In [190]: np.abs(tsdf)
Out[190]:
   A      B      C
2000-01-01 0.428759 0.864890 0.675341
2000-01-02 0.168731 1.338144 1.279321
```

(continues on next page)
Passing a single function to `.transform()` with a Series will yield a single Series in return.

```
In [191]: tsdf['A'].transform(np.abs)
Out[191]:
2000-01-01  0.428759
2000-01-02  0.168731
2000-01-03  1.621034
2000-01-04  NaN
2000-01-05  NaN
2000-01-06  NaN
2000-01-07  NaN
2000-01-08  0.254374
2000-01-09  0.157795
2000-01-10  0.030876
Freq: D, Name: A, dtype: float64
```

Transform with multiple functions

Passing multiple functions will yield a column MultiIndexed DataFrame. The first level will be the original frame column names; the second level will be the names of the transforming functions.

```
In [192]: tsdf.transform([np.abs, lambda x: x + 1])
Out[192]:
      absolute  <lambda_0>  absolute  <lambda_0>  absolute  <lambda_0>
2000-01-01  0.428759  0.168731  1.621034  0.864890  0.324659
2000-01-02  0.168731  2.338144  1.338144  1.279321 -0.279321
2000-01-03  1.621034  0.438107  1.438107  0.903794  1.903794
2000-01-04  NaN    NaN     NaN     NaN    NaN     NaN
2000-01-05  NaN    NaN     NaN     NaN    NaN     NaN
2000-01-06  NaN    NaN     NaN     NaN    NaN     NaN
2000-01-07  NaN    NaN     NaN     NaN    NaN     NaN
2000-01-08  0.254374  1.279321  1.240447 -0.240447  0.201052  0.903794
2000-01-09  0.157795  1.144209  0.791197  1.791197  0.144209  0.903794
2000-01-10  0.030876  1.061932  0.371900  1.371900  0.061932  1.061932
```

Passing multiple functions to a Series will yield a DataFrame. The resulting column names will be the transforming functions.

```
In [193]: tsdf['A'].transform([np.abs, lambda x: x + 1])
Out[193]:
      absolute  <lambda>
2000-01-01  0.428759
2000-01-02  0.168731
2000-01-03  1.621034
2000-01-04  NaN
2000-01-05  NaN
2000-01-06  NaN
2000-01-07  NaN
2000-01-08  0.254374
2000-01-09  0.157795
2000-01-10  0.030876
```

(continues on next page)
Transforming with a dict

Passing a dict of functions will allow selective transforming per column.

```
In [194]: tsdf.transform({'A': np.abs, 'B': lambda x: x + 1})
```

```
Out[194]:
    A    B
2000-01-01 0.428759 0.135110
2000-01-02 0.168731 2.338144
2000-01-03 1.621034 1.438107
2000-01-04 NaN NaN
2000-01-05 NaN NaN
2000-01-06 NaN NaN
2000-01-07 NaN NaN
2000-01-08 0.254374 -0.240447
2000-01-09 0.157795 1.791197
2000-01-10 0.030876 1.371900
```

Passing a dict of lists will generate a MultiIndexed DataFrame with these selective transforms.

```
In [195]: tsdf.transform({'A': np.abs, 'B': [lambda x: x + 1, 'sqrt']})
```

```
Out[195]:
    absolute <lambda_0>  sqrt
2000-01-01 0.428759 0.135110 NaN
2000-01-02 0.168731 2.338144 1.156782
2000-01-03 1.621034 1.438107 0.661897
2000-01-04 NaN NaN NaN
2000-01-05 NaN NaN NaN
2000-01-06 NaN NaN NaN
2000-01-07 NaN NaN NaN
2000-01-08 0.254374 -0.240447 NaN
2000-01-09 0.157795 1.791197 0.889493
2000-01-10 0.030876 1.371900 0.609836
```

Applying elementwise functions

Since not all functions can be vectorized (accept NumPy arrays and return another array or value), the methods `applymap()` on DataFrame and analogously `map()` on Series accept any Python function taking a single value and returning a single value. For example:

```
In [196]: df4
```

```
Out[196]:
    one   two   three
a 1.394981 1.772517  NaN
b 0.343054 1.912123 -0.050390
```
In [197]: def f(x):
.....:     return len(str(x))
.....:

In [198]: df4['one'].map(f)
Out[198):
a 18
b 19
c 18
d 3
Name: one, dtype: int64

In [199]: df4.applymap(f)
Out[199]:
       one  two  three
a  18  17  3
b  19  18  20
c  18  18  16
d   3  19  19

Series.map() has an additional feature; it can be used to easily “link” or “map” values defined by a secondary series. This is closely related to merging/joining functionality:

In [200]: s = pd.Series(['six', 'seven', 'six', 'seven', 'six'],
.....:     index=['a', 'b', 'c', 'd', 'e'])
.....:

In [201]: t = pd.Series({'six': 6., 'seven': 7.})

In [202]: s
Out[202]:
a six
b seven
c six
d seven
e six
dtype: object

In [203]: s.map(t)
Out[203]:
a 6.0
b 7.0
c 6.0
d 7.0
e 6.0
dtype: float64
2.3.7 Reindexing and altering labels

`reindex()` is the fundamental data alignment method in pandas. It is used to implement nearly all other features relying on label-alignment functionality. To reindex means to conform the data to match a given set of labels along a particular axis. This accomplishes several things:

- Reorders the existing data to match a new set of labels
- Inserts missing value (NA) markers in label locations where no data for that label existed
- If specified, fill data for missing labels using logic (highly relevant to working with time series data)

Here is a simple example:

```python
In [204]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [205]: s
Out[205]:
   a    1.695148
     b    1.328614
     c    1.234686
     d   -0.385845
     e   -1.326508
       dtype: float64

In [206]: s.reindex(['e', 'b', 'f', 'd'])
Out[206]:
   e   -1.326508
     b    1.328614
     f     NaN
     d   -0.385845
       dtype: float64
```

Here, the `f` label was not contained in the Series and hence appears as `NaN` in the result.

With a DataFrame, you can simultaneously reindex the index and columns:

```python
In [207]: df
Out[207]:
     one     two     three
   a  1.394981  1.772517     NaN
   b  0.343054  1.912123 -0.050390
   c  0.695246  1.478369  1.227435
   d     NaN     0.279344 -0.613172

In [208]: df.reindex(index=['c', 'f', 'b'], columns=['three', 'two', 'one'])
Out[208]:
     three     two     one
   c  1.227435  1.478369  0.695246
   f     NaN     NaN     NaN
   b -0.050390  1.912123  0.343054
```

You may also use `reindex` with an `axis` keyword:

```python
In [209]: df.reindex(['c', 'f', 'b'], axis='index')
Out[209]:
     one     two     three
   c  0.695246  1.478369  1.227435
   f     NaN     NaN     NaN
   b  0.343054  1.912123 -0.050390
```
Note that the Index objects containing the actual axis labels can be shared between objects. So if we have a Series and a DataFrame, the following can be done:

```
In [210]: rs = s.reindex(df.index)
In [211]: rs
Out[211]:
   a    1.695148
   b    1.328614
   c    1.234686
   d  -0.385845
   dtype: float64
In [212]: rs.index is df.index
Out[212]: True
```

This means that the reindexed Series’s index is the same Python object as the DataFrame’s index.

`DataFrame.reindex()` also supports an “axis-style” calling convention, where you specify a single labels argument and the axis it applies to.

```
In [213]: df.reindex(['c', 'f', 'b'], axis='index')
Out[213]:
     one    two    three
    c  0.695246  1.478369  1.227435
    f       NaN       NaN       NaN
    b  0.343054  1.912123 -0.050390
In [214]: df.reindex(['three', 'two', 'one'], axis='columns')
Out[214]:
       three    two    one  
      a  NaN  1.772517  1.394981
      b -0.050390  1.912123  0.343054
      c  1.227435  1.478369  0.695246
      d -0.613172  0.279344       NaN
```

See also:

`MultiIndex / Advanced Indexing` is an even more concise way of doing reindexing.

**Note:** When writing performance-sensitive code, there is a good reason to spend some time becoming a reindexing ninja: **many operations are faster on pre-aligned data.** Adding two unaligned DataFrames internally triggers a reindexing step. For exploratory analysis you will hardly notice the difference (because reindex has been heavily optimized), but when CPU cycles matter sprinkling a few explicit reindex calls here and there can have an impact.

### Reindexing to align with another object

You may wish to take an object and reindex its axes to be labeled the same as another object. While the syntax for this is straightforward albeit verbose, it is a common enough operation that the `reindex_like()` method is available to make this simpler:

```
In [215]: df2
Out[215]:
     one    two
    a  1.394981  1.772517
(continues on next page)```
Aligning objects with each other with align

The `align()` method is the fastest way to simultaneously align two objects. It supports a `join` argument (related to joining and merging):

- `join='outer'`: take the union of the indexes (default)
- `join='left'`: use the calling object’s index
- `join='right'`: use the passed object’s index
- `join='inner'`: intersect the indexes

It returns a tuple with both of the reindexed Series:

```
In [218]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])
In [219]: s1 = s[:4]
In [220]: s2 = s[1:]
In [221]: s1.align(s2)
Out[221]:
   (a   -0.186646  NaN
    b    1.692424  NaN
    c   -0.303893  NaN
    d   -1.425662  NaN
e   NaN
   dtype: float64)
In [222]: s1.align(s2, join='inner')
Out[222]:
   (b   -1.692424
    c   -0.303893
   dtype: float64)
```
For DataFrames, the join method will be applied to both the index and the columns by default:

```python
In [224]: df.align(df2, join='inner')
Out[224]:
          one   two
a  1.394981  1.772517
b  0.343054  1.912123
c  0.695246  1.478369,
    one   two
a  1.394981  1.772517
b  0.343054  1.912123
c  0.695246  1.478369
```

You can also pass an `axis` option to only align on the specified axis:

```python
In [225]: df.align(df2, join='inner', axis=0)
Out[225]:
          one   two   three
a  1.394981  1.772517  NaN
b  0.343054  1.912123 -0.050390
   one   two   three
a  1.394981  1.772517  NaN
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435,
```

If you pass a Series to `DataFrame.align()`, you can choose to align both objects either on the DataFrame’s index or columns using the `axis` argument:

```python
In [226]: df.align(df2.iloc[0], axis=1)
Out[226]:
          one   three   two
a  1.394981   NaN   1.772517
b  0.343054 -0.050390  1.912123
c  0.695246  1.227435  1.478369
d  NaN    0.279344  -0.613172
```

(continues on next page)
Filling while reindexing

`reindex()` takes an optional parameter `method` which is a filling method chosen from the following table:

<table>
<thead>
<tr>
<th>Method</th>
<th>Action</th>
</tr>
</thead>
<tbody>
<tr>
<td>pad / ffill</td>
<td>Fill values forward</td>
</tr>
<tr>
<td>bfill / backfill</td>
<td>Fill values backward</td>
</tr>
<tr>
<td>nearest</td>
<td>Fill from the nearest index value</td>
</tr>
</tbody>
</table>

We illustrate these fill methods on a simple Series:

```
In [227]: rng = pd.date_range('1/3/2000', periods=8)
In [228]: ts = pd.Series(np.random.randn(8), index=rng)
In [229]: ts2 = ts[[0, 3, 6]]
In [230]: ts
Out[230]:
2000-01-03  0.183051
2000-01-04  0.400528
2000-01-05 -0.015083
2000-01-06  2.395489
2000-01-07  1.414806
2000-01-08  0.118428
2000-01-09  0.733639
2000-01-10 -0.936077
Freq: D, dtype: float64
In [231]: ts2
Out[231]:
2000-01-03  0.183051
2000-01-06  2.395489
2000-01-09  0.733639
Freq: 3D, dtype: float64
In [232]: ts2.reindex(ts.index)
Out[232]:
2000-01-03  0.183051
2000-01-04  NaN
2000-01-05  NaN
2000-01-06  2.395489
2000-01-07  NaN
2000-01-08  NaN
2000-01-09  0.733639
2000-01-10  NaN
Freq: D, dtype: float64
In [233]: ts2.reindex(ts.index, method='ffill')
```

(continues on next page)
Out[233]:
2000-01-03  0.183051
2000-01-04  0.183051
2000-01-05  0.183051
2000-01-06  2.395489
2000-01-07  2.395489
2000-01-08  2.395489
2000-01-09  0.733639
2000-01-10  0.733639
Freq: D, dtype: float64

In [234]: ts2.reindex(ts.index, method='bfill')
Out[234]:
2000-01-03  0.183051
2000-01-04  2.395489
2000-01-05  2.395489
2000-01-06  2.395489
2000-01-07  0.733639
2000-01-08  0.733639
2000-01-09  0.733639
2000-01-10  NaN
Freq: D, dtype: float64

In [235]: ts2.reindex(ts.index, method='nearest')
Out[235]:
2000-01-03  0.183051
2000-01-04  0.183051
2000-01-05  2.395489
2000-01-06  2.395489
2000-01-07  2.395489
2000-01-08  0.733639
2000-01-09  0.733639
2000-01-10  0.733639
Freq: D, dtype: float64

These methods require that the indexes are ordered increasing or decreasing.

Note that the same result could have been achieved using **fillna** (except for **method='nearest'**) or **interpolate**:

Out[236]:
2000-01-03  0.183051
2000-01-04  0.183051
2000-01-05  0.183051
2000-01-06  2.395489
2000-01-07  2.395489
2000-01-08  2.395489
2000-01-09  0.733639
2000-01-10  0.733639
Freq: D, dtype: float64

reindex() will raise a ValueError if the index is not monotonically increasing or decreasing. fillna() and interpolate() will not perform any checks on the order of the index.
Limits on filling while reindexing

The limit and tolerance arguments provide additional control over filling while reindexing. Limit specifies the maximum count of consecutive matches:

```
In [237]: ts2.reindex(ts.index, method='ffill', limit=1)
Out[237]:
2000-01-03  0.183051
2000-01-04  0.183051
2000-01-05   NaN
2000-01-06  2.395489
2000-01-07  2.395489
2000-01-08   NaN
2000-01-09  0.733639
2000-01-10  0.733639
Freq: D, dtype: float64
```

In contrast, tolerance specifies the maximum distance between the index and indexer values:

```
In [238]: ts2.reindex(ts.index, method='ffill', tolerance='1 day')
Out[238]:
2000-01-03  0.183051
2000-01-04  0.183051
2000-01-05   NaN
2000-01-06  2.395489
2000-01-07  2.395489
2000-01-08   NaN
2000-01-09  0.733639
2000-01-10  0.733639
Freq: D, dtype: float64
```

Notice that when used on a `DatetimeIndex`, `TimedeltaIndex` or `PeriodIndex`, tolerance will coerced into a `Timedelta` if possible. This allows you to specify tolerance with appropriate strings.

Dropping labels from an axis

A method closely related to `reindex` is the `drop()` function. It removes a set of labels from an axis:

```
In [239]: df
Out[239]:
  one  two  three
a  1.394981  1.772517   NaN
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435
d   NaN      0.279344 -0.613172

In [240]: df.drop(['a', 'd'], axis=0)
Out[240]:
  one  two  three
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435

In [241]: df.drop(['one'], axis=1)
Out[241]:
  two  three
a  1.772517   NaN
```

(continues on next page)
Note that the following also works, but is a bit less obvious / clean:

```python
In [242]: df.reindex(df.index.difference(['a', 'd']))
Out[242]:
   one    two    three
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435
```

### Renaming / mapping labels

The `rename()` method allows you to relabel an axis based on some mapping (a dict or Series) or an arbitrary function.

```python
In [243]: s
Out[243]:
a  -0.186646
b  -1.692424
c  -0.303893
d  -1.425662
e   1.114285
dtype: float64

In [244]: s.rename(str.upper)
Out[244]:
A   -0.186646
B   -1.692424
C   -0.303893
D   -1.425662
E    1.114285
dtype: float64
```

If you pass a function, it must return a value when called with any of the labels (and must produce a set of unique values). A dict or Series can also be used:

```python
In [245]: df.rename(columns={'one': 'foo', 'two': 'bar'},
               index={'a': 'apple', 'b': 'banana', 'd': 'durian'})
Out[245]:
   foo    bar    three
apple  1.394981  1.772517  NaN
banana 0.343054  1.912123 -0.050390
c   0.695246  1.478369  1.227435
durian NaN  0.279344 -0.613172
```

If the mapping doesn’t include a column/index label, it isn’t renamed. Note that extra labels in the mapping don’t throw an error.

`DataFrame.rename()` also supports an “axis-style” calling convention, where you specify a single mapper and the axis to apply that mapping to.

```python
In [246]: df.rename({'one': 'foo', 'two': 'bar'}, axis='columns')
Out[246]:
```

(continues on next page)
The `rename()` method also provides an `inplace` named parameter that is by default `False` and copies the underlying data. Pass `inplace=True` to rename the data in place.

Finally, `rename()` also accepts a scalar or list-like for altering the `Series.name` attribute.

```python
In [248]: s.rename("scalar-name")
Out[248]:
a -0.186646  
b -1.692424  
c -0.303893  
d -1.425662  
e 1.114285
Name: scalar-name, dtype: float64
```

New in version 0.24.0.

The methods `DataFrame.rename_axis()` and `Series.rename_axis()` allow specific names of a `MultiIndex` to be changed (as opposed to the labels).

```python
In [249]: df = pd.DataFrame({'x': [1, 2, 3, 4, 5, 6],  
                      'y': [10, 20, 30, 40, 50, 60],  
                      index=pd.MultiIndex.from_product([['a', 'b', 'c'], [1, 2]],  
                      names=['let', 'num']))

In [250]: df
Out[250]:
   x  y  
let num  
a 1  1 10  
   2  2 20  
b 1  3 30  
   2  4 40  
c 1  5 50  
   2  6 60
```

```python
In [251]: df.rename_axis(index={'let': 'abc'})
Out[251]:
   x  y  
abc num  
a 1  1 10  
   2  2 20
```
b 1 3 30
  2 4 40
c 1 5 50
  2 6 60

In [252]: df.rename_axis(index=str.upper)
Out[252]:
   x   y
LET NUM
a 1 1 10
  2 2 20
b 1 3 30
  2 4 40
c 1 5 50
  2 6 60

2.3.8 Iteration

The behavior of basic iteration over pandas objects depends on the type. When iterating over a Series, it is regarded as array-like, and basic iteration produces the values. DataFrames follow the dict-like convention of iterating over the “keys” of the objects.

In short, basic iteration (for i in object) produces:

- **Series**: values
- **DataFrame**: column labels

Thus, for example, iterating over a DataFrame gives you the column names:

```python
def = pd.DataFrame({'col1': np.random.randn(3),
                   'col2': np.random.randn(3)}, index=['a', 'b', 'c'])

for col in df:
    print(col)
```

Pandas objects also have the dict-like `items()` method to iterate over the (key, value) pairs.

To iterate over the rows of a DataFrame, you can use the following methods:

- **iterrows()**: Iterate over the rows of a DataFrame as (index, Series) pairs. This converts the rows to Series objects, which can change the dtypes and has some performance implications.
- **itertuples()**: Iterate over the rows of a DataFrame as namedtuples of the values. This is a lot faster than `iterrows()`, and is in most cases preferable to use to iterate over the values of a DataFrame.

**Warning:** Iterating through pandas objects is generally slow. In many cases, iterating manually over the rows is not needed and can be avoided with one of the following approaches:

- Look for a vectorized solution: many operations can be performed using built-in methods or NumPy functions, (boolean) indexing, …
• When you have a function that cannot work on the full DataFrame/Series at once, it is better to use `apply()` instead of iterating over the values. See the docs on function application.

• If you need to do iterative manipulations on the values but performance is important, consider writing the inner loop with cython or numba. See the enhancing performance section for some examples of this approach.

**Warning:** You should never modify something you are iterating over. This is not guaranteed to work in all cases. Depending on the data types, the iterator returns a copy and not a view, and writing to it will have no effect!

For example, in the following case setting the value has no effect:

```python
In [255]: df = pd.DataFrame({'a': [1, 2, 3], 'b': ['a', 'b', 'c']})
In [256]: for index, row in df.iterrows():
.....:     row['a'] = 10
.....:
In [257]: df
Out[257]:
   a  b
0  1  a
1  2  b
2  3  c
```

**items**

Consistent with the dict-like interface, `items()` iterates through key-value pairs:

- **Series**: (index, scalar value) pairs
- **DataFrame**: (column, Series) pairs

For example:

```python
In [258]: for label, ser in df.items():
.....:     print(label)
.....:     print(ser)
.....:
a
0  1
1  2
2  3
Name: a, dtype: int64
b
0  a
1  b
2  c
Name: b, dtype: object
```
iterrows

`iterrows()` allows you to iterate through the rows of a DataFrame as Series objects. It returns an iterator yielding each index value along with a Series containing the data in each row:

```python
In [259]: for row_index, row in df.iterrows():
   ....:     print(row_index, row, sep='  
   ....:
0   a 1
b  a
Name: 0, dtype: object
1   a 2
b  b
Name: 1, dtype: object
2   a 3
b  c
Name: 2, dtype: object
```

**Note:** Because `iterrows()` returns a Series for each row, it does not preserve dtypes across the rows (dtypes are preserved across columns for DataFrames). For example,

```python
In [260]: df_orig = pd.DataFrame([[1, 1.5]], columns=['int', 'float'])
In [261]: df_orig.dtypes
Out[261]:
int     int64
float   float64
dtype: object
In [262]: row = next(df_orig.iterrows())[1]
In [263]: row
Out[263]:
int  1.0
float 1.5
Name: 0, dtype: float64
```

All values in `row`, returned as a Series, are now upcasted to floats, also the original integer value in column `x`:

```python
In [264]: row['int'].dtype
Out[264]: dtype('float64')
In [265]: df_orig['int'].dtype
Out[265]: dtype('int64')
```

To preserve dtypes while iterating over the rows, it is better to use `itertuples()` which returns namedtuples of the values and which is generally much faster than `iterrows()`.

For instance, a contrived way to transpose the DataFrame would be:

```python
In [266]: df2 = pd.DataFrame({'x': [1, 2, 3], 'y': [4, 5, 6]})
In [267]: print(df2)
```
In [268]: print(df2.T)
     0 1 2
    x 1 2 3
    y 4 5 6

In [269]: df2_t = pd.DataFrame({idx: values for idx, values in df2.iterrows()})

In [270]: print(df2_t)
     0 1 2
    x 1 2 3
    y 4 5 6

### itertuples

The `itertuples()` method will return an iterator yielding a namedtuple for each row in the DataFrame. The first element of the tuple will be the row’s corresponding index value, while the remaining values are the row values.

For instance:

```
In [271]: for row in df.itertuples():
   ....:     print(row)
   ....:
Pandas(Index=0, a=1, b='a')
Pandas(Index=1, a=2, b='b')
Pandas(Index=2, a=3, b='c')
```

This method does not convert the row to a Series object; it merely returns the values inside a namedtuple. Therefore, `itertuples()` preserves the data type of the values and is generally faster as `iterrows()`.

**Note:** The column names will be renamed to positional names if they are invalid Python identifiers, repeated, or start with an underscore. With a large number of columns (>255), regular tuples are returned.

### 2.3.9 .dt accessor

Series has an accessor to succinctly return datetime like properties for the values of the Series, if it is a datet ime/period like Series. This will return a Series, indexed like the existing Series.

```
# datetime
In [272]: s = pd.Series(pd.date_range('20130101 09:10:12', periods=4))

In [273]: s
Out[273]:
0  2013-01-01 09:10:12
1  2013-01-02 09:10:12
2  2013-01-03 09:10:12
3  2013-01-04 09:10:12
dtype: datetime64[ns]
```
In [274]: s.dt.hour
Out[274]:
0    9
1    9
2    9
3    9
dtype: int64

In [275]: s.dt.second
Out[275]:
0  12
1  12
2  12
3  12
dtype: int64

In [276]: s.dt.day
Out[276]:
0    1
1    2
2    3
3    4
dtype: int64

This enables nice expressions like this:

In [277]: s[s.dt.day == 2]
Out[277]:
1  2013-01-02 09:10:12
dtype: datetime64[ns]

You can easily produces tz aware transformations:

In [278]: stz = s.dt.tz_localize('US/Eastern')
In [279]: stz
Out[279]:
0  2013-01-01 09:10:12-05:00
1  2013-01-02 09:10:12-05:00
2  2013-01-03 09:10:12-05:00
3  2013-01-04 09:10:12-05:00
dtype: datetime64[ns, US/Eastern]

In [280]: stz.dt.tz
Out[280]: <DstTzInfo 'US/Eastern' LMT-1 day, 19:04:00 STD>

You can also chain these types of operations:

In [281]: s.dt.tz_localize('UTC').dt.tz_convert('US/Eastern')
Out[281]:
0  2013-01-01 04:10:12-05:00
1  2013-01-02 04:10:12-05:00
2  2013-01-03 04:10:12-05:00
3  2013-01-04 04:10:12-05:00
dtype: datetime64[ns, US/Eastern]
You can also format datetime values as strings with `Series.strftime()` which supports the same format as the standard `strftime()`.

```python
# DatetimeIndex
In [282]: s = pd.Series(pd.date_range('20130101', periods=4))

In [283]: s
Out[283]:
     0  2013-01-01
     1  2013-01-02
     2  2013-01-03
     3  2013-01-04
       dtype: datetime64[ns]

In [284]: s.dt.strftime('%Y/%m/%d')
Out[284]:
     0  2013/01/01
     1  2013/01/02
     2  2013/01/03
     3  2013/01/04
       dtype: object

# PeriodIndex
In [285]: s = pd.Series(pd.period_range('20130101', periods=4))

In [286]: s
Out[286]:
     0  2013-01-01
     1  2013-01-02
     2  2013-01-03
     3  2013-01-04
       dtype: period[D]

In [287]: s.dt.strftime('%Y/%m/%d')
Out[287]:
     0  2013/01/01
     1  2013/01/02
     2  2013/01/03
     3  2013/01/04
       dtype: object
```

The `.dt` accessor works for period and timedelta dtypes.

```python
# period
In [288]: s = pd.Series(pd.period_range('20130101', periods=4, freq='D'))

In [289]: s
Out[289]:
     0  2013-01-01
     1  2013-01-02
     2  2013-01-03
     3  2013-01-04
       dtype: period[D]

In [290]: s.dt.year
Out[290]:
     0  2013
     1  2013
```

(continues on next page)
2013
3 2013
dtype: int64

In [291]: s.dt.day
Out[291]:
0  1
1  2
2  3
3  4
dtype: int64

# timedelta
In [292]: s = pd.Series(pd.timedelta_range('1 day 00:00:05', periods=4, freq='s'))

In [293]: s
Out[293]:
0   1 days 00:00:05
1   1 days 00:00:06
2   1 days 00:00:07
3   1 days 00:00:08
dtype: timedelta64[ns]

In [294]: s.dt.days
Out[294]:
0   1
1   1
2   1
3   1
dtype: int64

In [295]: s.dt.seconds
Out[295]:
0   5
1   6
2   7
3   8
dtype: int64

In [296]: s.dt.components
Out[296]:
   days  hours  minutes  seconds  milliseconds  microseconds  nanoseconds
0      0       0         0         5                0              0           0
1      1       0         0         6                0              0           0
2      1       0         0         7                0              0           0
3      1       0         0         8                0              0           0

Note: Series.dt will raise a TypeError if you access with a non-datetime-like values.
2.3.10 Vectorized string methods

Series is equipped with a set of string processing methods that make it easy to operate on each element of the array. Perhaps most importantly, these methods exclude missing/NA values automatically. These are accessed via the Series’s `str` attribute and generally have names matching the equivalent (scalar) built-in string methods. For example:

```python
In [297]: s = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog
    →', 'cat'],
       ......: dtype="string")
       ......:
In [298]: s.str.lower()
Out[298]:
    0     a
    1     b
    2     c
    3   aaba
    4    baca
    5     <NA>
    6    caba
    7     dog
    8     cat
    dtype: string
```

Powerful pattern-matching methods are provided as well, but note that pattern-matching generally uses regular expressions by default (and in some cases always uses them).

---

**Note:** Prior to pandas 1.0, string methods were only available on `object`-dtype Series. Pandas 1.0 added the `StringDtype` which is dedicated to strings. See Text data types for more.

---

Please see Vectorized String Methods for a complete description.

2.3.11 Sorting

Pandas supports three kinds of sorting: sorting by index labels, sorting by column values, and sorting by a combination of both.

### By index

The `Series.sort_index()` and `DataFrame.sort_index()` methods are used to sort a pandas object by its index levels.

```python
In [299]: df = pd.DataFrame({
       ......:    'one': pd.Series(np.random.randn(3), index=['a', 'b', 'c']),
       ......:    'two': pd.Series(np.random.randn(4), index=['a', 'b', 'c', 'd']),
       ......:    'three': pd.Series(np.random.randn(3), index=['b', 'c', 'd']))
       ......:
In [300]: unsorted_df = df.reindex(index=['a', 'd', 'c', 'b'],
       ......:    columns=['three', 'two', 'one'])
       ......:
In [301]: unsorted_df
```

(continues on next page)
New in version 1.1.0.

Sorting by index also supports a key parameter that takes a callable function to apply to the index being sorted. For MultiIndex objects, the key is applied per-level to the levels specified by level.

```
In [306]: s1 = pd.DataFrame({
.....:     "a": ['B', 'A', 'C'],
.....:     "b": [1, 2, 3],
.....:     "c": [2, 3, 4]  
.....: }).set_index(list("ab"))
.....:

In [307]: s1
Out[307]:
     c
a b  
A  2
B  3
C  4
```
In [308]: s1.sort_index(level="a")
Out[308]:
   c
   a b
   B 1 2
   C 3 4
   a 2 3

In [309]: s1.sort_index(level="a", key=lambda idx: idx.str.lower())
Out[309]:
   c
   a b
   a 2 3
   B 1 2
   C 3 4

For information on key sorting by value, see value sorting.

By values

The Series.sort_values() method is used to sort a Series by its values. The DataFrame.sort_values() method is used to sort a DataFrame by its column or row values. The optional by parameter to DataFrame.sort_values() may be used to specify one or more columns to use to determine the sorted order.

In [310]: df1 = pd.DataFrame({'one': [2, 1, 1, 1],
            'two': [1, 3, 2, 4],
            'three': [5, 4, 3, 2]})
In [311]: df1.sort_values(by='two')
Out[311]:
   one two three
0  2  1  5
2  1  2  3
1  1  3  4
3  1  4  2

The by parameter can take a list of column names, e.g.:

In [312]: df1[['one', 'two', 'three']].sort_values(by=['one', 'two'])
Out[312]:
   one two three
2  1  2  3
1  1  3  4
3  1  4  2
0  2  1  5

These methods have special treatment of NA values via the na_position argument:

In [313]: s[2] = np.nan

(continues on next page)
In [314]: s.sort_values()
Out[314]:
0    A
3   Aaba
1    B
4    Baca
6    CABA
8     cat
7     dog
2    <NA>
5    <NA>
dtype: string

In [315]: s.sort_values(na_position='first')
Out[315]:
2    <NA>
5    <NA>
0    A
3   Aaba
1    B
4    Baca
6    CABA
8     cat
7     dog
dtype: string

New in version 1.1.0.

Sorting also supports a key parameter that takes a callable function to apply to the values being sorted.

In [316]: s1 = pd.Series(['B', 'a', 'C'])

In [317]: s1.sort_values()
Out[317]:
0    B
2    C
1    a
dtype: object

In [318]: s1.sort_values(key=lambda x: x.str.lower())
Out[318]:
1    a
0    B
2    C
dtype: object

key will be given the Series of values and should return a Series or array of the same shape with the transformed values. For DataFrame objects, the key is applied per column, so the key should still expect a Series and return a Series, e.g.

In [319]: df = pd.DataFrame({'a': ['B', 'a', 'C'], 'b': [1, 2, 3]})

In [320]: df.sort_values(by='a')
Out[320]:
a  b
0  B  1
(continues on next page)
In [321]: df.sort_values(by='a', key=lambda col: col.str.lower())
Out[321]:
   a  b
0  a  2
1  b  1
2  c  3

The name or type of each column can be used to apply different functions to different columns.

### By indexes and values

New in version 0.23.0.

Strings passed as the `by` parameter to `DataFrame.sort_values()` may refer to either columns or index level names.

```python
# Build MultiIndex
In [322]: idx = pd.MultiIndex.from_tuples([('a', 1), ('a', 2), ('a', 2),
                                      ('b', 2), ('b', 1), ('b', 1)])

# Build DataFrame
In [323]: idx.names = ['first', 'second']

In [324]: df_multi = pd.DataFrame({'A': np.arange(6, 0, -1)},
                              index=idx)

In [325]: df_multi
Out[325]:
    first  second
   a     1     6
          2     5
          2     4
   b     2     3
          1     2
          1     1

Sort by ‘second’ (index) and ‘A’ (column)

In [326]: df_multi.sort_values(by=['second', 'A'])
Out[326]:
    first  second
   b     1     1
          1     2
   a     1     6
          2     3
   a     2     4
          2     5
```

2.3. Essential basic functionality
Note: If a string matches both a column name and an index level name then a warning is issued and the column takes precedence. This will result in an ambiguity error in a future version.

searchsorted

Series has the `searchsorted()` method, which works similarly to `numpy.ndarray.searchsorted()`.

```
In [327]: ser = pd.Series([1, 2, 3])
In [328]: ser.searchsorted([0, 3])
Out[328]: array([0, 2])
In [329]: ser.searchsorted([0, 4])
Out[329]: array([0, 3])
In [330]: ser.searchsorted([1, 3], side='right')
Out[330]: array([1, 3])
In [331]: ser.searchsorted([1, 3], side='left')
Out[331]: array([0, 2])
In [332]: ser = pd.Series([3, 1, 2])
In [333]: ser.searchsorted([0, 3], sorter=np.argsort(ser))
Out[333]: array([0, 2])
```

smallest / largest values

Series has the `nsmallest()` and `nlargest()` methods which return the smallest or largest $n$ values. For a large Series this can be much faster than sorting the entire Series and calling `head(n)` on the result.

```
In [334]: s = pd.Series(np.random.permutation(10))
In [335]: s
Out[335]:
0    2
1    0
2    3
3    7
4    1
5    5
6    9
7    6
8    8
9    4
 dtype: int64
In [336]: s.sort_values()
Out[336]:
1    0
4    1
0    2
2    3
```

(continues on next page)
DataFrame also has the `nlargest` and `nsmallest` methods.

In [339]: df = pd.DataFrame({'a': [-2, -1, 1, 10, 8, 11, -1],
                        'b': list('abdceff'),
                        'c': [1.0, 2.0, 4.0, 3.2, np.nan, 3.0, 4.0]})

In [340]: df.nlargest(3, 'a')
Out[340]:
   a  b  c
0 -2  a  1.0
1 -1  b  2.0
2  1  d  4.0
3  8  e  NaN
4 11  f  3.0

In [341]: df.nlargest(5, ['a', 'c'])
Out[341]:
   a  b  c
0 -2  a  1.0
1 -1  b  2.0
2  1  d  4.0
3  8  e  NaN
4 11  f  3.0
5  6  f  4.0

In [342]: df.nsmallest(3, 'a')
Out[342]:
   a  b  c
0 -2  a  1.0
1 -1  b  2.0
2  6  f  4.0

In [343]: df.nsmallest(5, ['a', 'c'])
Out[343]:
   a  b  c
0 -2  a  1.0
1 -1  b  2.0

(continues on next page)
Sorting by a MultiIndex column

You must be explicit about sorting when the column is a MultiIndex, and fully specify all levels to by.

```
In [344]: df1.columns = pd.MultiIndex.from_tuples((
              ("a", 'one'),
              ("a", 'two'),
              ("b", 'three')))  
In [345]: df1.sort_values(by=('a', 'two'))
Out[345]:
    a   b
e   one  two  three
0  2  1   5
1  1  2   3
2  1  3   4
3  1  4   2
```

2.3.12 Copying

The `copy()` method on pandas objects copies the underlying data (though not the axis indexes, since they are immutable) and returns a new object. Note that it is seldom necessary to copy objects. For example, there are only a handful of ways to alter a DataFrame in-place:

- Inserting, deleting, or modifying a column.
- Assigning to the `index` or `columns` attributes.
- For homogeneous data, directly modifying the values via the `values` attribute or advanced indexing.

To be clear, no pandas method has the side effect of modifying your data; almost every method returns a new object, leaving the original object untouched. If the data is modified, it is because you did so explicitly.

2.3.13 dtypes

For the most part, pandas uses NumPy arrays and dtypes for Series or individual columns of a DataFrame. NumPy provides support for `float`, `int`, `bool`, `timedelta64[ns]` and `datetime64[ns]` (note that NumPy does not support timezone-aware datetimes).

Pandas and third-party libraries extend NumPy’s type system in a few places. This section describes the extensions pandas has made internally. See Extension types for how to write your own extension that works with pandas. See ecosystem.extensions for a list of third-party libraries that have implemented an extension.

The following table lists all of pandas extension types. For methods requiring `dtype` arguments, strings can be specified as indicated. See the respective documentation sections for more on each type.
Pandas has two ways to store strings.

1. **object dtype**, which can hold any Python object, including strings.
2. **StringDtype**, which is dedicated to strings.

Generally, we recommend using **StringDtype**. See **Text data types** for more.

Finally, arbitrary objects may be stored using the `object` dtype, but should be avoided to the extent possible (for performance and interoperability with other libraries and methods. See **object conversion**).

A convenient **dtypes** attribute for DataFrame returns a Series with the data type of each column.

```python
In [346]: dft = pd.DataFrame({'A': np.random.rand(3),
                      'B': 1,
                      'C': 'foo',
                      'D': pd.Timestamp('20010102'),
                      'E': pd.Series([1.0] * 3).astype('float32'),
                      'F': False,
                      'G': pd.Series([1] * 3, dtype='int8')})

In [347]: dft
Out[347]:
   A  B   C       D       E       F       G
0  0.5  1.0 'foo' 2001-01-02  1.0     False 1
1  0.9  1.0 'foo' 2001-01-02  1.0     False 1
2  0.3  1.0 'foo' 2001-01-02  1.0     False 1
```

(continues on next page)
### pandas: powerful Python data analysis toolkit, Release 1.1.1

0 0.035962 1 foo 2001-01-02 1.0 False 1
1 0.701379 1 foo 2001-01-02 1.0 False 1
2 0.281885 1 foo 2001-01-02 1.0 False 1

In [348]: dft.dtypes
Out[348]:
A    float64
B     int64
C    object
D  datetime64[ns]
E  float32
F      bool
G     int8
dtype: object

On a Series object, use the dtype attribute.

In [349]: dft['A'].dtype
Out[349]: dtype('float64')

If a pandas object contains data with multiple dtypes in a single column, the dtype of the column will be chosen to accommodate all of the data types (object is the most general).

# these ints are coerced to floats
In [350]: pd.Series([1, 2, 3, 4, 5, 6.])
Out[350]:
0 1.0
1 2.0
2 3.0
3 4.0
4 5.0
5 6.0
dtype: float64

# string data forces an `object` dtype
In [351]: pd.Series([1, 2, 3, 6., 'foo'])
Out[351]:
0 1
1 2
2 3
3 6
4   foo
dtype: object

The number of columns of each type in a DataFrame can be found by calling DataFrame.dtypes.value_counts().

In [352]: dft.dtypes.value_counts()
Out[352]:
float64    1
bool       1
float32    1
object     1
int64      1
int8       1
datetime64[ns]  1
dtype: int64
Numeric dtypes will propagate and can coexist in DataFrames. If a dtype is passed (either directly via the `dtype` keyword, a passed `ndarray`, or a passed `Series`), then it will be preserved in DataFrame operations. Furthermore, different numeric dtypes will **NOT** be combined. The following example will give you a taste.

```python
In [353]: df1 = pd.DataFrame(np.random.randn(8, 1), columns=['A'], dtype='float32')

In [354]: df1
Out[354]:
     A
0 0.224364
1 1.890546
2 0.182879
3 0.787847
4 -0.188449
5 0.667715
6 -0.011736
7 -0.399073

In [355]: df1.dtypes
Out[355]:
A     float32
dtype: object

In [356]: df2 = pd.DataFrame({'A': pd.Series(np.random.randn(8), dtype='float16'),
                        'B': pd.Series(np.random.randn(8)),
                        'C': pd.Series(np.array(np.random.randn(8),
                                              dtype='uint8'))})

In [357]: df2
Out[357]:
     A   B   C
0 0.823242 0.256090 0
1 1.607422 1.426469 0
2 -0.333740 -0.416203 255
3 -0.063477 1.139976 0
4 -1.014648 -1.193477 0
5 0.678711 0.096706 0
6 -0.040863 -1.956850 1
7 -0.357422 -0.714337 0

In [358]: df2.dtypes
Out[358]:
A    float16
B    float64
C    uint8
dtype: object
```
By default integer types are \texttt{int64} and float types are \texttt{float64}, \textit{regardless} of platform (32-bit or 64-bit). The following will all result in \texttt{int64} dtypes.

\begin{verbatim}
In [359]: pd.DataFrame([1, 2], columns=['a']).dtypes
Out[359]:
   a     int64
dtype: object

In [360]: pd.DataFrame({'a': [1, 2]}).dtypes
Out[360]:
   a     int64
dtype: object

In [361]: pd.DataFrame({'a': 1}, index=list(range(2))).dtypes
Out[361]:
   a     int64
dtype: object
\end{verbatim}

Note that Numpy will choose \textit{platform-dependent} types when creating arrays. The following \textbf{WILL} result in \texttt{int32} on 32-bit platform.

\begin{verbatim}
In [362]: frame = pd.DataFrame(np.array([1, 2]))
\end{verbatim}

\section*{upcasting}

Types can potentially be \textit{upcasted} when combined with other types, meaning they are promoted from the current type (e.g. \texttt{int} to \texttt{float}).

\begin{verbatim}
In [363]: df3 = df1.reindex_like(df2).fillna(value=0.0) + df2

In [364]: df3
Out[364]:
   A         B         C
0  1.047606  0.256090  0.0
1  3.497968  1.426469  0.0
2 -0.150862 -0.416203 255.0
3  0.724370  1.139976  0.0
4 -1.203098 -1.193477  0.0
5  1.346426  0.096706  0.0
6  0.352599  0.956850  1.0
7 -0.756495 -0.714337  0.0

In [365]: df3.dtypes
Out[365]:
   A    float32
   B    float64
   C    float64
dtype: object
\end{verbatim}

\texttt{DataFrame.to_numpy()} \textbf{will return the lower-common-denominator} of the dtypes, meaning the dtype that can accommodate \textbf{ALL} of the types in the resulting homogeneous dtyped NumPy array. This can force some \textit{upcasting}.

\begin{verbatim}
In [366]: df3.to_numpy().dtype
Out[366]: dtype('float64')
\end{verbatim}
**astype**

You can use the `astype()` method to explicitly convert dtypes from one to another. These will by default return a copy, even if the dtype was unchanged (pass `copy=False` to change this behavior). In addition, they will raise an exception if the astype operation is invalid.

Upcasting is always according to the `numpy` rules. If two different dtypes are involved in an operation, then the more general one will be used as the result of the operation.

```python
In [367]: df3
Out[367]:
     A     B     C
0  1.0476  0.2561  0.0
1  3.4979  1.4265  0.0
2 -1.5086 -0.4162  255
3  0.7244  1.1399  0.0
4 -1.2031 -1.1935  0.0
5  1.3464  0.0967  0.0
6 -0.0526 -1.9569  1.0
7 -0.7565 -0.7143  0.0
```

```python
In [368]: df3.dtypes
Out[368]:
A float32
B float64
C float64
dtype: object
```

```python
In [369]: df3.astype('float32').dtypes
Out[369]:
A float32
B float32
C float32
dtype: object
```

Convert a subset of columns to a specified type using `astype()`.

```python
In [370]: dft = pd.DataFrame({'a': [1, 2, 3], 'b': [4, 5, 6], 'c': [7, 8, 9]})
```

```python
In [371]: dft[['a', 'b']] = dft[['a', 'b']].astype(np.uint8)
```

```python
In [372]: dft
Out[372]:
     a  b  c
0   1  4  7
1   2  5  8
2   3  6  9
```

```python
In [373]: dft.dtypes
Out[373]:
A uint8
B uint8
c int64
dtype: object
```

Convert certain columns to a specific dtype by passing a dict to `astype()`.
pandas: powerful Python data analysis toolkit, Release 1.1.1

In [374]: dft1 = pd.DataFrame({'a': [1, 0, 1], 'b': [4, 5, 6], 'c': [7, 8, 9]})

In [375]: dft1 = dft1.astype({'a': np.bool, 'c': np.float64})

In [376]: dft1
Out[376]:
   a  b  c
0  True 4  7.0
1  False 5  8.0
2  True  6  9.0

In [377]: dft1.dtypes
Out[377]:
a   bool
b  int64
c  float64
dtype: object

Note: When trying to convert a subset of columns to a specified type using `astype()` and `loc()`, upcasting occurs. `loc()` tries to fit in what we are assigning to the current dtypes, while [] will overwrite them taking the dtype from the right hand side. Therefore the following piece of code produces the unintended result.

In [378]: dft = pd.DataFrame({'a': [1, 2, 3], 'b': [4, 5, 6], 'c': [7, 8, 9]})

In [379]: dft.loc[:, ['a', 'b']].astype(np.uint8).dtypes
Out[379]:
a  uint8
b  uint8
dtype: object

In [380]: dft.loc[:, ['a', 'b']] = dft.loc[:, ['a', 'b']].astype(np.uint8)

In [381]: dft.dtypes
Out[381]:
a  int64
b  int64
c  int64
dtype: object

**object conversion**

pandas offers various functions to try to force conversion of types from the object dtype to other types. In cases where the data is already of the correct type, but stored in an object array, the `DataFrame.infer_objects()` and `Series.infer_objects()` methods can be used to soft convert to the correct type.

In [382]: import datetime

In [383]: df = pd.DataFrame([[1, 2],
                   ......:  ['a', 'b'],
                   ......:  [datetime.datetime(2016, 3, 2),
                   ......:    datetime.datetime(2016, 3, 2)]])

(continues on next page)
In [384]: df = df.T

In [385]: df
Out[385]:
   0 1 2
 0 1 2 a 2016-03-02
 1 2 1 b 2016-03-02

In [386]: df.dtypes
Out[386]:
0    object
1    object
2  datetime64[ns]
dtype: object

Because the data was transposed the original inference stored all columns as object, which `infer_objects` will correct.

In [387]: df.infer_objects().dtypes
Out[387]:
0   int64
1    object
2  datetime64[ns]
dtype: object

The following functions are available for one dimensional object arrays or scalars to perform hard conversion of objects to a specified type:

- `to_numeric()` (conversion to numeric dtypes)

In [388]: m = ['1.1', 2, 3]

In [389]: pd.to_numeric(m)
Out[389]: array([1.1, 2. , 3. ])  

- `to_datetime()` (conversion to datetime objects)

In [390]: import datetime

In [391]: m = ['2016-07-09', datetime.datetime(2016, 3, 2)]

In [392]: pd.to_datetime(m)
Out[392]: DatetimeIndex(['2016-07-09', '2016-03-02'], dtype='datetime64[ns]', freq=None)

- `to_timedelta()` (conversion to timedelta objects)

In [393]: m = ['5us', pd.Timedelta('1day')]

In [394]: pd.to_timedelta(m)
Out[394]: TimedeltaIndex(['0 days 00:00:00.000005', '1 days 00:00:00'], dtype='timedelta64[ns]', freq=None)

To force a conversion, we can pass in an `errors` argument, which specifies how pandas should deal with elements that cannot be converted to desired dtype or object. By default, `errors='raise'`, meaning that any errors encountered will be raised during the conversion process. However, if `errors='coerce'`, these errors will be ignored and pandas will convert problematic elements to `pd.NaT` (for datetime and timedelta) or `np.nan` (for numeric).

2.3. Essential basic functionality
This might be useful if you are reading in data which is mostly of the desired dtype (e.g. numeric, datetime), but occasionally has non-conforming elements intermixed that you want to represent as missing:

```
In [395]: import datetime
In [396]: m = ['apple', datetime.datetime(2016, 3, 2)]
In [397]: pd.to_datetime(m, errors='coerce')
Out[397]: DatetimeIndex(['NaT', '2016-03-02'], dtype='datetime64[ns]', freq=None)
In [398]: m = ['apple', 2, 3]
In [399]: pd.to_numeric(m, errors='coerce')
Out[399]: array([nan, 2., 3.])
In [400]: m = ['apple', pd.Timedelta('1day')]
In [401]: pd.to_timedelta(m, errors='coerce')
Out[401]: TimedeltaIndex([NaT, '1 days'], dtype='timedelta64[ns]', freq=None)
```

The `errors` parameter has a third option of `errors='ignore'`, which will simply return the passed in data if it encounters any errors with the conversion to a desired data type:

```
In [402]: import datetime
In [403]: m = ['apple', datetime.datetime(2016, 3, 2)]
In [404]: pd.to_datetime(m, errors='ignore')
Out[404]: Index(['apple', 2016-03-02 00:00:00], dtype='object')
In [405]: m = ['apple', 2, 3]
In [406]: pd.to_numeric(m, errors='ignore')
Out[406]: array(['apple', 2, 3], dtype=object)
In [407]: m = ['apple', pd.Timedelta('1day')]
In [408]: pd.to_timedelta(m, errors='ignore')
Out[408]: array(['apple', Timedelta('1 days 00:00:00')], dtype=object)
```

In addition to object conversion, `to_numeric()` provides another argument `downcast`, which gives the option of downcasting the newly (or already) numeric data to a smaller dtype, which can conserve memory:

```
In [409]: m = ['1', 2, 3]
In [410]: pd.to_numeric(m, downcast='integer')  # smallest signed int dtype
Out[410]: array([1, 2, 3], dtype=int8)
In [411]: pd.to_numeric(m, downcast='signed')  # same as 'integer'
Out[411]: array([1, 2, 3], dtype=int8)
In [412]: pd.to_numeric(m, downcast='unsigned')  # smallest unsigned int dtype
Out[412]: array([1, 2, 3], dtype=uint8)
In [413]: pd.to_numeric(m, downcast='float')  # smallest float dtype
Out[413]: array([1., 2., 3.], dtype=float32)
```

As these methods apply only to one-dimensional arrays, lists or scalars; they cannot be used directly on multi-
dimensional objects such as DataFrames. However, with `apply()`, we can “apply” the function over each column efficiently:

```python
In [414]: import datetime
In [415]: df = pd.DataFrame(
.....:     [['2016-07-09', datetime.datetime(2016, 3, 2)] * 2, dtype='O'])
.....:
In [416]: df
Out[416]:
   0                 1
0 2016-07-09 2016-03-02 00:00:00
1 2016-07-09 2016-03-02 00:00:00
In [417]: df.apply(pd.to_datetime)
Out[417]:
   0   1
0   2016-07-09 2016-03-02
1   2016-07-09 2016-03-02
In [418]: df = pd.DataFrame(
.....:     [['1.1', 2, 3]] * 2, dtype='O')
.....:
In [419]: df
Out[419]:
   0  1  2
0  1.1 2  3
1  1.1 2  3
In [420]: df.apply(pd.to_numeric)
Out[420]:
   0  1  2
0  1.1 2  3
1  1.1 2  3
In [421]: df = pd.DataFrame(
.....:     [['5us', pd.Timedelta('1day')]] * 2, dtype='O')
.....:
In [422]: df
Out[422]:
   0  1
0  5us 1 days 00:00:00
1  5us 1 days 00:00:00
In [423]: df.apply(pd.to_timedelta)
Out[423]:
   0  1
0 0 days 00:00:00.000005 1 days
1 0 days 00:00:00.000005 1 days
```

2.3. Essential basic functionality
gotchas

Performing selection operations on integer type data can easily upcast the data to floating. The dtype of the input data will be preserved in cases where nans are not introduced. See also Support for integer NA.

```
In [424]: dfi = df3.astype('int32')
In [425]: dfi['E'] = 1
In [426]: dfi
Out[426]:
   A  B  C  E
0  1  0  0  1
1  3  1  0  1
2  0  0 255  1
3  0  1  0  1
4 -1 -1  0  1
5  1  0  0  1
6  0 -1  1  1
7  0  0  0  1
```

```
In [427]: dfi.dtypes
Out[427]:
A   int32
B   int32
C   int32
E   int64
dtype: object
```

```
In [428]: casted = dfi[dfi > 0]
In [429]: casted
Out[429]:
   A  B  C  E
0  1.0 NaN NaN  1
1  3.0 1.0 NaN  1
2 NaN NaN 255.0  1
3 NaN 1.0 NaN  1
4 NaN NaN NaN  1
5  1.0 NaN NaN  1
6 NaN NaN  1.0  1
7 NaN NaN NaN  1
```

```
In [430]: casted.dtypes
Out[430]:
A   float64
B   float64
C   float64
E   int64
dtype: object
```

While float dtypes are unchanged.

```
In [431]: dfa = df3.copy()
In [432]: dfa['A'] = dfa['A'].astype('float32')
In [433]: dfa.dtypes
```

(continues on next page)
Out[433]:
A  float32  
B  float64  
C  float64  
dtype: object

In [434]: casted = dfa[df2 > 0]

In [435]: casted
Out[435]:
   A          B         C
0  1.047606  0.256090  NaN
1  3.497968  1.426469  NaN
2  NaN       NaN   255.0
3  NaN     1.139976  NaN
4  NaN      NaN       NaN
5  1.346426  0.096706  NaN
6  NaN      NaN       1.0
7  NaN      NaN       NaN

In [436]: casted.dtypes
Out[436]:
A  float32  
B  float64  
C  float64  
dtype: object

2.3.14 Selecting columns based on dtype

The select_dtypes() method implements subsetting of columns based on their dtype.

First, let’s create a DataFrame with a slew of different dtypes:

In [437]: df = pd.DataFrame({'string': list('abc'),
                   'int64': list(range(1, 4)),
                   'uint8': np.arange(3, 6).astype('u1'),
                   'float64': np.arange(4.0, 7.0),
                   'bool1': [True, False, True],
                   'bool2': [False, True, False],
                   'dates': pd.date_range('now', periods=3),
                   'category': pd.Series(list("ABC")).astype('category')})

In [438]: df['tdeltas'] = df.dates.diff()

In [439]: df['uint64'] = np.arange(3, 6).astype('u8')

In [440]: df['other_dates'] = pd.date_range('20130101', periods=3)

In [441]: df['tz_aware_dates'] = pd.date_range('20130101', periods=3, tz='US/Eastern')

In [442]: df
Out[442]:
   string  int64  uint8  float64  bool1  bool2  dates  category  
      ---  ------  -----  ------  -----  -----  -----  -------  
                   tdeltas  uint64  other_dates  tz_aware_dates

2.3. Essential basic functionality
And the dtypes:

```
In [443]: df.dtypes
Out[443]:
string            object
int64            int64
uint8            uint8
float64          float64
bool1            bool
bool2            bool
dates            datetime64[ns]
category         category
tdeltas          timedelta64[ns]
uint64           uint64
other_dates      datetime64[ns]
tz_aware_dates   datetime64[ns, US/Eastern]
dtype: object
```

`select_dtypes()` has two parameters `include` and `exclude` that allow you to say “give me the columns with these dtypes” (include) and/or “give the columns without these dtypes” (exclude).

For example, to select `bool` columns:

```
In [444]: df.select_dtypes(include=[bool])
Out[444]:
bool1    bool2
0    True  False
1    False  True
2       True  False
```

You can also pass the name of a dtype in the NumPy dtype hierarchy:

```
In [445]: df.select_dtypes(include=['bool'])
Out[445]:
bool1    bool2
0    True  False
1    False  True
2       True  False
```

`select_dtypes()` also works with generic dtypes as well.

For example, to select all numeric and boolean columns while excluding unsigned integers:

```
In [446]: df.select_dtypes(include=['number', 'bool'], exclude=['unsignedinteger'])
Out[446]:
int64  float64    bool1   bool2   tdeltas
0   1   4.0    True  False  NaT
1   2   5.0  False    True   1 days
2   3   6.0    True  False   1 days
```

To select string columns you must use the `object` dtype:
To see all the child dtypes of a generic `dtype` like `numpy.number` you can define a function that returns a tree of child dtypes:

```python
In [448]: def subdtypes(dtype):
    ....:     subs = dtype.__subclasses__()
    ....:     if not subs:
    ....:         return dtype
    ....:     return [dtype, [subdtypes(dt) for dt in subs]]
```

All NumPy dtypes are subclasses of `numpy.generic`:

```python
In [449]: subdtypes(np.generic)
Out[449]:
[numpy.generic,
 [[numpy.number,
   [[numpy.integer,
     [[numpy.signedinteger,
       [numpy.int8,
       numpy.int16,
       numpy.int32,
       numpy.int64,
       numpy.longlong,
       numpy.timedelta64]],
     [numpy.unsignedinteger,
       [numpy.uint8,
       numpy.uint16,
       numpy.uint32,
       numpy.uint64,
       numpy.ulonglong]]]],
   [numpy.inexact,
     [[numpy.floating,
       [numpy.float16, numpy.float32, numpy.float64, numpy.float128]],
     [numpy.complexfloating,
       [numpy.complex64, numpy.complex128, numpy.complex256]]]]],
 [numpy.flexible,
   [[numpy.character, [numpy.bytes_, numpy.str_]],
    [numpy.void, [numpy.record]]],
    numpy.bool_,
    numpy.datetime64,
    numpy.object_]]
```

Note: Pandas also defines the types `category` and `datetime64[ns, tz]`, which are not integrated into the normal NumPy hierarchy and won’t show up with the above function.
2.4 IO tools (text, CSV, HDF5, …)

The pandas I/O API is a set of top level reader functions accessed like `pandas.read_csv()` that generally return a pandas object. The corresponding writer functions are object methods that are accessed like `DataFrame.to_csv()`. Below is a table containing available readers and writers.

<table>
<thead>
<tr>
<th>Format Type</th>
<th>Data Description</th>
<th>Reader</th>
<th>Writer</th>
</tr>
</thead>
<tbody>
<tr>
<td>text</td>
<td>CSV</td>
<td><code>read_csv</code></td>
<td><code>to_csv</code></td>
</tr>
<tr>
<td>text</td>
<td>Fixed-Width Text File</td>
<td><code>read_fwf</code></td>
<td></td>
</tr>
<tr>
<td>text</td>
<td>JSON</td>
<td><code>read_json</code></td>
<td><code>to_json</code></td>
</tr>
<tr>
<td>text</td>
<td>HTML</td>
<td><code>read_html</code></td>
<td><code>to_html</code></td>
</tr>
<tr>
<td>text</td>
<td>Local clipboard</td>
<td><code>read_clipboard</code></td>
<td><code>to_clipboard</code></td>
</tr>
<tr>
<td></td>
<td>MS Excel</td>
<td><code>read_excel</code></td>
<td><code>to_excel</code></td>
</tr>
<tr>
<td>binary</td>
<td>OpenDocument</td>
<td><code>read_excel</code></td>
<td></td>
</tr>
<tr>
<td>binary</td>
<td>HDF5 Format</td>
<td><code>read_hdf</code></td>
<td><code>to_hdf</code></td>
</tr>
<tr>
<td>binary</td>
<td>Feather Format</td>
<td><code>read_feather</code></td>
<td><code>to_feather</code></td>
</tr>
<tr>
<td>binary</td>
<td>Parquet Format</td>
<td><code>read_parquet</code></td>
<td><code>to_parquet</code></td>
</tr>
<tr>
<td>binary</td>
<td>ORC Format</td>
<td><code>read_orc</code></td>
<td></td>
</tr>
<tr>
<td>binary</td>
<td>Msgpack</td>
<td><code>read_msgpack</code></td>
<td><code>to_msgpack</code></td>
</tr>
<tr>
<td>binary</td>
<td>Stata</td>
<td><code>read_stata</code></td>
<td><code>to_stata</code></td>
</tr>
<tr>
<td>binary</td>
<td>SAS</td>
<td><code>read_sas</code></td>
<td></td>
</tr>
<tr>
<td>binary</td>
<td>Python Pickle Format</td>
<td><code>read_pickle</code></td>
<td><code>to_pickle</code></td>
</tr>
<tr>
<td>SQL</td>
<td>SQL</td>
<td><code>read_sql</code></td>
<td><code>to_sql</code></td>
</tr>
<tr>
<td>SQL</td>
<td>Google BigQuery</td>
<td><code>read_gbq</code></td>
<td><code>to_gbq</code></td>
</tr>
</tbody>
</table>

Here is an informal performance comparison for some of these IO methods.

Note: For examples that use the `StringIO` class, make sure you import it with `from io import StringIO` for Python 3.

2.4.1 CSV & text files

The workhorse function for reading text files (a.k.a. flat files) is `read_csv()`. See the cookbook for some advanced strategies.

Parsing options

`read_csv()` accepts the following common arguments:
Basic

filepath_or_buffer [various] Either a path to a file (a str, pathlib.Path, or py._path.local.LocalPath), URL (including http, ftp, and S3 locations), or any object with a read() method (such as an open file or StringIO).

sep [str, defaults to ', ' for read_csv(), \t for read_table()] Delimiter to use. If sep is None, the C engine cannot automatically detect the separator, but the Python parsing engine can, meaning the latter will be used and automatically detect the separator by Python’s builtin sniffer tool, csv.Sniffer. In addition, separators longer than 1 character and different from '\s+' will be interpreted as regular expressions and will also force the use of the Python parsing engine. Note that regex delimiters are prone to ignoring quoted data. Regex example: '\\r\\t'.

delimiter [str, default None] Alternative argument name for sep.

delim_whitespace [boolean, default False] Specifies whether or not whitespace (e.g. ' ' or '\t ') will be used as the delimiter. Equivalent to setting sep='\s+'. If this option is set to True, nothing should be passed in for the delimiter parameter.

Column and index locations and names

header [int or list of ints, default 'infer'] Row number(s) to use as the column names, and the start of the data. Default behavior is to infer the column names: if no names are passed the behavior is identical to header=0 and column names are inferred from the first line of the file, if column names are passed explicitly then the behavior is identical to header=None. Explicitly pass header=0 to be able to replace existing names.

The header can be a list of ints that specify row locations for a MultiIndex on the columns e.g. [0,1,3]. Intervening rows that are not specified will be skipped (e.g. 2 in this example is skipped). Note that this parameter ignores commented lines and empty lines if skip_blank_lines=True, so header=0 denotes the first line of data rather than the first line of the file.

names [array-like, default None] List of column names to use. If file contains no header row, then you should explicitly pass header=None. Duplicates in this list are not allowed.

index_col [int, str, sequence of int / str, or False, default None] Column(s) to use as the row labels of the DataFrame, either given as string name or column index. If a sequence of int / str is given, a MultiIndex is used.

Note: index_col=False can be used to force pandas to not use the first column as the index, e.g. when you have a malformed file with delimiters at the end of each line.

The default value of None instructs pandas to guess. If the number of fields in the column header row is equal to the number of fields in the body of the data file, then a default index is used. If it is one larger, then the first field is used as an index.

usecols [list-like or callable, default None] Return a subset of the columns. If list-like, all elements must either be positional (i.e. integer indices into the document columns) or strings that correspond to column names provided either by the user in names or inferred from the document header row(s). For example, a valid list-like usecols parameter would be [0, 1, 2] or ['foo', 'bar', 'baz'].

Element order is ignored, so usecols=[0, 1] is the same as [1, 0]. To instantiate a DataFrame from data with element order preserved use pd.read_csv(data, usecols= ['foo', 'bar'])[['foo', 'bar']] for columns in ['foo', 'bar'] order or pd.read_csv(data, usecols= ['foo', 'bar'])[['bar', 'foo']] for ['bar', 'foo'] order.

If callable, the callable function will be evaluated against the column names, returning names where the callable function evaluates to True:
In [1]: import pandas as pd
In [2]: from io import StringIO
In [3]:
  data = ('col1,col2,col3
  ...
  a,b,1
  ...
  a,b,2
  ...
  c,d,3')
In [4]: pd.read_csv(StringIO(data))
Out[4]:
     col1  col2  col3
0     a     b     1
1     a     b     2
2     c     d     3

In [5]: pd.read_csv(StringIO(data), usecols=\lambda x: x.upper() in ['COL1', 'COL3 '])
Out[5]:
     col1  col3
0     a     1
1     a     2
2     c     3

Using this parameter results in much faster parsing time and lower memory usage.

**squeeze** [boolean, default False] If the parsed data only contains one column then return a Series.

**prefix** [str, default None] Prefix to add to column numbers when no header, e.g. ‘X’ for X0, X1, …

**mangle_dupe_cols** [boolean, default True] Duplicate columns will be specified as ‘X’, ‘X.1’…’X.N’, rather than ‘X’…’X’. Passing in False will cause data to be overwritten if there are duplicate names in the columns.

### General parsing configuration

**dtype** [Type name or dict of column -> type, default None] Data type for data or columns. E.g. {'a': np.float64, 'b': np.int32} (unsupported with engine='python'). Use str or object together with suitable na_values settings to preserve and not interpret dtype.

**engine** [{'c', 'python'}] Parser engine to use. The C engine is faster while the Python engine is currently more feature-complete.

**converters** [dict, default None] Dict of functions for converting values in certain columns. Keys can either be integers or column labels.

**true_values** [list, default None] Values to consider as True.

**false_values** [list, default None] Values to consider as False.

**skipinitialspace** [boolean, default False] Skip spaces after delimiter.

**skiprows** [list-like or integer, default None] Line numbers to skip (0-indexed) or number of lines to skip (int) at the start of the file.

  If callable, the callable function will be evaluated against the row indices, returning True if the row should be skipped and False otherwise:
In [6]: data = ('col1,col2,col3
   ...:   'a,b,1
   ...:   'a,b,2
   ...:   'c,d,3')
   ...

In [7]: pd.read_csv(StringIO(data))
Out[7]:
    col1  col2  col3
0    a    b    1
1    a    b    2
2    c    d    3

In [8]: pd.read_csv(StringIO(data), skiprows=lambda x: x % 2 != 0)
Out[8]:
    col1  col2  col3
0    a    b    2

skipfooter [int, default 0] Number of lines at bottom of file to skip (unsupported with engine='c').
nrows [int, default None] Number of rows of file to read. Useful for reading pieces of large files.
low_memory [boolean, default True] Internally process the file in chunks, resulting in lower memory use while parsing, but possibly mixed type inference. To ensure no mixed types either set False, or specify the type with the dtype parameter. Note that the entire file is read into a single DataFrame regardless, use the chunksize or iterator parameter to return the data in chunks. (Only valid with C parser)
memory_map [boolean, default False] If a filepath is provided for filepath_or_buffer, map the file object directly onto memory and access the data directly from there. Using this option can improve performance because there is no longer any I/O overhead.

NA and missing data handling

na_values [scalar, str, list-like, or dict, default None] Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values. See na values const below for a list of the values interpreted as NaN by default.
keep_default_na [boolean, default True] Whether or not to include the default NaN values when parsing the data. Depending on whether na_values is passed in, the behavior is as follows:

- If keep_default_na is True, and na_values are specified, na_values is appended to the default NaN values used for parsing.
- If keep_default_na is True, and na_values are not specified, only the default NaN values are used for parsing.
- If keep_default_na is False, and na_values are specified, only the NaN values specified na_values are used for parsing.
- If keep_default_na is False, and na_values are not specified, no strings will be parsed as NaN.

Note that if na_filter is passed in as False, the keep_default_na and na_values parameters will be ignored.
na_filter [boolean, default True] Detect missing value markers (empty strings and the value of na_values). In data without any NAs, passing na_filter=False can improve the performance of reading a large file.
verbose [boolean, default False] Indicate number of NA values placed in non-numeric columns.
skip_blank_lines [boolean, default True] If True, skip over blank lines rather than interpreting as NaN values.
Datetime handling

**parse_dates** [boolean or list of ints or names or list of lists or dict, default False.]
- If True -> try parsing the index.
- If [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column.
- If [[1, 3]] -> combine columns 1 and 3 and parse as a single date column.
- If {'foo': [1, 3]} -> parse columns 1, 3 as date and call result ‘foo’. A fast-path exists for iso8601-formatted dates.

**infer_datetime_format** [boolean, default False] If True and parse_dates is enabled for a column, attempt to infer the datetime format to speed up the processing.

**keep_date_col** [boolean, default False] If True and parse_dates specifies combining multiple columns then keep the original columns.

**date_parser** [function, default None] Function to use for converting a sequence of string columns to an array of datetime instances. The default uses dateutil.parser.parser to do the conversion. pandas will try to call date_parser in three different ways, advancing to the next if an exception occurs: 1) Pass one or more arrays (as defined by parse_dates) as arguments; 2) concatenate (row-wise) the string values from the columns defined by parse_dates into a single array and pass that; and 3) call date_parser once for each row using one or more strings (corresponding to the columns defined by parse_dates) as arguments.

**dayfirst** [boolean, default False] DD/MM format dates, international and European format.

**cache_dates** [boolean, default True] If True, use a cache of unique, converted dates to apply the datetime conversion. May produce significant speed-up when parsing duplicate date strings, especially ones with timezone offsets.

New in version 0.25.0.

Iteration

**iterator** [boolean, default False] Return TextFileReader object for iteration or getting chunks with get_chunk().

**chunksize** [int, default None] Return TextFileReader object for iteration. See iterating and chunking below.

Quoting, compression, and file format

**compression** [['infer', 'gzip', 'bz2', 'zip', 'xz', None, dict], default 'infer'] For on-the-fly decompression of on-disk data. If ‘infer’, then use gzip, bz2, zip, or xz if filepath_or_buffer is a string ending in ‘.gz’, ‘.bz2’, ‘.zip’, or ‘.xz’, respectively, and no decompression otherwise. If using ‘zip’, the ZIP file must contain only one data file to be read in. Set to None for no decompression. Can also be a dict with key 'method' set to one of {'zip', 'gzip', 'bz2'}, and other keys set to compression settings. As an example, the following could be passed for faster compression: compression={'method': 'gzip', 'compresslevel': 1}.

Changed in version 0.24.0: ‘infer’ option added and set to default.

Changed in version 1.1.0: dict option extended to support gzip and bz2.

**thousands** [str, default None] Thousands separator.

**decimal** [str, default ','] Character to recognize as decimal point. E.g. use ', ' for European data.

**float_precision** [string, default None] Specifies which converter the C engine should use for floating-point values. The options are None for the ordinary converter, high for the high-precision converter, and round_trip for the round-trip converter.
lineterminator [str (length 1), default None] Character to break file into lines. Only valid with C parser.

quotechar [str (length 1)] The character used to denote the start and end of a quoted item. Quoted items can include the delimiter and it will be ignored.

quoting [int or csv.QUOTE_* instance, default 0] Control field quoting behavior per csv.QUOTE_* constants. Use one of QUOTE_MINIMAL (0), QUOTE_ALL (1), QUOTE_NONNUMERIC (2) or QUOTE_NONE (3).

doublequote [boolean, default True] When quotechar is specified and quoting is not QUOTE_NONE, indicate whether or not to interpret two consecutive quotechar elements inside a field as a single quotechar element.

escapechar [str (length 1), default None] One-character string used to escape delimiter when quoting is QUOTE_NONE.

comment [str, default None] Indicates remainder of line should not be parsed. If found at the beginning of a line, the line will be ignored altogether. This parameter must be a single character. Like empty lines (as long as skip_blank_lines=True), fully commented lines are ignored by the parameter header but not by skiprows. For example, if comment='#', parsing '#empty\na,b,c\n1,2,3' with header=0 will result in 'a,b,c' being treated as the header.

encoding [str, default None] Encoding to use for UTF when reading/writing (e.g. 'utf-8'). List of Python standard encodings.

dialect [str or csv.Dialect instance, default None] If provided, this parameter will override values (default or not) for the following parameters: delimiter, doublequote, escapechar, skipinitialspace, quotechar, and quoting. If it is necessary to override values, a ParserWarning will be issued. See csv.Dialect documentation for more details.

Error handling

error_bad_lines [boolean, default True] Lines with too many fields (e.g. a csv line with too many commas) will by default cause an exception to be raised, and no DataFrame will be returned. If False, then these “bad lines” will dropped from the DataFrame that is returned. See bad lines below.

warn_bad_lines [boolean, default True] If error_bad_lines is False, and warn_bad_lines is True, a warning for each “bad line” will be output.

Specifying column data types

You can indicate the data type for the whole DataFrame or individual columns:

```
In [9]: import numpy as np

In [10]: data = ('a,b,c,d\n' '1,2,3,4\n' '5,6,7,8\n' '9,10,11')

In [11]: print(data)
a,b,c,d
1,2,3,4
5,6,7,8
9,10,11

In [12]: df = pd.read_csv(StringIO(data), dtype=object)
```

(continues on next page)
In [13]: df
Out[13]:
   a  b  c  d
0  1  2  3  4
1  5  6  7  8
2  9 10 11 NaN

In [14]: df['a'][0]
Out[14]: '1'

In [15]: df = pd.read_csv(StringIO(data),
   ....:    dtype={'b': object, 'c': np.float64, 'd': 'Int64'})
   ....:

In [16]: df.dtypes
Out[16]:
   a  int64
   b  object
   c  float64
   d  Int64
dtype: object

Fortunately, pandas offers more than one way to ensure that your column(s) contain only one dtype. If you’re unfamiliar with these concepts, you can see here to learn more about dtypes, and here to learn more about object conversion in pandas.

For instance, you can use the converters argument of read_csv():

In [17]: data = ("col_1\n".....:  "1\n".....:  "2\n".....:  "'A'\n".....:  "4.22")

In [18]: df = pd.read_csv(StringIO(data), converters={'col_1': str})

In [19]: df
Out[19]:
   col_1
0   1
1   2
2  'A'
3  4.22

In [20]: df['col_1'].apply(type).value_counts()
Out[20]:
<class 'str'>  4
Name: col_1, dtype: int64

Or you can use the to_numeric() function to coerce the dtypes after reading in the data,

In [21]: df2 = pd.read_csv(StringIO(data))

In [22]: df2['col_1'] = pd.to_numeric(df2['col_1'], errors='coerce')
In [23]: df2
Out[23]:
    col_1
0    1.00
1    2.00
2     NaN
3    4.22

In [24]: df2['col_1'].apply(type).value_counts()
Out[24]:
<class 'float'>    4
Name: col_1, dtype: int64

which will convert all valid parsing to floats, leaving the invalid parsing as NaN.

Ultimately, how you deal with reading in columns containing mixed dtypes depends on your specific needs. In the case above, if you wanted to NaN out the data anomalies, then `to_numeric()` is probably your best option. However, if you wanted for all the data to be coerced, no matter the type, then using the `converters` argument of `read_csv()` would certainly be worth trying.

Note: In some cases, reading in abnormal data with columns containing mixed dtypes will result in an inconsistent dataset. If you rely on pandas to infer the dtypes of your columns, the parsing engine will go and infer the dtypes for different chunks of the data, rather than the whole dataset at once. Consequently, you can end up with column(s) with mixed dtypes. For example,

In [25]: col_1 = list(range(500000)) + ['a', 'b'] + list(range(500000))
In [26]: df = pd.DataFrame({'col_1': col_1})
In [27]: df.to_csv('foo.csv')
In [28]: mixed_df = pd.read_csv('foo.csv')
In [29]: mixed_df['col_1'].apply(type).value_counts()
Out[29]:
<class 'int'>   737858
<class 'str'>   262144
Name: col_1, dtype: int64
In [30]: mixed_df['col_1'].dtype
Out[30]: dtype('O')

will result with `mixed_df` containing an `int` dtype for certain chunks of the column, and `str` for others due to the mixed dtypes from the data that was read in. It is important to note that the overall column will be marked with a `dtype` of `object`, which is used for columns with mixed dtypes.
Specifying categorical dtype

Categorical columns can be parsed directly by specifying dtype='category' or dtype=CategoricalDtype(categories, ordered).

```python
In [31]: data = ('col1,col2,col3
       ....:  'a,b,1\n       ....:  'a,b,2\n       ....:  'c,d,3')
       ....:

In [32]: pd.read_csv(StringIO(data))
Out[32]:
         col1  col2  col3
0       a     b     1
1       a     b     2
2       c     d     3

In [33]: pd.read_csv(StringIO(data)).dtypes
Out[33]:
         col1  col2  col3
dtype: object

In [34]: pd.read_csv(StringIO(data), dtype='category').dtypes
Out[34]:
         col1  col2  col3
dtype: object

Individual columns can be parsed as a Categorical using a dict specification:

```python
In [35]: pd.read_csv(StringIO(data), dtype={'col1': 'category'}).dtypes
Out[35]:
         col1  col2  col3
dtype: object
```

Specifying dtype='category' will result in an unordered Categorical whose categories are the unique values observed in the data. For more control on the categories and order, create a CategoricalDtype ahead of time, and pass that for that column’s dtype.

```python
In [36]: from pandas.api.types import CategoricalDtype

In [37]: dtype = CategoricalDtype(['d', 'c', 'b', 'a'], ordered=True)

In [38]: pd.read_csv(StringIO(data), dtype={'col1': dtype}).dtypes
Out[38]:
         col1  col2  col3
dtype: object
```

When using dtype=CategoricalDtype, “unexpected” values outside of dtype.categories are treated as missing values.
In [39]: dtype = CategoricalDtype(['a', 'b', 'd'])  # No 'c'

In [40]: pd.read_csv(StringIO(data), dtype={'col1': dtype}).col1
Out[40]:
    0   a  
   1   a  
   2  NaN
Name: col1, dtype: category
Categories (3, object): ['a', 'b', 'd']

This matches the behavior of `Categorical.set_categories()`.

**Note:** With `dtype='category'`, the resulting categories will always be parsed as strings (object dtype). If the categories are numeric they can be converted using the `to_numeric()` function, or as appropriate, another converter such as `to_datetime()`.

When `dtype` is a `CategoricalDtype` with homogeneous categories (all numeric, all datetimes, etc.), the conversion is done automatically.

In [41]: df = pd.read_csv(StringIO(data), dtype='category')

In [42]: df.dtypes
Out[42]:
col1  category
col2  category
col3  category
dtype: object

In [43]: df['col3']
Out[43]:
    0  1
   1  2
   2  3
Name: col3, dtype: category
Categories (3, object): ['1', '2', '3']

In [44]: df['col3'].cat.categories = pd.to_numeric(df['col3'].cat.categories)

In [45]: df['col3']
Out[45]:
    0  1
   1  2
   2  3
Name: col3, dtype: category
Categories (3, int64): [1, 2, 3]
Naming and using columns

Handling column names

A file may or may not have a header row. pandas assumes the first row should be used as the column names:

```python
In [46]: data = ('a,b,c
   ....:   '1,2,3
   ....:   '4,5,6
   ....:   '7,8,9')
   ....:

In [47]: print(data)
a,b,c
1,2,3
4,5,6
7,8,9

In [48]: pd.read_csv(StringIO(data))
Out[48]:
      a  b  c
   0  1  2  3
   1  4  5  6
   2  7  8  9

By specifying the names argument in conjunction with header you can indicate other names to use and whether or not to throw away the header row (if any):

```python
In [49]: print(data)
a,b,c
1,2,3
4,5,6
7,8,9

In [50]: pd.read_csv(StringIO(data), names=['foo', 'bar', 'baz'], header=0)
Out[50]:
   foo  bar  baz
   0  1  2  3
   1  4  5  6
   2  7  8  9

In [51]: pd.read_csv(StringIO(data), names=['foo', 'bar', 'baz'], header=None)
Out[51]:
   foo  bar  baz
   0  a  b  c
   1  1  2  3
   2  4  5  6
   3  7  8  9

If the header is in a row other than the first, pass the row number to header. This will skip the preceding rows:

```python
In [52]: data = ('skip this skip it
   ....:   'a,b,c
   ....:   '1,2,3
   ....:   '4,5,6
   ....:   '7,8,9')
   ....:

(continues on next page)
In [53]: pd.read_csv(StringIO(data), header=1)
Out[53]:
   a  b  c
0  1  2  3
1  4  5  6
2  7  8  9

Note: Default behavior is to infer the column names: if no names are passed the behavior is identical to header=0 and column names are inferred from the first non-blank line of the file, if column names are passed explicitly then the behavior is identical to header=None.

**Duplicate names parsing**

If the file or header contains duplicate names, pandas will by default distinguish between them so as to prevent overwriting data:

In [54]: data = ('a,b,a
   ....: 0,1,2
   ....: 3,4,5')
   ....:
In [55]: pd.read_csv(StringIO(data))
Out[55]:
   a  b  a.1
  0  2  1  2
  1  3  4  5

There is no more duplicate data because mangle_dupe_cols=True by default, which modifies a series of duplicate columns ‘X’, ‘X’, ‘X’ to become ‘X’, ‘X.1’, ‘X.2’, ‘X.3’. If mangle_dupe_cols=False, duplicate data can arise:

In [2]: data = 'a,b,a
   ....: 0,1,2
   ....: 3,4,5'
In [3]: pd.read_csv(StringIO(data), mangle_dupe_cols=False)
Out[3]:
   a  b  a
  0  2  1  2
  1  5  4  5

To prevent users from encountering this problem with duplicate data, a **ValueError** exception is raised if mangle_dupe_cols != True:

In [2]: data = 'a,b,a
   ....: 0,1,2
   ....: 3,4,5'
In [3]: pd.read_csv(StringIO(data), mangle_dupe_cols=False)
...
ValueError: Setting mangle_dupe_cols=False is not supported yet.
Filtering columns (`usecols`)

The `usecols` argument allows you to select any subset of the columns in a file, either using the column names, position numbers or a callable:

```python
In [56]: data = 'a,b,c,d
1,2,3,foo
4,5,6,bar
7,8,9,baz'

In [57]: pd.read_csv(StringIO(data))
Out[57]:
   a  b  c  d
0  1  2  3  foo
1  4  5  6  bar
2  7  8  9  baz

In [58]: pd.read_csv(StringIO(data), usecols=['b', 'd'])
Out[58]:
   b  d
0  2  foo
1  5  bar
2  8  baz

In [59]: pd.read_csv(StringIO(data), usecols=[0, 2, 3])
Out[59]:
   a  c  d
0  1  3  foo
1  4  6  bar
2  7  9  baz

In [60]: pd.read_csv(StringIO(data), usecols=lambda x: x.upper() in ['A', 'C'])
Out[60]:
   a  c
0  1  3
1  4  6
2  7  9
```

The `usecols` argument can also be used to specify which columns not to use in the final result:

```python
In [61]: pd.read_csv(StringIO(data), usecols=lambda x: x not in ['a', 'c'])
Out[61]:
   b  d
0  2  foo
1  5  bar
2  8  baz
```

In this case, the callable is specifying that we exclude the “a” and “c” columns from the output.

Comments and empty lines

Ignoring line comments and empty lines

If the `comment` parameter is specified, then completely commented lines will be ignored. By default, completely blank lines will be ignored as well.

```python
In [62]: data = (...:
    ...: 'a,b,c
    ...:    
    ...:   
```

(continues on next page)
In [63]: print(data)

a,b,c

# commented line
1,2,3
4,5,6

In [64]: pd.read_csv(StringIO(data), comment='#')
Out[64]:
   a  b  c
0 1  2  3
1 4  5  6

If skip_blank_lines=False, then read_csv will not ignore blank lines:

In [65]: data = ('a,b,c
....:  
....:  "1,2,3"
....:  
....:  "4,5,6"
....:  

In [66]: pd.read_csv(StringIO(data), skip_blank_lines=False)
Out[66]:
   a  b  c
0 NaN NaN NaN
1 1.0 2.0 3.0
2 NaN NaN NaN
3 NaN NaN NaN
4 4.0 5.0 6.0

**Warning:** The presence of ignored lines might create ambiguities involving line numbers; the parameter header uses row numbers (ignoring commented/empty lines), while skiprows uses line numbers (including commented/empty lines):

In [67]: data = ('#comment
....:  
....:  "a,b,c"
....:  
....:  "A,B,C"
....:  

In [68]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[68]:
   A  B  C
0 1  2  3

In [69]: data = ('A,B,C
....:  
....:  "1,2,3"
....:  
....:  "4,5,6"
....:  

In [69]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[69]:
   A  B  C
0 1  2  3

In [69]: data = ('A,B,C
....:  
....:  "1,2,3"
....:  
....:  "4,5,6"
....:  

In [69]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[69]:
   A  B  C
0 1  2  3

In [69]: data = ('A,B,C
....:  
....:  "1,2,3"
....:  
....:  "4,5,6"
....:  

In [69]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[69]:
   A  B  C
0 1  2  3

In [69]: data = ('A,B,C
....:  
....:  "1,2,3"
....:  
....:  "4,5,6"
....:  

In [69]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[69]:
   A  B  C
0 1  2  3

In [69]: data = ('A,B,C
....:  
....:  "1,2,3"
....:  
....:  "4,5,6"
....:  

In [69]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[69]:
   A  B  C
0 1  2  3

In [69]: data = ('A,B,C
....:  
....:  "1,2,3"
....:  
....:  "4,5,6"
....:  

In [69]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[69]:
   A  B  C
0 1  2  3

In [69]: data = ('A,B,C
....:  
....:  "1,2,3"
....:  
....:  "4,5,6"
....:  

In [69]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[69]:
   A  B  C
0 1  2  3

In [69]: data = ('A,B,C
....:  
....:  "1,2,3"
....:  
....:  "4,5,6"
....:  

In [69]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[69]:
   A  B  C
0 1  2  3

In [69]: data = ('A,B,C
....:  
....:  "1,2,3"
....:  
....:  "4,5,6"
....:  

In [69]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[69]:
   A  B  C
0 1  2  3

In [69]: data = ('A,B,C
....:  
....:  "1,2,3"
....:  
....:  "4,5,6"
....:  

In [69]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[69]:
   A  B  C
0 1  2  3

In [69]: data = ('A,B,C
....:  
....:  "1,2,3"
....:  
....:  "4,5,6"
....:  

In [69]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[69]:
   A  B  C
0 1  2  3

In [69]: data = ('A,B,C
....:  
....:  "1,2,3"
....:  
....:  "4,5,6"
....:  

In [69]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[69]:
   A  B  C
0 1  2  3

In [69]: data = ('A,B,C
....:  
....:  "1,2,3"
....:  
....:  "4,5,6"
....:  

In [69]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[69]:
   A  B  C
0 1  2  3

In [69]: data = ('A,B,C
....:  
....:  "1,2,3"
....:  
....:  "4,5,6"
....:  

In [69]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[69]:
   A  B  C
0 1  2  3

In [69]: data = ('A,B,C
....:  
....:  "1,2,3"
....:  
....:  "4,5,6"
....:  

In [69]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[69]:
   A  B  C
0 1  2  3

In [69]: data = ('A,B,C
....:  
....:  "1,2,3"
....:  
....:  "4,5,6"
....:  

In [69]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[69]:
   A  B  C
0 1  2  3

In [69]: data = ('A,B,C
....:  
....:  "1,2,3"
....:  
....:  "4,5,6"
....:  

In [69]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[69]:
   A  B  C
0 1  2  3

In [69]: data = ('A,B,C
....:  
....:  "1,2,3"
....:  
....:  "4,5,6"
....:  

In [69]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[69]:
   A  B  C
0 1  2  3

In [69]: data = ('A,B,C
....:  
....:  "1,2,3"
....:  
....:  "4,5,6"
....:  

In [69]: pd.read_csv(StringIO(data), comment='#', header=1)
In [70]: pd.read_csv(StringIO(data), comment='#', skiprows=2)
Out[70]:
    a  b  c
0  1  2  3

If both header and skiprows are specified, header will be relative to the end of skiprows. For example:

In [71]: data = ('# empty
   ...:    '# second empty line
   ...:    '# third emptyline
   ...:    'X,Y,Z
   ...:    '1,2,3
   ...:    'A,B,C
   ...:    '1,2.,4.
   ...:    '5.,NaN,10.0
   ...

In [72]: print(data)
# empty
# second empty line
# third emptyline
X,Y,Z
1,2,3
A,B,C
1,2.,4.
5.,NaN,10.0

In [73]: pd.read_csv(StringIO(data), comment='#', skiprows=4, header=1)
Out[73]:
      A  B  C
0  1.0  2.0  4.0
1  5.0  NaN 10.0

Comments

Sometimes comments or meta data may be included in a file:

In [74]: print(open('tmp.csv').read())
ID,level,category
Patient1,123000,x # really unpleasant
Patient2,23000,y # wouldn't take his medicine
Patient3,1234018,z # awesome

By default, the parser includes the comments in the output:

In [75]: df = pd.read_csv('tmp.csv')
In [76]: df

(continues on next page)
We can suppress the comments using the `comment` keyword:

```
In [77]: df = pd.read_csv('tmp.csv', comment='#')

In [78]: df
Out[78]:
   ID   level  category
0 Patient1  123000     x  # really unpleasant
1 Patient2  23000      y  # wouldn't take his medicine
2 Patient3  1234018    z  # awesome
```

### Dealing with Unicode data

The `encoding` argument should be used for encoded unicode data, which will result in byte strings being decoded to unicode in the result:

```
In [79]: from io import BytesIO

In [80]: data = (b'word,length
....:
....:
....:
....:

In [81]: data = data.decode('utf8').encode('latin-1')

In [82]: df = pd.read_csv(BytesIO(data), encoding='latin-1')

In [83]: df
Out[83]:
   word  length
0  Träumen     7
1   Grüße     5

In [84]: df['word'][1]
Out[84]: 'Grüße'
```

Some formats which encode all characters as multiple bytes, like UTF-16, won’t parse correctly at all without specifying the encoding. Full list of Python standard encodings.
Index columns and trailing delimiters

If a file has one more column of data than the number of column names, the first column will be used as the DataFrame's row names:

In [85]: data = ('a,b,c
.....:  '4,apple,bat,5.7\n.....:  '8,orange,cow,10')
.....:

In [86]: pd.read_csv(StringIO(data))
Out[86]:
   a  b  c
0  4  apple  bat  5.7
1  8  orange  cow  10.0

In [87]: data = ('index,a,b,c
.....:  '4,apple,bat,5.7\n.....:  '8,orange,cow,10')
.....:

In [88]: pd.read_csv(StringIO(data), index_col=0)
Out[88]:
   index  a  b  c
0  4     apple  bat  5.7
1  8   orange  cow  10.0

Ordinarily, you can achieve this behavior using the index_col option.

There are some exception cases when a file has been prepared with delimiters at the end of each data line, confusing the parser. To explicitly disable the index column inference and discard the last column, pass index_col=False:

In [89]: data = ('a,b,c
.....:  '4,apple,bat,
.....:  '8,orange,cow,')
.....:

In [90]: print(data)
a,b,c
4,apple,bat,
8,orange,cow,

In [91]: pd.read_csv(StringIO(data))
Out[91]:
   a  b  c
0  4  apple  bat  NaN
1  8  orange  cow  NaN

In [92]: pd.read_csv(StringIO(data), index_col=False)
Out[92]:
   a  b  c
0  4  apple  bat
1  8  orange  cow

If a subset of data is being parsed using the usecols option, the index_col specification is based on that subset, not the original data.
In [93]: data = ('a,b,c
       ....:  '4,apple,bat,
       ....:  '8,orange,cow,
       ....:

In [94]: print(data)
a,b,c
4,apple,bat,
8,orange,cow,

In [95]: pd.read_csv(StringIO(data), usecols=['b', 'c'])
Out[95]:
  b  c
4  bat NaN
8  cow NaN

In [96]: pd.read_csv(StringIO(data), usecols=['b', 'c'], index_col=0)
Out[96]:
  b  c
4  bat NaN
8  cow NaN

Date Handling

Specifying date columns

To better facilitate working with datetime data, \texttt{read_csv()} uses the keyword arguments \texttt{parse\_dates} and \texttt{date\_parser} to allow users to specify a variety of columns and date/time formats to turn the input text data into \texttt{datetime} objects.

The simplest case is to just pass in \texttt{parse\_dates=True}:

\[
\begin{verbatim}
In [97]: df = pd.read_csv('foo.csv', index_col=0, parse_dates=True)

In [98]: df
\end{verbatim}
\]

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>date</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2009-01-01 a 1 2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2009-01-02 b 3 4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2009-01-03 c 4 5</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\[
\begin{verbatim}
# These are Python datetime objects
In [99]: df.index
Out[99]: DatetimeIndex(['2009-01-01', '2009-01-02', '2009-01-03'], ...)
\end{verbatim}
\]

It is often the case that we may want to store date and time data separately, or store various date fields separately. the \texttt{parse\_dates} keyword can be used to specify a combination of columns to parse the dates and/or times from.

You can specify a list of column lists to \texttt{parse\_dates}, the resulting date columns will be prepended to the output (so as to not affect the existing column order) and the new column names will be the concatenation of the component column names:
In [100]: print(open('tmp.csv').read())
KORD,19990127, 19:00:00, 18:56:00, 0.8100
KORD,19990127, 20:00:00, 19:56:00, 0.0100
KORD,19990127, 21:00:00, 20:56:00, -0.5900
KORD,19990127, 21:00:00, 21:18:00, -0.9900
KORD,19990127, 22:00:00, 21:56:00, -0.5900
KORD,19990127, 23:00:00, 22:56:00, -0.5900

In [101]: df = pd.read_csv('tmp.csv', header=None, parse_dates=[[1, 2], [1, 3]])

In [102]: df
Out[102]:
        1_2   1_3     0
0  1999-01-27 19:00:00 1999-01-27 18:56:00 KORD  0.81
1  1999-01-27 20:00:00 1999-01-27 19:56:00 KORD  0.01
2  1999-01-27 21:00:00 1999-01-27 20:56:00 KORD -0.59
3  1999-01-27 21:00:00 1999-01-27 21:18:00 KORD -0.99
4  1999-01-27 22:00:00 1999-01-27 21:56:00 KORD -0.59
5  1999-01-27 23:00:00 1999-01-27 22:56:00 KORD -0.59

By default the parser removes the component date columns, but you can choose to retain them via the
keep_date_col keyword:

In [103]: df = pd.read_csv('tmp.csv', header=None, parse_dates=[[1, 2], [1, 3]],
                      keep_date_col=True)

In [104]: df
Out[104]:
     1_2  1_3     0     1    2    3    4
0  1999-01-27 19:00:00 1999-01-27 18:56:00 KORD 19990127 19:00:00 18:56:00 0.81
1  1999-01-27 20:00:00 1999-01-27 19:56:00 KORD 19990127 20:00:00 19:56:00 0.01
2  1999-01-27 21:00:00 1999-01-27 20:56:00 KORD 19990127 21:00:00 20:56:00 -0.59
3  1999-01-27 21:00:00 1999-01-27 21:18:00 KORD 19990127 21:00:00 21:18:00 -0.99
4  1999-01-27 22:00:00 1999-01-27 21:56:00 KORD 19990127 22:00:00 21:56:00 -0.59
5  1999-01-27 23:00:00 1999-01-27 22:56:00 KORD 19990127 23:00:00 22:56:00 -0.59

Note that if you wish to combine multiple columns into a single date column, a nested list must be used. In other
words, parse_dates=[1, 2] indicates that the second and third columns should each be parsed as separate date
columns while parse_dates=[[1, 2]] means the two columns should be parsed into a single column.

You can also use a dict to specify custom name columns:

In [105]: date_spec = {'nominal': [1, 2], 'actual': [1, 3]}

In [106]: df = pd.read_csv('tmp.csv', header=None, parse_dates=date_spec)

In [107]: df
Out[107]:
     nominal  actual     0    4
0  1999-01-27 19:00:00 1999-01-27 18:56:00 KORD  0.81
1  1999-01-27 20:00:00 1999-01-27 19:56:00 KORD  0.01
2  1999-01-27 21:00:00 1999-01-27 20:56:00 KORD -0.59
3  1999-01-27 21:00:00 1999-01-27 21:18:00 KORD -0.99
4  1999-01-27 22:00:00 1999-01-27 21:56:00 KORD -0.59
5  1999-01-27 23:00:00 1999-01-27 22:56:00 KORD -0.59

It is important to remember that if multiple text columns are to be parsed into a single date column, then a new column
is prepended to the data. The index_col specification is based off of this new set of columns rather than the original data columns:

```python
In [108]: date_spec = {'nominal': [1, 2], 'actual': [1, 3]}
In [109]: df = pd.read_csv('tmp.csv', header=None, parse_dates=date_spec,
                        index_col=0)  # index is the nominal column
In [110]: df
Out[110]:
          actual
nominal   0  4
1999-01-27 19:00:00 1999-01-27 18:56:00 KORD  0.81
1999-01-27 20:00:00 1999-01-27 19:56:00 KORD  0.01
1999-01-27 21:00:00 1999-01-27 20:56:00 KORD -0.59
1999-01-27 21:00:00 1999-01-27 21:18:00 KORD -0.99
1999-01-27 22:00:00 1999-01-27 21:56:00 KORD -0.59
1999-01-27 23:00:00 1999-01-27 22:56:00 KORD -0.59
```

**Note:** If a column or index contains an unparsable date, the entire column or index will be returned unaltered as an object data type. For non-standard datetime parsing, use `to_datetime()` after `pd.read_csv`.

**Note:** `read_csv` has a fast_path for parsing datetime strings in iso8601 format, e.g. “2000-01-01T00:01:02+00:00” and similar variations. If you can arrange for your data to store datetimes in this format, load times will be significantly faster, ~20x has been observed.

### Date parsing functions

Finally, the parser allows you to specify a custom `date_parser` function to take full advantage of the flexibility of the date parsing API:

```python
In [111]: df = pd.read_csv('tmp.csv', header=None, parse_dates=date_spec,
                        date_parser=pd.io.date_converters.parse_date_time)
In [112]: df
Out[112]:
          actual
nominal   0  4
0 1999-01-27 19:00:00 1999-01-27 18:56:00 KORD  0.81
1 1999-01-27 20:00:00 1999-01-27 19:56:00 KORD  0.01
2 1999-01-27 21:00:00 1999-01-27 20:56:00 KORD -0.59
3 1999-01-27 21:00:00 1999-01-27 21:18:00 KORD -0.99
4 1999-01-27 22:00:00 1999-01-27 21:56:00 KORD -0.59
5 1999-01-27 23:00:00 1999-01-27 22:56:00 KORD -0.59
```

Pandas will try to call the `date_parser` function in three different ways. If an exception is raised, the next one is tried:

1. `date_parser` is first called with one or more arrays as arguments, as defined using `parse_dates` (e.g., `date_parser(['2013', '2013'], [1, 2]))`. 

---

2.4. IO tools (text, CSV, HDF5, …)
2. If #1 fails, date_parser is called with all the columns concatenated row-wise into a single array (e.g.,
date_parser(['2013 1', '2013 2'])).

3. If #2 fails, date_parser is called once for every row with one or more string arguments from
the columns indicated with parse_dates (e.g., date_parser('2013', '1') for the first row,
date_parser('2013', '2') for the second, etc.).

Note that performance-wise, you should try these methods of parsing dates in order:

1. Try to infer the format using infer_datetime_format=True (see section below).

2. If you know the format, use pd.to_datetime():
date_parser=lambda x: pd.
to_datetime(x, format=...).

3. If you have a really non-standard format, use a custom date_parser function. For optimal performance, this
should be vectorized, i.e., it should accept arrays as arguments.

You can explore the date parsing functionality in date_converters.py and add your own. We would love to turn this
module into a community supported set of date/time parsers. To get you started, date_converters.py contains
functions to parse dual date and time columns, year/month/day columns, and year/month/day/hour/minute/second
columns. It also contains a generic_parser function so you can curry it with a function that deals with a single
date rather than the entire array.

Parsing a CSV with mixed timezones

Pandas cannot natively represent a column or index with mixed timezones. If your CSV file contains columns with a
mixture of timezones, the default result will be an object-dtype column with strings, even with parse_dates.

```
In [113]: content = """
 .....: a
 .....: 2000-01-01T00:00:00+05:00
 .....: 2000-01-01T00:00:00+06:00"
 .....:

In [114]: df = pd.read_csv(StringIO(content), parse_dates=['a'])

In [115]: df['a']
Out[115]:
0  2000-01-01 00:00:00+05:00
1  2000-01-01 00:00:00+06:00
Name: a, dtype: object
```

To parse the mixed-timezone values as a datetime column, pass a partially-applied to_datetime() with
utc=True as the date_parser.

```
In [116]: df = pd.read_csv(StringIO(content), parse_dates=['a'],
 .....: date_parser=lambda col: pd.to_datetime(col, utc=True))
 .....:

In [117]: df['a']
Out[117]:
0  1999-12-31 19:00:00+00:00
1  1999-12-31 18:00:00+00:00
Name: a, dtype: datetime64[ns, UTC]
```
Inferring datetime format

If you have `parse_dates` enabled for some or all of your columns, and your datetime strings are all formatted the same way, you may get a large speed up by setting `infer_datetime_format=True`. If set, pandas will attempt to guess the format of your datetime strings, and then use a faster means of parsing the strings. 5-10x parsing speeds have been observed. pandas will fallback to the usual parsing if either the format cannot be guessed or the format that was guessed cannot properly parse the entire column of strings. So in general, `infer_datetime_format` should not have any negative consequences if enabled.

Here are some examples of datetime strings that can be guessed (All representing December 30th, 2011 at 00:00:00):

- “20111230”
- “2011/12/30”
- “20111230 00:00:00”
- “12/30/2011 00:00:00”
- “30/Dec/2011 00:00:00”
- “30/December/2011 00:00:00”

Note that `infer_datetime_format` is sensitive to `dayfirst`. With `dayfirst=True`, it will guess “01/12/2011” to be December 1st. With `dayfirst=False` (default) it will guess “01/12/2011” to be January 12th.

```
# Try to infer the format for the index column
In [118]: df = pd.read_csv('foo.csv', index_col=0, parse_dates=True,
                      infer_datetime_format=True)

In [119]: df
Out[119]:
   A  B  C
date
2009-01-01  a  1  2
2009-01-02  b  3  4
2009-01-03  c  4  5
```

International date formats

While US date formats tend to be MM/DD/YYYY, many international formats use DD/MM/YYYY instead. For convenience, a `dayfirst` keyword is provided:

```
In [120]: print(open('tmp.csv').read())
date,value,cat
1/6/2000,5,a
2/6/2000,10,b
3/6/2000,15,c

In [121]: pd.read_csv('tmp.csv', parse_dates=[0])
Out[121]:
   date  value  cat
0 2000-01-06  5  a
1 2000-02-06 10  b
2 2000-03-06 15  c
```

(continues on next page)
Specifying method for floating-point conversion

The parameter `float_precision` can be specified in order to use a specific floating-point converter during parsing with the C engine. The options are the ordinary converter, the high-precision converter, and the round-trip converter (which is guaranteed to round-trip values after writing to a file). For example:

```python
In [123]: val = '0.3066101993807954715666981359501369297504425048828125'
In [124]: data = 'a,b,c\n1,2,' + val
In [125]: abs(pd.read_csv(StringIO(data), engine='c',
                      float_precision=None)['c'][0] - float(val))
Out[125]: 1.1102230246251565e-16
In [126]: abs(pd.read_csv(StringIO(data), engine='c',
                      float_precision='high')['c'][0] - float(val))
Out[126]: 5.551115123125783e-17
In [127]: abs(pd.read_csv(StringIO(data), engine='c',
                      float_precision='round_trip')['c'][0] - float(val))
Out[127]: 0.0
```

Thousand separators

For large numbers that have been written with a thousands separator, you can set the `thousands` keyword to a string of length 1 so that integers will be parsed correctly:

By default, numbers with a thousands separator will be parsed as strings:

```python
In [128]: print(open('tmp.csv').read())
ID|level|category
Patient1|123,000|x
Patient2|23,000|y
Patient3|1,234,018|z
In [129]: df = pd.read_csv('tmp.csv', sep='|')
In [130]: df
Out[130]:
   ID    level    category
0 Patient1  123,000    x
1 Patient2  23,000     y
2 Patient3 1,234,018    z
```

(continues on next page)
The thousands keyword allows integers to be parsed correctly:

```python
In [132]: print(open('tmp.csv').read())
ID|level|category   
Patient1|123,000|x
Patient2|23,000|y
Patient3|1,234,018|z
In [133]: df = pd.read_csv('tmp.csv', sep='|', thousands=',')
In [134]: df
Out[134]:
   ID    level  category
0  Patient1  123000      x
1  Patient2   23000      y
2  Patient3  1234018     z
```

### NA values

To control which values are parsed as missing values (which are signified by NaN), specify a string in `na_values`. If you specify a list of strings, then all values in it are considered to be missing values. If you specify a number (a float, like 5.0 or an integer like 5), the corresponding equivalent values will also imply a missing value (in this case effectively [5.0, 5] are recognized as NaN).

To completely override the default values that are recognized as missing, specify `keep_default_na=False`.

The default NaN recognized values are ['-1.#IND', '1.#QNAN', '1.#IND', '-1.#QNAN', '#N/A N/A', '#N/A', 'N/A', 'n/a', 'NA', '<NA>', '#NA', 'NULL', 'null', 'NaN', '-NaN', 'nan', '-nan', ''].

Let us consider some examples:

```python
pd.read_csv('path_to_file.csv', na_values=[5])
```

In the example above 5 and 5.0 will be recognized as NaN, in addition to the defaults. A string will first be interpreted as a numerical 5, then as a NaN.

```python
pd.read_csv('path_to_file.csv', keep_default_na=False, na_values=[''])
```

Above, only an empty field will be recognized as NaN.

```python
pd.read_csv('path_to_file.csv', keep_default_na=False, na_values=['NA', '0'])
```

Above, both NA and 0 as strings are NaN.

```python
pd.read_csv('path_to_file.csv', na_values=['Nope'])
```

The default values, in addition to the string "Nope" are recognized as NaN.
Infinity

Inf like values will be parsed as np.inf (positive infinity), and -inf as -np.inf (negative infinity). These will ignore the case of the value, meaning Inf, will also be parsed as np.inf.

Returning Series

Using the squeeze keyword, the parser will return output with a single column as a Series:

```python
In [136]: print(open('tmp.csv').read())
level
Patient1,123000
Patient2,23000
Patient3,1234018

In [137]: output = pd.read_csv('tmp.csv', squeeze=True)

In [138]: output
Out[138]:
Patient1    123000
Patient2    23000
Patient3    1234018
Name: level, dtype: int64

In [139]: type(output)
Out[139]: pandas.core.series.Series
```

Boolean values

The common values True, False, TRUE, and FALSE are all recognized as boolean. Occasionally you might want to recognize other values as being boolean. To do this, use the true_values and false_values options as follows:

```python
In [140]: data = ('a,b,c
   ......:   '1,Yes,2
   ......:   '3,No,4')

In [141]: print(data)
a,b,c
1,Yes,2
3,No,4

In [142]: pd.read_csv(StringIO(data))
Out[142]:
   a   b   c
0  1   Yes  2
1  3   No   4

In [143]: pd.read_csv(StringIO(data), true_values=['Yes'], false_values=['No'])
Out[143]:
   a   b   c
0  1     True  2
1  3     False  4
```
Handling “bad” lines

Some files may have malformed lines with too few fields or too many. Lines with too few fields will have NA values filled in the trailing fields. Lines with too many fields will raise an error by default:

```
In [144]: data = ('a,b,c
......:  '1,2,3\n......:  '4,5,6,\n......:  '8,9,10')
......:

In [145]: pd.read_csv(StringIO(data))
---------------------------------------------------------------------------
ParserError Traceback (most recent call last)
<ipython-input-145-6388c394e6b8> in <module>
----> 1 pd.read_csv(StringIO(data))

/pandas-release/pandas/pandas/parsers.py in read_csv(filepath_or_buffer, sep, ...
    delimiter, header, names, index_col, usecols, squeeze, prefix, mangle_dupe_cols, ...
    dtype, engine, converters, true_values, false_values, skipinitialspace, skiprows, ...
    skipfooter, na_values, keep_default_na, na_filter, verbose, skip_blank_lines, ...
    parse_dates, infer_datetime_format, keep_date_col, date_parser, dayfirst, cache_
    dates, iterator, chunksize, compression, thousands, decimal, lineterminator, ...
    quotechar, quoting, doublequote, escapechar, comment, encoding, dialect, error_bad_
    lines, warn_bad_lines, delim_whitespace, low_memory, memory_map, float_precision)  
  684     return _read(filepath_or_buffer, kwds)
  685 
  --> 686 return _read(filepath_or_buffer, kwds)
  687  
  688 /pandas-release/pandas/pandas/parsers.py in _read(filepath_or_buffer, kwds)
     456     try:
     457         data = parser.read(nrows)
     --> 458 finally:
     459     parser.close()

/pandas-release/pandas/pandas/parsers.py in read(self, nrows)
    1184     def read(self, nrows=None):
    1185         nrows = _validate_integer("nrows", nrows)
    --> 1186         ret = self._engine.read(nrows)
    1187     # May alter columns / col_dict
    1188

/pandas-release/pandas/pandas/parsers.py in read(self, nrows)
    2143     def read(self, nrows=None):
    2144     try:
    --> 2145         data = self._reader.read(nrows)
    2146     except StopIteration:
    2147         if self._first_chunk:

/pandas-release/pandas/pandas/_libs/parsers.pyx in pandas._libs.parsers.TextReader._read()

/pandas-release/pandas/pandas/_libs/parsers.pyx in pandas._libs.parsers.TextReader._read_low_memory()
```
You can elect to skip bad lines:

```
In [29]: pd.read_csv(StringIO(data), error_bad_lines=False)
Skipping line 3: expected 3 fields, saw 4
```

```
Out[29]:
     a  b  c
0   1  2  3
1   8  9 10
```

You can also use the `usecols` parameter to eliminate extraneous column data that appear in some lines but not others:

```
In [30]: pd.read_csv(StringIO(data), usecols=[0, 1, 2])
```

```
Out[30]:
     a  b  c
0   1  2  3
1   4  5  6
2   8  9 10
```

### Dialect

The `dialect` keyword gives greater flexibility in specifying the file format. By default it uses the Excel dialect but you can specify either the dialect name or a `csv.Dialect` instance.

Suppose you had data with unenclosed quotes:

```
In [146]: print(data)
label1,label2,label3
index1,"a,c,e
index2,b,d,f
```

By default, `read_csv` uses the Excel dialect and treats the double quote as the quote character, which causes it to fail when it finds a newline before it finds the closing double quote.

We can get around this using `dialect`:

```
In [147]: import csv
In [148]: dia = csv.excel()
In [149]: dia.quoting = csv.QUOTE_NONE
In [150]: pd.read_csv(StringIO(data), dialect=dia)
```

(continues on next page)
All of the dialect options can be specified separately by keyword arguments:

```python
In [151]: data = 'a,b,c-1,2,3-4,5,6'
In [152]: pd.read_csv(StringIO(data), lineterminator='~')
Out[152]:
   a  b  c
0  1  2  3
1  4  5  6
```

Another common dialect option is `skipinitialspace`, to skip any whitespace after a delimiter:

```python
In [153]: data = 'a, b, c
    1, 2, 3
    4, 5, 6'
In [154]: print(data)
a, b, c
1, 2, 3
4, 5, 6
In [155]: pd.read_csv(StringIO(data), skipinitialspace=True)
Out[155]:
   a  b  c
0  1  2  3
1  4  5  6
```

The parsers make every attempt to “do the right thing” and not be fragile. Type inference is a pretty big deal. If a column can be coerced to integer dtype without altering the contents, the parser will do so. Any non-numeric columns will come through as object dtype as with the rest of pandas objects.

### Quoting and Escape Characters

Quotes (and other escape characters) in embedded fields can be handled in any number of ways. One way is to use backslashes; to properly parse this data, you should pass the `escapechar` option:

```python
In [156]: data = 'a,b\n"hello, \"Bob\", nice to see you",5'
In [157]: print(data)
a, b
"hello, "Bob", nice to see you", 5
In [158]: pd.read_csv(StringIO(data), escapechar='\')
Out[158]:
   a  b
0 hello, "Bob", nice to see you  5
Files with fixed width columns

While `read_csv()` reads delimited data, the `read_fwf()` function works with data files that have known and fixed column widths. The function parameters to `read_fwf` are largely the same as `read_csv` with two extra parameters, and a different usage of the `delimiter` parameter:

- `colspecs`: A list of pairs (tuples) giving the extents of the fixed-width fields of each line as half-open intervals (i.e., `[from, to[`). String value ‘infer’ can be used to instruct the parser to try detecting the column specifications from the first 100 rows of the data. Default behavior, if not specified, is to infer.
- `widths`: A list of field widths which can be used instead of ‘colspecs’ if the intervals are contiguous.
- `delimiter`: Characters to consider as filler characters in the fixed-width file. Can be used to specify the filler character of the fields if it is not spaces (e.g., ‘~’).

Consider a typical fixed-width data file:

```python
In [159]: print(open('bar.csv').read())
id8141 360.242940 149.910199 11950.7
id1594 444.953632 166.985655 11788.4
id1849 364.136849 183.628767 11806.2
id1230 413.836124 184.375703 11916.8
id1948 502.953953 173.237159 12468.3
```

In order to parse this file into a DataFrame, we simply need to supply the column specifications to the `read_fwf` function along with the file name:

```python
In [160]: colspecs = [(0, 6), (8, 20), (21, 33), (34, 43)]
In [161]: df = pd.read_fwf('bar.csv', colspecs=colspecs, header=None, index_col=0)
In [162]: df
Out[162]:
   1     2      3
0  id8141 360.242940 149.910199 11950.7
1  id1594 444.953632 166.985655 11788.4
2  id1849 364.136849 183.628767 11806.2
3  id1230 413.836124 184.375703 11916.8
4  id1948 502.953953 173.237159 12468.3
```

Note how the parser automatically picks column names X.<column number> when `header=None` argument is specified. Alternatively, you can supply just the column widths for contiguous columns:

```python
In [163]: widths = [6, 14, 13, 10]
In [164]: df = pd.read_fwf('bar.csv', widths=widths, header=None)
In [165]: df
Out[165]:
     0     1     2     3
0  id8141 360.242940 149.910199 11950.7
1  id1594 444.953632 166.985655 11788.4
2  id1849 364.136849 183.628767 11806.2
3  id1230 413.836124 184.375703 11916.8
4  id1948 502.953953 173.237159 12468.3
```
The parser will take care of extra white spaces around the columns so it’s ok to have extra separation between the columns in the file.

By default, `read_fwf` will try to infer the file’s `colspecs` by using the first 100 rows of the file. It can do it only in cases when the columns are aligned and correctly separated by the provided `delimiter` (default delimiter is whitespace).

```python
In [166]: df = pd.read_fwf('bar.csv', header=None, index_col=0)
In [167]: df
Out[167]:
     1      2  3
0  id8141  360.242940  149.910199  11950.7
id1594  444.953632  166.985655  11788.4
id1849  364.136849  183.628767  11806.2
id1230  413.836124  184.375703  11916.8
id1948  502.953953  173.237159  12468.3
```

`read_fwf` supports the `dtype` parameter for specifying the types of parsed columns to be different from the inferred type.

```python
In [168]: pd.read_fwf('bar.csv', header=None, index_col=0).dtypes
Out[168]:
0  object
1  float64
2  float64
3  float64
dtype: object
In [169]: pd.read_fwf('bar.csv', header=None, dtype={2: 'object'}).dtypes
Out[169]:
0  object
1  float64
2  object
3  float64
dtype: object
```

### Indexes

#### Files with an “implicit” index column

Consider a file with one less entry in the header than the number of data column:

```python
In [170]: print(open('foo.csv').read())
A,B,C
20090101,a,1,2
20090102,b,3,4
20090103,c,4,5
```

In this special case, `read_csv` assumes that the first column is to be used as the index of the DataFrame:

```python
In [171]: pd.read_csv('foo.csv')
```

(continues on next page)
20090102  b  3  4
20090103  c  4  5

Note that the dates weren’t automatically parsed. In that case you would need to do as before:

```python
In [172]: df = pd.read_csv('foo.csv', parse_dates=True)
In [173]: df.index
Out[173]: DatetimeIndex(['2009-01-01', '2009-01-02', '2009-01-03'], dtype='datetime64[ns]', freq=None)
```

Reading an index with a MultiIndex

Suppose you have data indexed by two columns:

```python
In [174]: print(open('data/mindex_ex.csv').read())
year,indiv,zit,xit
1977,"A",1.2,.6
1977,"B",1.5,.5
1977,"C",1.7,.8
1978,"A",.2,.06
1978,"B",.7,.2
1978,"C",.8,.3
1978,"D",.9,.5
1978,"E",1.4,.9
1979,"C",.2,.15
1979,"D",.14,.05
1979,"E",.5,.15
1979,"F",1.2,.5
1979,"G",3.4,1.9
1979,"H",5.4,2.7
1979,"I",6.4,1.2
```

The `index_col` argument to `read_csv` can take a list of column numbers to turn multiple columns into a `MultiIndex` for the index of the returned object:

```python
In [175]: df = pd.read_csv("data/mindex_ex.csv", index_col=[0, 1])
In [176]: df
Out[176]:
   zit  xit
year indiv
1977   A   1.20  0.60
       B   1.50  0.50
       C   1.70  0.80
1978   A   0.20  0.06
       B   0.70  0.20
       C   0.80  0.30
       D   0.90  0.50
       E   1.40  0.90
1979   C   0.20  0.15
       D   0.14  0.05
       E   0.50  0.15
       F   1.20  0.50
       G   3.40  1.90
```

(continues on next page)
In [177]: df.loc[1978]
Out[177]:
   zit  xit
  indiv
    A  0.2  0.06
    B  0.7  0.20
    C  0.8  0.30
    D  0.9  0.50
    E  1.4  0.90

Reading columns with a MultiIndex

By specifying list of row locations for the header argument, you can read in a MultiIndex for the columns. Specifying non-consecutive rows will skip the intervening rows.

In [178]: from pandas._testing import makeCustomDataframe as mkdf
In [179]: df = mkdf(5, 3, r_idx_nlevels=2, c_idx_nlevels=4)
In [180]: df.to_csv('mi.csv')
In [181]: print(open('mi.csv').read())
C0,,C_l0_g0,C_l0_g1,C_l0_g2
C1,,C_l1_g0,C_l1_g1,C_l1_g2
C2,,C_l2_g0,C_l2_g1,C_l2_g2
C3,,C_l3_g0,C_l3_g1,C_l3_g2
R0,R1,,
   R_l0_g0,R_l1_g0,R0C0,R0C1,R0C2
   R_l0_g1,R_l1_g1,R1C0,R1C1,R1C2
   R_l0_g2,R_l1_g2,R2C0,R2C1,R2C2
   R_l0_g3,R_l1_g3,R3C0,R3C1,R3C2
   R_l0_g4,R_l1_g4,R4C0,R4C1,R4C2

In [182]: pd.read_csv('mi.csv', header=[0, 1, 2, 3], index_col=[0, 1])
Out[182]:
   C0   C_l0_g0  C_l0_g1  C_l0_g2
   C1   C_l1_g0  C_l1_g1  C_l1_g2
   C2   C_l2_g0  C_l2_g1  C_l2_g2
   C3   C_l3_g0  C_l3_g1  C_l3_g2
   R0   R1       
   R_l0_g0 R_l1_g0 R0C0  R0C1  R0C2
   R_l0_g1 R_l1_g1 R1C0  R1C1  R1C2
   R_l0_g2 R_l1_g2 R2C0  R2C1  R2C2
   R_l0_g3 R_l1_g3 R3C0  R3C1  R3C2
   R_l0_g4 R_l1_g4 R4C0  R4C1  R4C2

read_csv is also able to interpret a more common format of multi-columns indices.

In [183]: print(open('mi2.csv').read())
,,a,a,b,c,c
,q,r,s,t,u,v

(continues on next page)
In [184]: pd.read_csv('mi2.csv', header=[0, 1], index_col=0)
Out[184]:
   a  b  c
  q  r  s  t  u  v
one 1  2  3  4  5  6
two 7  8  9 10 11 12

Note: If an index_col is not specified (e.g. you don’t have an index, or wrote it with df.to_csv(..., index=False)), then any names on the columns index will be lost.

Automatically “sniffing” the delimiter

read_csv is capable of inferring delimited (not necessarily comma-separated) files, as pandas uses the csv.Sniffer class of the csv module. For this, you have to specify sep=None.

In [185]: print(open('tmp2.sv').read())
:
0:0.4691122990718633 -0.2828634343286633 -1.5090585031735124 -1.1356323710171934
1:1.2121120250208506 -0.17321464905330858 -0.11920871129693428 -1.0442359662799567
2:-0.8618489633477999 -2.104569218894086 -0.4949292740687813 1.071803807037338
3:0.721551622443669 -0.7067711336300845 -1.0395749851146963 0.2718598855428296
4:-0.4249723297883753 0.5670203497936720 0.2763201927771873 -1.08400691259915
5:-0.6736897080883706 0.1136484096888855 -1.4784265524372235 0.5249876671147047
6:0.4047052186802365 0.5770459859204836 1.07150020161146375 -1.0392684835147725
7:-0.3706468582364464 -1.1578922506419993 -1.344311812731667 -0.8448851414284841
8:1.0757697837155533 -0.1090499752802223 1.6435630703622064 -1.4693879595399115
9:0.3570205641330908 -0.6746001037299882 -1.776903716971867 -0.9689138124473498

In [186]: pd.read_csv('tmp2.sv', sep=None, engine='python')
Out[186]:
       Unnamed: 0  0  0  1  2  3
0  0.469112 -0.282863 -1.509059 -1.135632
1  1.212112 -0.173215 0.119209 -1.044236
2 -0.861849 -2.104569 -0.494929 1.071804
3  0.721555 -0.706771 -1.039575 0.271860
4 -0.424972 0.567020 0.276232 -1.087401
5 -0.673690 0.113648 -1.478427 0.524988
6  0.404705 0.577046 -1.715002 -1.039268
7 -0.370647 -1.157892 -1.344312 0.844885
8  1.075770 -0.109050 1.643563 -1.469388
9  0.357021 -0.674600 -1.776904 -0.968914
Reading multiple files to create a single DataFrame

It’s best to use `concat()` to combine multiple files. See the cookbook for an example.

Iterating through files chunk by chunk

Suppose you wish to iterate through a (potentially very large) file lazily rather than reading the entire file into memory, such as the following:

```python
In [187]: print(open('tmp.sv').read())
```

<table>
<thead>
<tr>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.469112</td>
<td>-0.282863</td>
<td>-1.509058</td>
</tr>
<tr>
<td>1</td>
<td>1.212112</td>
<td>-0.173216</td>
<td>0.119209</td>
</tr>
<tr>
<td>2</td>
<td>-0.861849</td>
<td>-2.104569</td>
<td>-0.494929</td>
</tr>
<tr>
<td>3</td>
<td>0.721551</td>
<td>-0.706771</td>
<td>-1.343118</td>
</tr>
<tr>
<td>4</td>
<td>-0.424972</td>
<td>0.567020</td>
<td>0.570459</td>
</tr>
<tr>
<td>5</td>
<td>-0.673697</td>
<td>0.113648</td>
<td>1.643563</td>
</tr>
<tr>
<td>6</td>
<td>0.404705</td>
<td>-0.674600</td>
<td>-1.776903</td>
</tr>
</tbody>
</table>

```python
In [188]: table = pd.read_csv('tmp.sv', sep='|')
```

```python
In [189]: table
Out[189]:
```

<table>
<thead>
<tr>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.469112</td>
<td>-0.282863</td>
<td>-1.509058</td>
</tr>
<tr>
<td>1</td>
<td>1.212112</td>
<td>-0.173216</td>
<td>0.119209</td>
</tr>
<tr>
<td>2</td>
<td>-0.861849</td>
<td>-2.104569</td>
<td>-0.494929</td>
</tr>
<tr>
<td>3</td>
<td>0.721551</td>
<td>-0.706771</td>
<td>-1.343118</td>
</tr>
<tr>
<td>4</td>
<td>-0.424972</td>
<td>0.567020</td>
<td>0.570459</td>
</tr>
<tr>
<td>5</td>
<td>-0.673697</td>
<td>0.113648</td>
<td>1.643563</td>
</tr>
</tbody>
</table>

By specifying a chunksize to `read_csv`, the return value will be an iterable object of type TextFileReader:

```python
In [190]: reader = pd.read_csv('tmp.sv', sep='|', chunksize=4)
```

```python
In [191]: reader
Out[191]: <pandas.io.parsers.TextFileReader at 0x7fe28e50c0a0>
```

```python
In [192]: for chunk in reader:
......:     print(chunk)
```

(continues on next page)
Specifying `iterator=True` will also return the `TextFileReader` object:

```python
In [193]: reader = pd.read_csv('tmp.sv', sep='|', iterator=True)
```

```python
In [194]: reader.get_chunk(5)
```

```
Out[194]:
   Unnamed 0 1 2 3
0      0 0.469112 -0.282863 -1.509059 -1.135632
1      1 1.212112 -0.173215  0.119209 -1.044236
2      2 -0.861849 -2.104569 -0.494929  1.071804
3      3  0.721555 -0.706771 -1.039575  0.271860
4      4 -0.424972  0.567020  0.276232 -1.087401
```

**Specifying the parser engine**

Under the hood pandas uses a fast and efficient parser implemented in C as well as a Python implementation which is currently more feature-complete. Where possible pandas uses the C parser (specified as `engine='c'`), but may fall back to Python if C-unsupported options are specified. Currently, C-unsupported options include:

- `sep` other than a single character (e.g. regex separators)
- `skipfooter`
- `sep=None` with `delim_whitespace=False`

Specifying any of the above options will produce a `ParserWarning` unless the python engine is selected explicitly using `engine='python'`.

**Reading remote files**

You can pass in a URL to a CSV file:

```python
df = pd.read_csv('https://download.bls.gov/pub/time.series/cu/cu.item', sep='\t')
```

S3 URLs are handled as well but require installing the S3Fs library:

```python
df = pd.read_csv('s3://pandas-test/tips.csv')
```

If your S3 bucket requires credentials you will need to set them as environment variables or in the `~/.aws/credentials` config file, refer to the S3Fs documentation on credentials.
Writing out data

Writing to CSV format

The `Series` and `DataFrame` objects have an instance method `to_csv` which allows storing the contents of the object as a comma-separated-values file. The function takes a number of arguments. Only the first is required.

- `path_or_buf`: A string path to the file to write or a file object. If a file object it must be opened with `newline=''`
- `sep`: Field delimiter for the output file (default ````)
- `na_rep`: A string representation of a missing value (default '')
- `float_format`: Format string for floating point numbers
- `columns`: Columns to write (default None)
- `header`: Whether to write out the column names (default True)
- `index`: Whether to write row (index) names (default True)
- `index_label`: Column label(s) for index column(s) if desired. If None (default), and `header` and `index` are True, then the index names are used. (A sequence should be given if the `DataFrame` uses MultiIndex).
- `mode`: Python write mode, default ‘w’
- `encoding`: a string representing the encoding to use if the contents are non-ASCII, for Python versions prior to 3
- `line_terminator`: Character sequence denoting line end (default `os.linesep`)  
- `quoting`: Set quoting rules as in csv module (default csv.QUOTE_MINIMAL). Note that if you have set a `float_format` then floats are converted to strings and csv.QUOTE_NONNUMERIC will treat them as non-numeric
- `quotechar`: Character used to quote fields (default ‘”’)
- `doublequote`: Control quoting of `quotechar` in fields (default True)
- `escapechar`: Character used to escape `sep` and `quotechar` when appropriate (default None)
- `chunksize`: Number of rows to write at a time
- `date_format`: Format string for datetime objects

Writing a formatted string

The `DataFrame` object has an instance method `to_string` which allows control over the string representation of the object. All arguments are optional:

- `buf` default None, for example a StringIO object
- `columns` default None, which columns to write
- `col_space` default None, minimum width of each column.
- `na_rep` default NaN, representation of NA value
- `formatters` default None, a dictionary (by column) of functions each of which takes a single argument and returns a formatted string
- `float_format` default None, a function which takes a single (float) argument and returns a formatted string: to be applied to floats in the `DataFrame`.  

2.4. IO tools (text, CSV, HDF5, ...)
pandas: powerful Python data analysis toolkit, Release 1.1.1

- sparsify default True, set to False for a DataFrame with a hierarchical index to print every MultiIndex key at each row.
- index_names default True, will print the names of the indices
- index default True, will print the index (ie, row labels)
- header default True, will print the column labels
- justify default left, will print column headers left- or right-justified

The Series object also has a to_string method, but with only the buf, na_rep, float_format arguments. There is also a length argument which, if set to True, will additionally output the length of the Series.

2.4.2 JSON

Read and write JSON format files and strings.

Writing JSON

A Series or DataFrame can be converted to a valid JSON string. Use to_json with optional parameters:

- path_or_buf: the pathname or buffer to write the output This can be None in which case a JSON string is returned
- orient:
  - Series:  
    - default is index
    - allowed values are {split, records, index}
  - DataFrame:  
    - default is columns
    - allowed values are {split, records, index, columns, values, table}

The format of the JSON string

<table>
<thead>
<tr>
<th>split</th>
<th>dict like {index -&gt; [index], columns -&gt; [columns], data -&gt; [values]}</th>
</tr>
</thead>
<tbody>
<tr>
<td>records</td>
<td>list like [[column -&gt; value], ..., [column -&gt; value]]</td>
</tr>
<tr>
<td>index</td>
<td>dict like {index -&gt; [column -&gt; value]}</td>
</tr>
<tr>
<td>columns</td>
<td>dict like {column -&gt; [index -&gt; value]}</td>
</tr>
<tr>
<td>values</td>
<td>just the values array</td>
</tr>
</tbody>
</table>

- date_format: string, type of date conversion, ‘epoch’ for timestamp, ‘iso’ for ISO8601.
- double_precision: The number of decimal places to use when encoding floating point values, default 10.
- force_ascii: force encoded string to be ASCII, default True.
- date_unit: The time unit to encode to, governs timestamp and ISO8601 precision. One of ‘s’, ‘ms’, ‘us’ or ‘ns’ for seconds, milliseconds, microseconds and nanoseconds respectively. Default ‘ms’.
- default_handler: The handler to call if an object cannot otherwise be converted to a suitable format for JSON. Takes a single argument, which is the object to convert, and returns a serializable object.
- lines: If records orient, then will write each record per line as json.
Note NaN's, NaT's and None will be converted to null and datetime objects will be converted based on the date_format and date_unit parameters.

```python
In [195]: dfj = pd.DataFrame(np.random.randn(5, 2), columns=list('AB'))
In [196]: json = dfj.to_json()
In [197]: json
Out[197]: '{"A":{"0":-1.2945235903,"1":0.2766617129,"2":-0.0139597524,"3":-0.0061535699,"4":0.8957173022},"B":{"0":0.4137381054,"1":-0.923060654,"2":0.8052440254}}'
```

### Orient options

There are a number of different options for the format of the resulting JSON file / string. Consider the following DataFrame and Series:

```python
In [198]: dfjo = pd.DataFrame(dict(A=range(1, 4), B=range(4, 7), C=range(7, 10)), columns=list('ABC'), index=list('xyz'))
In [199]: dfjo
Out[199]:
   A  B  C
x 1  4  7
y 2  5  8
z 3  6  9
In [200]: sjo = pd.Series(dict(x=15, y=16, z=17), name='D')
In [201]: sjo
Out[201]:
  x    15
  y    16
  z    17
Name: D, dtype: int64
```

**Column oriented** (the default for DataFrame) serializes the data as nested JSON objects with column labels acting as the primary index:

```python
In [202]: dfjo.to_json(orient="columns")
Out[202]: '{"A":{"x":1,"y":4,"z":7},"B":{"x":4,"y":5,"z":8},"C":{"x":7,"y":8,"z":9}}'
```

**Index oriented** (the default for Series) similar to column oriented but the index labels are now primary:

```python
In [203]: dfjo.to_json(orient="index")
```

**Record oriented** serializes the data to a JSON array of column -> value records, index labels are not included. This is useful for passing DataFrame data to plotting libraries, for example the JavaScript library d3.js:

```python
In [204]: dfjo.to_json(orient="index")
Out[204]: '{"x":15,"y":16,"z":17}('
```
Value oriented is a bare-bones option which serializes to nested JSON arrays of values only, column and index labels are not included:

Split oriented serializes to a JSON object containing separate entries for values, index and columns. Name is also included for Series:

Table oriented serializes to the JSON Table Schema, allowing for the preservation of metadata including but not limited to dtypes and index names.

Note: Any orient option that encodes to a JSON object will not preserve the ordering of index and column labels during round-trip serialization. If you wish to preserve label ordering use the split option as it uses ordered containers.

Date handling

Writing in ISO date format:

Writing in ISO date format, with microseconds:
pandas: powerful Python data analysis toolkit, Release 1.1.1

(continued from previous page)

In [216]: json
Out[216]: '{"date":{"0":"2013-01-01T00:00:00.000000Z","1":"2013-01-01T00:00:00.000000Z
˓→","2":"2013-01-01T00:00:00.000000Z","3":"2013-01-01T00:00:00.000000Z","4":"2013-01˓→01T00:00:00.000000Z"},"B":{"0":2.5656459463,"1":1.3403088498,"2":-0.2261692849,"3":
˓→0.8138502857,"4":-0.8273169356},"A":{"0":-1.2064117817,"1":1.4312559863,"2":-1.
˓→1702987971,"3":0.4108345112,"4":0.1320031703}}'

Epoch timestamps, in seconds:
In [217]: json = dfd.to_json(date_format='epoch', date_unit='s')
In [218]: json
Out[218]: '{"date":{"0":1356998400,"1":1356998400,"2":1356998400,"3":1356998400,"4":
˓→1356998400},"B":{"0":2.5656459463,"1":1.3403088498,"2":-0.2261692849,"3":0.
˓→8138502857,"4":-0.8273169356},"A":{"0":-1.2064117817,"1":1.4312559863,"2":-1.
˓→1702987971,"3":0.4108345112,"4":0.1320031703}}'

Writing to a file, with a date index and a date column:
In [219]: dfj2 = dfj.copy()
In [220]: dfj2['date'] = pd.Timestamp('20130101')
In [221]: dfj2['ints'] = list(range(5))
In [222]: dfj2['bools'] = True
In [223]: dfj2.index = pd.date_range('20130101', periods=5)
In [224]: dfj2.to_json('test.json')
In [225]: with open('test.json') as fh:
.....:
print(fh.read())
.....:
{"A":{"1356998400000":-1.2945235903,"1357084800000":0.2766617129,"1357171200000":-0.
˓→0139597524,"1357257600000":-0.0061535699,"1357344000000":0.8957173022},"B":{
˓→"1356998400000":0.4137381054,"1357084800000":-0.472034511,"1357171200000":-0.
˓→3625429925,"1357257600000":-0.923060654,"1357344000000":0.8052440254},"date":{
˓→"1356998400000":1356998400000,"1357084800000":1356998400000,"1357171200000":
˓→1356998400000,"1357257600000":1356998400000,"1357344000000":1356998400000},"ints":{
˓→"1356998400000":0,"1357084800000":1,"1357171200000":2,"1357257600000":3,
˓→"1357344000000":4},"bools":{"1356998400000":true,"1357084800000":true,"1357171200000
˓→":true,"1357257600000":true,"1357344000000":true}}

Fallback behavior
If the JSON serializer cannot handle the container contents directly it will fall back in the following manner:
• if the dtype is unsupported (e.g. np.complex_) then the default_handler, if provided, will be called for
each value, otherwise an exception is raised.
• if an object is unsupported it will attempt the following:
– check if the object has defined a toDict method and call it. A toDict method should return a dict
which will then be JSON serialized.
– invoke the default_handler if one was provided.
2.4. IO tools (text, CSV, HDF5, . . . )

269


convert the object to a `dict` by traversing its contents. However this will often fail with an `OverflowError` or give unexpected results.

In general the best approach for unsupported objects or dtypes is to provide a `default_handler`. For example:

```python
>>> DataFrame([1.0, 2.0, complex(1.0, 2.0)]).to_json()  # raises
RuntimeError: Unhandled numpy dtype 15
```

can be dealt with by specifying a simple `default_handler`:

```python
In [226]: pd.DataFrame([1.0, 2.0, complex(1.0, 2.0)]).to_json(default_handler=str)
Out[226]: '{"0":"(1+0j)","1":"(2+0j)","2":"(1+2j)"}'
```

### Reading JSON

Reading a JSON string to pandas object can take a number of parameters. The parser will try to parse a DataFrame if `typ` is not supplied or is `None`. To explicitly force Series parsing, pass `typ=series`

- `filepath_or_buffer`: a **valid** JSON string or file handle / `StringIO`. The string could be a URL. Valid URL schemes include http, ftp, S3, and file. For file URLs, a host is expected. For instance, a local file could be file://localhost/path/to/table.json
- `typ`: type of object to recover (series or frame), default ‘frame’
- `orient`:
  - **Series**:
    - default is `index`
    - allowed values are {split, records, index}
  - **DataFrame**:
    - default is `columns`
    - allowed values are {split, records, index, columns, values, table}

The format of the JSON string

<table>
<thead>
<tr>
<th>split</th>
<th>dict like {index -&gt; [index], columns -&gt; [columns], data -&gt; [values]}</th>
</tr>
</thead>
<tbody>
<tr>
<td>records</td>
<td>list like [[column -&gt; value], ..., [column -&gt; value]]</td>
</tr>
<tr>
<td>index</td>
<td>dict like {index -&gt; [column -&gt; value]}</td>
</tr>
<tr>
<td>columns</td>
<td>dict like {column -&gt; [index -&gt; value]}</td>
</tr>
<tr>
<td>values</td>
<td>just the values array</td>
</tr>
<tr>
<td>table</td>
<td>adhering to the JSON Table Schema</td>
</tr>
</tbody>
</table>

- `dtype`: if `True`, infer dtypes, if a dict of column to dtype, then use those, if `False`, then don’t infer dtypes at all, default is `True`, apply only to the data.
- `convert_axes`: boolean, try to convert the axes to the proper dtypes, default is `True`
- `convert_dates`: a list of columns to parse for dates; If `True`, then try to parse date-like columns, default is `True`.
- `keep_default_dates`: boolean, default `True`. If parsing dates, then parse the default date-like columns.
- `numpy`: direct decoding to NumPy arrays. default is `False`; Supports numeric data only, although labels may be non-numeric. Also note that the JSON ordering **MUST** be the same for each term if `numpy=True`.  
- **precise_float**: boolean, default False. Set to enable usage of higher precision (strtod) function when decoding string to double values. Default (False) is to use fast but less precise built-in functionality.

- **date_unit**: string, the timestamp unit to detect if converting dates. Default None. By default the timestamp precision will be detected, if this is not desired then pass one of ‘s’, ‘ms’, ‘us’ or ‘ns’ to force timestamp precision to seconds, milliseconds, microseconds or nanoseconds respectively.

- **lines**: reads file as one json object per line.

- **encoding**: The encoding to use to decode py3 bytes.

- **chunksize**: when used in combination with lines=True, return a JsonReader which reads in chunksize lines per iteration.

The parser will raise one of ValueError/TypeError/AssertionError if the JSON is not parseable.

If a non-default orient was used when encoding to JSON be sure to pass the same option here so that decoding produces sensible results, see Orient Options for an overview.

### Data conversion

The default of convert_axes=True, dtype=True, and convert_dates=True will try to parse the axes, and all of the data into appropriate types, including dates. If you need to override specific dtypes, pass a dict to dtype. convert_axes should only be set to False if you need to preserve string-like numbers (e.g. ‘1’, ‘2’) in an axes.

**Note**: Large integer values may be converted to dates if convert_dates=True and the data and / or column labels appear ‘date-like’. The exact threshold depends on the date_unit specified. ‘date-like’ means that the column label meets one of the following criteria:

- it ends with '_at'
- it ends with '_time'
- it begins with 'timestamp'
- it is 'modified'
- it is 'date'

**Warning**: When reading JSON data, automatic coercing into dtypes has some quirks:

- an index can be reconstructed in a different order from serialization, that is, the returned order is not guaranteed to be the same as before serialization
- a column that was float data will be converted to integer if it can be done safely, e.g. a column of 1.
- bool columns will be converted to integer on reconstruction

Thus there are times where you may want to specify specific dtypes via the dtype keyword argument.

Reading from a JSON string:

```python
In [227]: pd.read_json(json)
Out[227]:
<table>
<thead>
<tr>
<th>date</th>
<th>B</th>
<th>A</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013-01-01</td>
<td>2.565646</td>
<td>-1.206412</td>
</tr>
<tr>
<td>2013-01-01</td>
<td>1.340309</td>
<td>1.431256</td>
</tr>
</tbody>
</table>
```

(continues on next page)
Reading from a file:

```
In [228]: pd.read_json('test.json')
Out[228]:
  A    B  date         ints  bools
2013-01-01 -1.294524 0.413738 2013-01-01 0   True
2013-01-02  0.276662 -0.472035 2013-01-01 1   True
2013-01-03 -0.013960 -0.362543 2013-01-01 2   True
2013-01-04 -0.006154 -0.923061 2013-01-01 3   True
2013-01-05  0.895717  0.805244 2013-01-01 4   True
```

Don’t convert any data (but still convert axes and dates):

```
In [229]: pd.read_json('test.json', dtype=object).dtypes
Out[229]:
A    object
B    object
date  object
ints  object
bools object
dtype: object
```

Specify dtypes for conversion:

```
In [230]: pd.read_json('test.json', dtype={'A': 'float32', 'bools': 'int8'}).dtypes
Out[230]:
A    float32
B    float64
date  datetime64[ns]
ints  int64
bools int8
dtype: object
```

Preserve string indices:

```
In [231]: si = pd.DataFrame(np.zeros((4, 4)), columns=list(range(4)),
                      index=[str(i) for i in range(4)])
......:

In [232]: si
Out[232]:
   0 1 2 3
0 0.0 0.0 0.0 0.0
1 0.0 0.0 0.0 0.0
2 0.0 0.0 0.0 0.0
3 0.0 0.0 0.0 0.0
```

```
In [233]: si.index
Out[233]: Index(['0', '1', '2', '3'], dtype='object')
```

```
In [234]: si.columns
Out[234]: Int64Index([0, 1, 2, 3], dtype='int64')
```
Dates written in nanoseconds need to be read back in nanoseconds:

```python
In [240]: json = dfj2.to_json(date_unit='ns')

# Try to parse timestamps as milliseconds -> Won't Work
In [241]: dfju = pd.read_json(json, date_unit='ms')

In [242]: dfju
```

```
A    B  date     ints  bools
1356998400000000000 0.413738 1356998400000000000 0  True
1357084800000000000 -0.472035 1356998400000000000 1  True
1357171200000000000 -0.362543 1356998400000000000 2  True
1357257600000000000 -0.006154 -0.923061 1356998400000000000 3  True
1357344000000000000 0.895717 0.805244 1356998400000000000 4  True
```

# Let pandas detect the correct precision

```python
In [243]: dfju = pd.read_json(json)
```

```
A    B  date     ints  bools
2013-01-01 -1.294524 0.413738 2013-01-01 0  True
2013-01-02 0.276662 -0.472035 2013-01-01 1  True
2013-01-03 -0.013960 -0.362543 2013-01-01 2  True
2013-01-04 -0.006154 -0.923061 2013-01-01 3  True
2013-01-05 0.895717 0.805244 2013-01-01 4  True
```

# Or specify that all timestamps are in nanoseconds

```python
In [245]: dfju = pd.read_json(json, date_unit='ns')
```

```
A    B  date     ints  bools
2013-01-01 -1.294524 0.413738 2013-01-01 0  True
2013-01-02 0.276662 -0.472035 2013-01-01 1  True
2013-01-03 -0.013960 -0.362543 2013-01-01 2  True
2013-01-04 -0.006154 -0.923061 2013-01-01 3  True
2013-01-05 0.895717 0.805244 2013-01-01 4  True
```

(continues on next page)
The Numpy parameter

**Note:** This param has been deprecated as of version 1.0.0 and will raise a `FutureWarning`.

This supports numeric data only. Index and columns labels may be non-numeric, e.g. strings, dates etc.

If `numpy=True` is passed to `read_json` an attempt will be made to sniff an appropriate dtype during deserialization and to subsequently decode directly to NumPy arrays, bypassing the need for intermediate Python objects.

This can provide speedups if you are deserialising a large amount of numeric data:

```
In [247]: randfloats = np.random.uniform(-100, 1000, 10000)
In [248]: randfloats.shape = (1000, 10)
In [249]: dffloats = pd.DataFrame(randfloats, columns=list('ABCDEFGHIJ'))
In [250]: jsonfloats = dffloats.to_json()
```

```
In [251]: %timeit pd.read_json(jsonfloats)
19.7 ms +- 955 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

```
In [252]: %timeit pd.read_json(jsonfloats, numpy=True)
16.1 ms +- 1.21 ms per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

The speedup is less noticeable for smaller datasets:

```
In [253]: jsonfloats = dffloats.head(100).to_json()
```

```
In [254]: %timeit pd.read_json(jsonfloats)
11.6 ms +- 1.04 ms per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

```
In [255]: %timeit pd.read_json(jsonfloats, numpy=True)
9.25 ms +- 208 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

**Warning:** Direct NumPy decoding makes a number of assumptions and may fail or produce unexpected output if these assumptions are not satisfied:

- data is numeric.
- data is uniform. The dtype is sniffed from the first value decoded. A `ValueError` may be raised, or incorrect output may be produced if this condition is not satisfied.
- labels are ordered. Labels are only read from the first container, it is assumed that each subsequent row / column has been encoded in the same order. This should be satisfied if the data was encoded using `to_json` but may not be the case if the JSON is from another source.
Normalization

pandas provides a utility function to take a dict or list of dicts and *normalize* this semi-structured data into a flat table.

```python
In [256]: data = [{'id': 1, 'name': {'first': 'Coleen', 'last': 'Volk'}},
            .....:      {'name': {'given': 'Mose', 'family': 'Regner'}},
            .....:      {'id': 2, 'name': 'Faye Raker'}]

In [257]: pd.json_normalize(data)
Out[257]:
       id  name.first  name.last  name.given  name.family  name
0  1.0    Coleen      Volk         NaN         NaN        NaN
1  NaN    NaN         NaN      Mose       Regner        NaN
2  2.0    NaN         NaN         NaN         NaN    Faye Raker

In [258]: data = [{'state': 'Florida',
            .....:      'shortname': 'FL',
            .....:      'info': {'governor': 'Rick Scott'},
            .....:      'county': [{'name': 'Dade', 'population': 12345},
            .....:        {'name': 'Broward', 'population': 40000},
            .....:        {'name': 'Palm Beach', 'population': 60000}]},
            .....:      {'state': 'Ohio',
            .....:      'shortname': 'OH',
            .....:      'info': {'governor': 'John Kasich'},
            .....:      'county': [{'name': 'Summit', 'population': 1234},
            .....:        {'name': 'Cuyahoga', 'population': 1337}]}

In [259]: pd.json_normalize(data, 'county', ['state', 'shortname', ['info', 'governor']])
Out[259]:
     name population  state  shortname    info.governor
0       Dade      12345  Florida     FL    Rick Scott
1      Broward     40000  Florida     FL    Rick Scott
2     Palm Beach    60000  Florida     FL    Rick Scott
3       Summit      1234   Ohio       OH    John Kasich
4  Cuyahoga         1337   Ohio       OH    John Kasich

The `max_level` parameter provides more control over which level to end normalization. With `max_level=1` the following snippet normalizes until 1st nesting level of the provided dict.

```python
In [260]: data = [{'CreatedBy': {'Name': 'User001'},
            .....:      'Lookup': {'TextField': 'Some text',
            .....:      'UserField': {'Id': 'ID001',
            .....:        'Name': 'Name001'}},
            .....:      'Image': {'a': 'b'}}

In [261]: pd.json_normalize(data, max_level=1)
Out[261]:
     CreatedBy.Name  Lookup.TextField  Lookup.UserField.Name  Image.a
0          User001  Some text            {'Id': 'ID001',
```
Line delimited json

pandas is able to read and write line-delimited json files that are common in data processing pipelines using Hadoop or Spark.

For line-delimited json files, pandas can also return an iterator which reads in chunksize lines at a time. This can be useful for large files or to read from a stream.

```python
In [262]: jsonl = '''
   .......
   {"a": 1, "b": 2}
   .......
   {"a": 3, "b": 4}
   .......
   '''

In [263]: df = pd.read_json(jsonl, lines=True)

In [264]: df
Out[264]:
   a  b
0  1  2
1  3  4

In [265]: df.to_json(orient='records', lines=True)
Out[265]: '{"a":1,"b":2}\n{"a":3,"b":4}'

# reader is an iterator that returns `chunksize` lines each iteration
In [266]: reader = pd.read_json(StringIO(jsonl), lines=True, chunksize=1)

In [267]: reader
Out[267]: <pandas.io.json._json.JsonReader at 0x7fe28e3453d0>

In [268]: for chunk in reader:
   .......
   print(chunk)
   .......
Empty DataFrame
Columns: []
Index: []
   a  b
0  1  2
   a  b
1  3  4
```

Table schema

Table Schema is a spec for describing tabular datasets as a JSON object. The JSON includes information on the field names, types, and other attributes. You can use the orient table to build a JSON string with two fields, schema and data.

```python
In [269]: df = pd.DataFrame({'A': [1, 2, 3],
   .......
   'B': ['a', 'b', 'c'],
   .......
   'C': pd.date_range('2016-01-01', freq='d', periods=3),
   .......
   'idx': pd.Index(range(3), name='idx')})

In [270]: df
Out[270]:
```

(continues on next page)
The schema field contains the fields key, which itself contains a list of column name to type pairs, including the Index or MultiIndex (see below for a list of types). The schema field also contains a primaryKey field if the (Multi)index is unique.

The second field, data, contains the serialized data with the records orient. The index is included, and any datetimes are ISO 8601 formatted, as required by the Table Schema spec.

The full list of types supported are described in the Table Schema spec. This table shows the mapping from pandas types:

<table>
<thead>
<tr>
<th>Pandas type</th>
<th>Table Schema type</th>
</tr>
</thead>
<tbody>
<tr>
<td>int64</td>
<td>integer</td>
</tr>
<tr>
<td>float64</td>
<td>number</td>
</tr>
<tr>
<td>bool</td>
<td>boolean</td>
</tr>
<tr>
<td>datetime64[ns]</td>
<td>datetime</td>
</tr>
<tr>
<td>timedelta64[ns]</td>
<td>duration</td>
</tr>
<tr>
<td>categorical</td>
<td>any</td>
</tr>
<tr>
<td>object</td>
<td>str</td>
</tr>
</tbody>
</table>

A few notes on the generated table schema:

- The schema object contains a pandas_version field. This contains the version of pandas’ dialect of the schema, and will be incremented with each revision.
- All dates are converted to UTC when serializing. Even timezone naive values, which are treated as UTC with an offset of 0.

```
In [272]: from pandas.io.json import build_table_schema
In [273]: s = pd.Series(pd.date_range('2016', periods=4))
In [274]: build_table_schema(s)
Out[274]:
{'fields': [{'name': 'index', 'type': 'integer'},
            {'name': 'values', 'type': 'datetime'},
            'primaryKey': ['index'],
            'pandas_version': '0.20.0'}
```

- datetimes with a timezone (before serializing), include an additional field tz with the time zone name (e.g. 'US/Central').

```
In [275]: s_tz = pd.Series(pd.date_range('2016', periods=12, 
                              tz='US/Central'))
```

(continues on next page)
In [276]: build_table_schema(s_tz)
Out[276]:
{'fields': [{'name': 'index', 'type': 'integer'},
            {'name': 'values', 'type': 'datetime', 'tz': 'US/Central'}],
       'primaryKey': ['index'],
       'pandas_version': '0.20.0'}

- Periods are converted to timestamps before serialization, and so have the same behavior of being converted to UTC. In addition, periods will contain and additional field freq with the period’s frequency, e.g. 'A-DEC'.

In [277]: s_per = pd.Series(1, index=pd.period_range('2016', freq='A-DEC', periods=4))

In [278]: build_table_schema(s_per)
Out[278]:
{'fields': [{'name': 'index', 'type': 'datetime', 'freq': 'A-DEC'},
            {'name': 'values', 'type': 'integer'}],
       'primaryKey': ['index'],
       'pandas_version': '0.20.0'}

- Categoricals use the any type and an enum constraint listing the set of possible values. Additionally, an ordered field is included:

In [279]: s_cat = pd.Series(pd.Categorical(['a', 'b', 'a']))

In [280]: build_table_schema(s_cat)
Out[280]:
{'fields': [{'name': 'index', 'type': 'integer'},
            {'name': 'values', 'type': 'any',
             'constraints': {'enum': ['a', 'b']},
             'ordered': False},
            'primaryKey': ['index'],
            'pandas_version': '0.20.0'}

- A primaryKey field, containing an array of labels, is included if the index is unique:

In [281]: s_dupe = pd.Series([1, 2], index=[1, 1])

In [282]: build_table_schema(s_dupe)
Out[282]:
{'fields': [{'name': 'index', 'type': 'integer'},
            {'name': 'values', 'type': 'integer'}],
       'pandas_version': '0.20.0'}

- The primaryKey behavior is the same with MultiIndexes, but in this case the primaryKey is an array:

In [283]: s_multi = pd.Series(1, index=pd.MultiIndex.from_product([('a', 'b'), (0, 1)]))

In [284]: build_table_schema(s_multi)
Out[284]:
(continues on next page)
• The default naming roughly follows these rules:
  – For series, the object.name is used. If that’s none, then the name is values
  – For DataFrames, the stringified version of the column name is used
  – For Index (not MultiIndex), index.name is used, with a fallback to index if that is None.
  – For MultiIndex, mi.names is used. If any level has no name, then level_<i> is used.

New in version 0.23.0.

read_json also accepts orient='table' as an argument. This allows for the preservation of metadata such as dtypes and index names in a round-trippable manner.

```python
In [285]: df = pd.DataFrame({'foo': [1, 2, 3, 4],
                        'bar': ['a', 'b', 'c', 'd'],
                        'baz': pd.date_range('2018-01-01', freq='d', periods=4),
                        'qux': pd.Categorical(['a', 'b', 'c', 'c'])}, index=pd.Index(range(4), name='idx'))

In [286]: df
Out[286]:
   foo  bar    baz         qux
   idx
 0  1  a  2018-01-01    a
 1  2  b  2018-01-02    b
 2  3  c  2018-01-03    c
 3  4  d  2018-01-04    c

In [287]: df.dtypes
Out[287]:
foo     int64
bar     object
baz  datetime64[ns]
qux     category
dtype: object

In [288]: df.to_json('test.json', orient='table')

In [289]: new_df = pd.read_json('test.json', orient='table')

In [290]: new_df
Out[290]:
   foo  bar    baz         qux
   idx
 0  1  a  2018-01-01    a
 1  2  b  2018-01-02    b
 2  3  c  2018-01-03    c
 3  4  d  2018-01-04    c

In [291]: new_df.dtypes
```

(continues on next page)
Please note that the literal string ‘index’ as the name of an `Index` is not round-trippable, nor are any names beginning with 'level_' within a `MultiIndex`. These are used by default in `DataFrame.to_json()` to indicate missing values and the subsequent read cannot distinguish the intent.

```python
In [292]: df.index.name = 'index'

In [293]: df.to_json('test.json', orient='table')

In [294]: new_df = pd.read_json('test.json', orient='table')

In [295]: print(new_df.index.name)
None
```

### 2.4.3 HTML

#### Reading HTML content

**Warning:** We highly encourage you to read the *HTML Table Parsing gotchas* below regarding the issues surrounding the BeautifulSoup4/html5lib/lxml parsers.

The top-level `read_html()` function can accept an HTML string/file/URL and will parse HTML tables into list of pandas `DataFrame`s. Let's look at a few examples.

**Note:** `read_html` returns a list of `DataFrame` objects, even if there is only a single table contained in the HTML content.

Read a URL with no options:

```python
In [296]: url = 'https://www.fdic.gov/bank/individual/failed/banklist.html'

In [297]: dfs = pd.read_html(url)

In [298]: dfs
Out[298]:
[ Bank Name City ST CERT
 0 The First State Bank Barboursville WV 14361
 1 MVB Bank, Inc. April 3, 2020
 2 Ericson State Bank Ericson NE 18265 Farmers
 3 City National Bank of New Jersey Newark NJ 21111
 4 Industrial Bank November 1, 2019
 5 Resolute Bank Maumee OH 58317
 6 Buckeye State Bank October 25, 2019
```

(continues on next page)
Read in the content of the file from the above URL and pass it to `read_html` as a string:

```python
In [299]: with open(file_path, 'r') as f:
......:    dfs = pd.read_html(f.read())
......:

In [300]: dfs
Out[300]:
[505 rows x 7 columns]
```

Note: The data from the above URL changes every Monday so the resulting data above and the data below may be slightly different.
You can even pass in an instance of `StringIO` if you so desire:

```python
In [301]: with open(file_path, 'r') as f:
     ....:     sio = StringIO(f.read())
     ....:
In [302]: dfs = pd.read_html(sio)
In [303]: dfs
Out[303]:
[ Bank Name   City  ST  ...  
   Acquiring Institution  Closing Date  Updated Date  
0  Banks of Wisconsin d/b/a Bank of Kenosha  Kenosha WI  
1  North Shore Bank, FSB  May 31, 2013  May 31, 2013  
2  Central Arizona Bank  Scottsdale AZ  
3  Western State Bank  May 14, 2013  May 20, 2013  
4  Sunrise Bank  Valdosta GA  
5  Synovus Bank  May 10, 2013  May 21, 2013  
6  Capital Bank, N.A.  May 10, 2013  May 14, 2013  
7  Douglas County Bank  Douglasville GA  
8  Hamilton State Bank  April 26, 2013  May 16, 2013  
9  Superior Bank, FSB  Hinsdale IL  
11 North Valley Bank  May 3, 2001  November 18, 2002  
12 First Alliance Bank & Trust Co.  Manchester NH  
13 Hampshire Bank & Trust  February 2, 2001  February 18, 2003  
14 National State Bank of Metropolis  Metropolis IL  
15 Banterra Bank of Marion  December 14, 2000  March 17, 2005  
16 Bank of the Orient  October 13, 2000  March 17, 2005  
[505 rows x 7 columns]
```

**Note:** The following examples are not run by the IPython evaluator due to the fact that having so many network-accessing functions slows down the documentation build. If you spot an error or an example that doesn’t run, please do not hesitate to report it over on pandas GitHub issues page.

Read a URL and match a table that contains specific text:

```python
match = 'Metcalf Bank'
df_list = pd.read_html(url, match=match)
```

Specify a header row (by default `<th>` or `<td>` elements located within a `<thead>` are used to form the column index, if multiple rows are contained within `<thead>` then a MultiIndex is created); if specified, the header row is taken from the data minus the parsed header elements (`<th>` elements).

```python
dfs = pd.read_html(url, header=0)
```

Specify an index column:

```python
dfs = pd.read_html(url, index_col=0)
```

Specify a number of rows to skip:
dfs = pd.read_html(url, skiprows=0)

Specify a number of rows to skip using a list (range works as well):

dfs = pd.read_html(url, skiprows=range(2))

Specify an HTML attribute:

dfs1 = pd.read_html(url, attrs={'id': 'table'})
dfs2 = pd.read_html(url, attrs={'class': 'sortable'})
print(np.array_equal(dfs1[0], dfs2[0]))  # Should be True

Specify values that should be converted to NaN:

dfs = pd.read_html(url, na_values=['No Acquirer'])

Specify whether to keep the default set of NaN values:

dfs = pd.read_html(url, keep_default_na=False)

Specify converters for columns. This is useful for numerical text data that has leading zeros. By default columns that are numerical are cast to numeric types and the leading zeros are lost. To avoid this, we can convert these columns to strings.

url_mcc = 'https://en.wikipedia.org/wiki/Mobile_country_code'
dfs = pd.read_html(url_mcc, match='Telekom Albania', header=0, converters={'MNC': str})

Use some combination of the above:

dfs = pd.read_html(url, match='Metcalf Bank', index_col=0)

Read in pandas to_html output (with some loss of floating point precision):

df = pd.DataFrame(np.random.randn(2, 2))
s = df.to_html(float_format='\0:.40g'.format)
dfin = pd.read_html(s, index_col=0)

The lxml backend will raise an error on a failed parse if that is the only parser you provide. If you only have a single parser you can provide just a string, but it is considered good practice to pass a list with one string if, for example, the function expects a sequence of strings. You may use:

dfs = pd.read_html(url, 'Metcalf Bank', index_col=0, flavor=['lxml'])

Or you could pass flavor='lxml' without a list:

dfs = pd.read_html(url, 'Metcalf Bank', index_col=0, flavor='lxml')

However, if you have bs4 and html5lib installed and pass None or ['lxml', 'bs4'] then the parse will most likely succeed. Note that as soon as a parse succeeds, the function will return.

dfs = pd.read_html(url, 'Metcalf Bank', index_col=0, flavor=['lxml', 'bs4'])
Writing to HTML files

DataFrame objects have an instance method `to_html` which renders the contents of the DataFrame as an HTML table. The function arguments are as in the method `to_string` described above.

**Note:** Not all of the possible options for `DataFrame.to_html` are shown here for brevity's sake. See `to_html()` for the full set of options.

```
In [304]: df = pd.DataFrame(np.random.randn(2, 2))

In [305]: df
Out[305]:
   0    1
0 -0.184744  0.496971
1 -0.856240  1.857977

In [306]: print(df.to_html())  # raw html
<table border="1" class="dataframe">
    <thead>
        <tr style="text-align: right;">  
            <th></th>
            <th>0</th>
            <th>1</th>
        </tr>
    </thead>
    <tbody>
        <tr>
            <th>0</th>
            <td>-0.184744</td>
            <td>0.496971</td>
        </tr>
        <tr>
            <th>1</th>
            <td>-0.856240</td>
            <td>1.857977</td>
        </tr>
    </tbody>
</table>
```

**HTML:**

The `columns` argument will limit the columns shown:

```
In [307]: print(df.to_html(columns=[0]))
<table border="1" class="dataframe">
    <thead>
        <tr style="text-align: right;">  
            <th></th>
            <th>0</th>
        </tr>
    </thead>
    <tbody>
        <tr>
            <th>0</th>
            <td>-0.184744</td>
        </tr>
        <tr>
            <th>1</th>
            <td>-0.856240</td>
        </tr>
    </tbody>
</table>
```

(continues on next page)
HTML:

`float_format` takes a Python callable to control the precision of floating point values:

```python
In [308]: print(df.to_html(float_format='{:0.10f}'.format))
```

```html
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>0</th>
      <th>1</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <td>0</td>
      <td>-0.1847438576</td>
      <td>0.4969711327</td>
    </tr>
    <tr>
      <td>1</td>
      <td>-0.8562396763</td>
      <td>1.8579766508</td>
    </tr>
  </tbody>
</table>
```

HTML:

`bold_rows` will make the row labels bold by default, but you can turn that off:

```python
In [309]: print(df.to_html(bold_rows=False))
```

```html
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>0</th>
      <th>1</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <td>0</td>
      <td>-0.184744</td>
      <td>0.496971</td>
    </tr>
    <tr>
      <td>1</td>
      <td>-0.856240</td>
      <td>1.857977</td>
    </tr>
  </tbody>
</table>
```
The `classes` argument provides the ability to give the resulting HTML table CSS classes. Note that these classes are **appended** to the existing 'dataframe' class.

```python
In [310]: print(df.to_html(classes=['awesome_table_class', 'even_more_awesome_class']))
```

```html
table border="1" class="dataframe awesome_table_class even_more_awesome_class">
<thead>
<tr style="text-align: right;">
<th></th>
<th>0</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<th>0</th>
<td>-0.184744</td>
<td>0.496971</td>
</tr>
<tr>
<th>1</th>
<td>-0.856240</td>
<td>1.857977</td>
</tr>
</tbody>
</table>
```

The `render_links` argument provides the ability to add hyperlinks to cells that contain URLs.

New in version 0.24.

```python
In [311]: url_df = pd.DataFrame({
.....:   'name': ['Python', 'Pandas'],
.....:   'url': ['https://www.python.org/', 'https://pandas.pydata.org']})
.....:

In [312]: print(url_df.to_html(render_links=True))
```

```html
table border="1" class="dataframe">
<thead>
<tr style="text-align: right;"> 
<th>name</th>
<th>url</th>
</tr>
</thead>
<tbody>
<tr>
<th>0</th>
<td><a href="https://www.python.org/" target="_blank">https://www.python.org/</a></td>
</tr>
<tr>
<th>1</th>
<td><a href="https://pandas.pydata.org/" target="_blank">https://pandas.pydata.org/</a></td>
</tr>
</tbody>
</table>
```

(continues on next page)
Finally, the escape argument allows you to control whether the “<”, “>” and “&” characters escaped in the resulting HTML (by default it is True). So to get the HTML without escaped characters pass escape=False

In [313]: df = pd.DataFrame({'a': list('&<>'), 'b': np.random.randn(3)})

Escaped:

In [314]: print(df.to_html())

Not escaped:

In [315]: print(df.to_html(escape=False))

(continues on next page)
Note: Some browsers may not show a difference in the rendering of the previous two HTML tables.

HTML Table Parsing Gotchas

There are some versioning issues surrounding the libraries that are used to parse HTML tables in the top-level pandas io function read_html.

Issues with lxml

- Benefits
  - lxml is very fast.
  - lxml requires Cython to install correctly.
- Drawbacks
  - lxml does not make any guarantees about the results of its parse unless it is given strictly valid markup.
  - In light of the above, we have chosen to allow you, the user, to use the lxml backend, but this backend will use html5lib if lxml fails to parse
  - It is therefore highly recommended that you install both BeautifulSoup4 and html5lib, so that you will still get a valid result (provided everything else is valid) even if lxml fails.

Issues with BeautifulSoup4 using lxml as a backend

- The above issues hold here as well since BeautifulSoup4 is essentially just a wrapper around a parser backend.

Issues with BeautifulSoup4 using html5lib as a backend

- Benefits
  - html5lib is far more lenient than lxml and consequently deals with real-life markup in a much saner way rather than just, e.g., dropping an element without notifying you.
  - html5lib generates valid HTML5 markup from invalid markup automatically. This is extremely important for parsing HTML tables, since it guarantees a valid document. However, that does NOT mean that it is “correct”, since the process of fixing markup does not have a single definition.
  - html5lib is pure Python and requires no additional build steps beyond its own installation.
• Drawbacks

- The biggest drawback to using html5lib is that it is slow as molasses. However consider the fact that many tables on the web are not big enough for the parsing algorithm runtime to matter. It is more likely that the bottleneck will be in the process of reading the raw text from the URL over the web, i.e., IO (input-output). For very large tables, this might not be true.

2.4.4 Excel files

The read_excel() method can read Excel 2003 (.xls) files using the xlrd Python module. Excel 2007+ (.xlsx) files can be read using either xlrd or openpyxl. Binary Excel (.xlsxb) files can be read using pyxlsb. The to_excel() instance method is used for saving a DataFrame to Excel. Generally the semantics are similar to working with csv data. See the cookbook for some advanced strategies.

Reading Excel files

In the most basic use-case, read_excel takes a path to an Excel file, and the sheet_name indicating which sheet to parse.

```python
# Returns a DataFrame
pd.read_excel('path_to_file.xls', sheet_name='Sheet1')
```

ExcelFile class

To facilitate working with multiple sheets from the same file, the ExcelFile class can be used to wrap the file and can be passed into read_excel. There will be a performance benefit for reading multiple sheets as the file is read into memory only once.

```python
xlsx = pd.ExcelFile('path_to_file.xls')
df = pd.read_excel(xlsx, 'Sheet1')
```

The ExcelFile class can also be used as a context manager.

```python
with pd.ExcelFile('path_to_file.xls') as xls:
    df1 = pd.read_excel(xls, 'Sheet1')
    df2 = pd.read_excel(xls, 'Sheet2')
```

The sheet_names property will generate a list of the sheet names in the file.

The primary use-case for an ExcelFile is parsing multiple sheets with different parameters:

```python
data = {}
# For when Sheet1's format differs from Sheet2
with pd.ExcelFile('path_to_file.xls') as xls:
    data['Sheet1'] = pd.read_excel(xls, 'Sheet1', index_col=None, na_values=['NA'])
    data['Sheet2'] = pd.read_excel(xls, 'Sheet2', index_col=1)
```

Note that if the same parsing parameters are used for all sheets, a list of sheet names can simply be passed to read_excel with no loss in performance.
# using the ExcelFile class

data = {}

with pd.ExcelFile('path_to_file.xls') as xls:
    data['Sheet1'] = pd.read_excel(xls, 'Sheet1', index_col=None, na_values=['NA'])
    data['Sheet2'] = pd.read_excel(xls, 'Sheet2', index_col=None, na_values=['NA'])

# equivalent using the read_excel function

data = pd.read_excel('path_to_file.xls', ['Sheet1', 'Sheet2'], index_col=None, na_values=['NA'])

ExcelFile can also be called with a xlrd.book.Book object as a parameter. This allows the user to control how the excel file is read. For example, sheets can be loaded on demand by calling `xlrd.open_workbook()` with `on_demand=True`.

```python
import xlrd

xlrd_book = xlrd.open_workbook('path_to_file.xls', on_demand=True)

with pd.ExcelFile(xlrd_book) as xls:
    df1 = pd.read_excel(xls, 'Sheet1')
    df2 = pd.read_excel(xls, 'Sheet2')
```

### Specifying sheets

**Note:** The second argument is `sheet_name`, not to be confused with `ExcelFile.sheet_names`.

**Note:** An `ExcelFile`’s attribute `sheet_names` provides access to a list of sheets.

- The arguments `sheet_name` allows specifying the sheet or sheets to read.
- The default value for `sheet_name` is 0, indicating to read the first sheet
- Pass a string to refer to the name of a particular sheet in the workbook.
- Pass an integer to refer to the index of a sheet. Indices follow Python convention, beginning at 0.
- Pass a list of either strings or integers, to return a dictionary of specified sheets.
- Pass a `None` to return a dictionary of all available sheets.

```python
# Returns a DataFrame

pd.read_excel('path_to_file.xls', 'Sheet1', index_col=None, na_values=['NA'])

Using the sheet index:

```python
# Returns a DataFrame

pd.read_excel('path_to_file.xls', 0, index_col=None, na_values=['NA'])

Using all default values:

```python
# Returns a DataFrame

pd.read_excel('path_to_file.xls')

Using None to get all sheets:
# Returns a dictionary of DataFrames
```python
pd.read_excel('path_to_file.xls', sheet_name=None)
```

Using a list to get multiple sheets:
```python
# Returns the 1st and 4th sheet, as a dictionary of DataFrames.
pd.read_excel('path_to_file.xls', sheet_name=['Sheet1', 3])
```

read_excel can read more than one sheet, by setting `sheet_name` to either a list of sheet names, a list of sheet positions, or `None` to read all sheets. Sheets can be specified by sheet index or sheet name, using an integer or string, respectively.

**Reading a MultiIndex**

read_excel can read a MultiIndex index, by passing a list of columns to `index_col` and a MultiIndex column by passing a list of rows to `header`. If either the index or columns have serialized level names those will be read in as well by specifying the rows/columns that make up the levels.

For example, to read in a MultiIndex index without names:

```python
In [316]: df = pd.DataFrame({'a': [1, 2, 3, 4], 'b': [5, 6, 7, 8]},
                       index=pd.MultiIndex.from_product([['a', 'b'], ['c', 'd']]))
In [317]: df.to_excel('path_to_file.xlsx')
In [318]: df = pd.read_excel('path_to_file.xlsx', index_col=[0, 1])
```

```python
In [319]: df
Out[319]:
   a  b
a c 1 5
d 2 6
b c 3 7
d 4 8
```

If the index has level names, they will parsed as well, using the same parameters.

```python
In [320]: df.index = df.index.set_names(['lvl1', 'lvl2'])
In [321]: df.to_excel('path_to_file.xlsx')
In [322]: df = pd.read_excel('path_to_file.xlsx', index_col=[0, 1])
```

```python
In [323]: df
Out[323]:
   lvl1  lvl2
a  c 1 5
   d 2 6
b  c 3 7
   d 4 8
```

If the source file has both MultiIndex index and columns, lists specifying each should be passed to `index_col` and `header`:

```python
2.4. IO tools (text, CSV, HDF5, …) 291
```
In [324]: df.columns = pd.MultiIndex.from_product([['a'], ['b', 'd']], names=['c1', 'c2'])
.....:
.....:

In [325]: df.to_excel('path_to_file.xlsx')

In [326]: df = pd.read_excel('path_to_file.xlsx', index_col=[0, 1], header=[0, 1])

In [327]: df
Out[327]:
    c1  a
    c2  b  d
  lvl1 lvl2
    a  c  1  5
d  2  6
    b  c  3  7
d  4  8

Parsing specific columns

It is often the case that users will insert columns to do temporary computations in Excel and you may not want to read in those columns. read_excel takes a usecols keyword to allow you to specify a subset of columns to parse.

Deprecated since version 0.24.0.

Passing in an integer for usecols has been deprecated. Please pass in a list of ints from 0 to usecols inclusive instead.

If usecols is an integer, then it is assumed to indicate the last column to be parsed.

You can also specify a comma-delimited set of Excel columns and ranges as a string:

You can also specify a comma-delimited set of Excel columns and ranges as a string:

If usecols is a list of integers, then it is assumed to be the file column indices to be parsed.

Element order is ignored, so usecols=[0, 1] is the same as [1, 0].

New in version 0.24.

If usecols is a list of strings, it is assumed that each string corresponds to a column name provided either by the user in names or inferred from the document header row(s). Those strings define which columns will be parsed:

Element order is ignored, so usecols=['baz', 'joe'] is the same as ['joe', 'baz'].

New in version 0.24.

If usecols is callable, the callable function will be evaluated against the column names, returning names where the callable function evaluates to True.
**Parsing dates**

Datetime-like values are normally automatically converted to the appropriate dtype when reading the excel file. But if you have a column of strings that *look* like dates (but are not actually formatted as dates in excel), you can use the `parse_dates` keyword to parse those strings to datetimes:

```python
pd.read_excel('path_to_file.xls', 'Sheet1', parse_dates=['date_strings'])
```

**Cell converters**

It is possible to transform the contents of Excel cells via the `converters` option. For instance, to convert a column to boolean:

```python
pd.read_excel('path_to_file.xls', 'Sheet1', converters={'MyBools': bool})
```

This option handles missing values and treats exceptions in the converters as missing data. Transformations are applied cell by cell rather than to the column as a whole, so the array dtype is not guaranteed. For instance, a column of integers with missing values cannot be transformed to an array with integer dtype, because NaN is strictly a float. You can manually mask missing data to recover integer dtype:

```python
def cfun(x):
    return int(x) if x else -1

pd.read_excel('path_to_file.xls', 'Sheet1', converters={'MyInts': cfun})
```

**Dtype specifications**

As an alternative to converters, the type for an entire column can be specified using the `dtype` keyword, which takes a dictionary mapping column names to types. To interpret data with no type inference, use the type `str` or `object`.

```python
pd.read_excel('path_to_file.xls', dtype={'MyInts': 'int64', 'MyText': str})
```

**Writing Excel files**

**Writing Excel files to disk**

To write a `DataFrame` object to a sheet of an Excel file, you can use the `to_excel` instance method. The arguments are largely the same as `to_csv` described above, the first argument being the name of the excel file, and the optional second argument the name of the sheet to which the `DataFrame` should be written. For example:

```python
df.to_excel('path_to_file.xlsx', sheet_name='Sheet1')
```

Files with a `.xls` extension will be written using `xlwt` and those with a `.xlsx` extension will be written using `xlsxwriter` (if available) or `openpyxl`.

The `DataFrame` will be written in a way that tries to mimic the REPL output. The `index_label` will be placed in the second row instead of the first. You can place it in the first row by setting the `merge_cells` option in `to_excel()` to `False`:
In order to write separate DataFrames to separate sheets in a single Excel file, one can pass an ExcelWriter.

```python
with pd.ExcelWriter('path_to_file.xlsx') as writer:
    df1.to_excel(writer, sheet_name='Sheet1')
    df2.to_excel(writer, sheet_name='Sheet2')
```

**Note:** Wringing a little more performance out of `read_excel` Internally, Excel stores all numeric data as floats. Because this can produce unexpected behavior when reading in data, pandas defaults to trying to convert integers to floats if it doesn’t lose information (1.0 --> 1). You can pass `convert_float=False` to disable this behavior, which may give a slight performance improvement.

---

**Writing Excel files to memory**

Pandas supports writing Excel files to buffer-like objects such as `StringIO` or `BytesIO` using ExcelWriter.

```python
from io import BytesIO

bio = BytesIO()

# By setting the 'engine' in the ExcelWriter constructor.
writer = pd.ExcelWriter(bio, engine='xlsxwriter')
df.to_excel(writer, sheet_name='Sheet1')

# Save the workbook
writer.save()

# Seek to the beginning and read to copy the workbook to a variable in memory
bio.seek(0)
workbook = bio.read()
```

**Note:** `engine` is optional but recommended. Setting the engine determines the version of workbook produced. Setting `engine='xlrd'` will produce an Excel 2003-format workbook (xls). Using either 'openpyxl' or 'xlsxwriter' will produce an Excel 2007-format workbook (xlsx). If omitted, an Excel 2007-formatted workbook is produced.

---

**Excel writer engines**

Pandas chooses an Excel writer via two methods:

1. the `engine` keyword argument
2. the filename extension (via the default specified in config options)

By default, pandas uses the `XlsxWriter` for `.xlsx`, `openpyxl` for `.xlsm`, and `xlwt` for `.xls` files. If you have multiple engines installed, you can set the default engine through `io.excel.xlsx.writer` and `io.excel.xls.writer`. pandas will fall back on `openpyxl` for `.xls` files if `Xlsxwriter` is not available.

To specify which writer you want to use, you can pass an engine keyword argument to `to_excel` and to `ExcelWriter`. The built-in engines are:
- openpyxl: version 2.4 or higher is required
- xlsxwriter
- xlwt

```python
# By setting the 'engine' in the DataFrame 'to_excel()' methods.
df.to_excel('path_to_file.xlsx', sheet_name='Sheet1', engine='xlsxwriter')

# By setting the 'engine' in the ExcelWriter constructor.
writer = pd.ExcelWriter('path_to_file.xlsx', engine='xlsxwriter')

# Or via pandas configuration.
from pandas import options  # noqa: E402
options.io.excel.xlsx.writer = 'xlsxwriter'
df.to_excel('path_to_file.xlsx', sheet_name='Sheet1')
```

**Style and formatting**

The look and feel of Excel worksheets created from pandas can be modified using the following parameters on the DataFrame's `to_excel` method.

- `float_format`: Format string for floating point numbers (default `None`).
- `freeze_panes`: A tuple of two integers representing the bottommost row and rightmost column to freeze. Each of these parameters is one-based, so `(1, 1)` will freeze the first row and first column (default `None`).

Using the `Xlsxwriter` engine provides many options for controlling the format of an Excel worksheet created with the `to_excel` method. Excellent examples can be found in the `Xlsxwriter` documentation here: https://xlsxwriter.readthedocs.io/working_with_pandas.html

### 2.4.5 OpenDocument Spreadsheets

New in version 0.25.

The `read_excel()` method can also read OpenDocument spreadsheets using the `odfpy` module. The semantics and features for reading OpenDocument spreadsheets match what can be done for Excel files using `engine='odf'`.

```python
# Returns a DataFrame
pd.read_excel('path_to_file.ods', engine='odf')
```

**Note:** Currently pandas only supports reading OpenDocument spreadsheets. Writing is not implemented.

### 2.4.6 Binary Excel (.xlsx) files

New in version 1.0.0.

The `read_excel()` method can also read binary Excel files using the `pyxlsb` module. The semantics and features for reading binary Excel files mostly match what can be done for Excel files using `engine='pyxlsb'`. `pyxlsb` does not recognize datetime types in files and will return floats instead.

```python
# Returns a DataFrame
pd.read_excel('path_to_file.xlsb', engine='pyxlsb')
```
Note: Currently pandas only supports reading binary Excel files. Writing is not implemented.

### 2.4.7 Clipboard

A handy way to grab data is to use the `read_clipboard()` method, which takes the contents of the clipboard buffer and passes them to the `read_csv` method. For instance, you can copy the following text to the clipboard (CTRL-C on many operating systems):

```
A  B  C
x 1  4 p
y 2  5 q
z 3  6 r
```

And then import the data directly to a DataFrame by calling:

```
>>> clipdf = pd.read_clipboard()
>>> clipdf
   A  B  C
  x 1  4 p
  y 2  5 q
  z 3  6 r
```

The `to_clipboard` method can be used to write the contents of a DataFrame to the clipboard. Following which you can paste the clipboard contents into other applications (CTRL-V on many operating systems). Here we illustrate writing a DataFrame into clipboard and reading it back.

```
>>> df = pd.DataFrame({'A': [1, 2, 3],
...                    'B': [4, 5, 6],
...                    'C': ['p', 'q', 'r']},
...                   index=['x', 'y', 'z'])
>>> df
   A  B  C
  x 1  4 p
  y 2  5 q
  z 3  6 r
>>> df.to_clipboard()
>>> pd.read_clipboard()
   A  B  C
  x 1  4 p
  y 2  5 q
  z 3  6 r
```

We can see that we got the same content back, which we had earlier written to the clipboard.

Note: You may need to install xclip or xsel (with PyQt5, PyQt4 or qtpy) on Linux to use these methods.
2.4.8 Pickling

All pandas objects are equipped with `to_pickle` methods which use Python’s cPickle module to save data structures to disk using the pickle format.

```python
In [328]: df
Out[328]:
c1 a
c2 b d
lvl1 lvl2
  a  c  1  5
      d  2  6
  b  c  3  7
      d  4  8
In [329]: df.to_pickle('foo.pkl')
```

The `read_pickle` function in the `pandas` namespace can be used to load any pickled pandas object (or any other pickled object) from file:

```python
In [330]: pd.read_pickle('foo.pkl')
Out[330]:
c1 a
  c2 b d
lvl1 lvl2
  a  c  1  5
      d  2  6
  b  c  3  7
      d  4  8
```

**Warning:** Loading pickled data received from untrusted sources can be unsafe.
See: https://docs.python.org/3/library/pickle.html

**Warning:** `read_pickle()` is only guaranteed backwards compatible back to pandas version 0.20.3

**Compressed pickle files**

`read_pickle()`, `DataFrame.to_pickle()` and `Series.to_pickle()` can read and write compressed pickle files. The compression types of gzip, bz2, xz are supported for reading and writing. The zip file format only supports reading and must contain only one data file to be read.

The compression type can be an explicit parameter or be inferred from the file extension. If `infer`, then use gzip, bz2, zip, or xz if filename ends in `.gz`, `.bz2`, `.zip`, or `.xz`, respectively.

The compression parameter can also be a `dict` in order to pass options to the compression protocol. It must have a 'method' key set to the name of the compression protocol, which must be one of {'zip', 'gzip', 'bz2'}. All other key-value pairs are passed to the underlying compression library.

```python
In [331]: df = pd.DataFrame({
        'A': np.random.randn(1000),
        'B': 'foo',
        ...
        'C': pd.date_range('20130101', periods=1000, freq='s'))
(continues on next page)
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

(continued from previous page)

.....:

In [332]: df
Out[332]:
   A         B         C
0 -0.288267  foo 2013-01-01 00:00:00
1 -0.084905  foo 2013-01-01 00:00:01
2  0.004772  foo 2013-01-01 00:00:02
3  1.382989  foo 2013-01-01 00:00:03
4  0.343635  foo 2013-01-01 00:00:04
... ... ... ...
995 -0.220893 foo 2013-01-01 00:16:35
996  0.492996 foo 2013-01-01 00:16:36
997 -0.461625 foo 2013-01-01 00:16:37
998  1.361779 foo 2013-01-01 00:16:38
999 -1.197988 foo 2013-01-01 00:16:39
[1000 rows x 3 columns]

Using an explicit compression type:

In [333]: df.to_pickle("data.pkl.compress", compression="gzip")
In [334]: rt = pd.read_pickle("data.pkl.compress", compression="gzip")
In [335]: rt
Out[335]:
   A         B         C
0 -0.288267  foo 2013-01-01 00:00:00
1 -0.084905  foo 2013-01-01 00:00:01
2  0.004772  foo 2013-01-01 00:00:02
3  1.382989  foo 2013-01-01 00:00:03
4  0.343635  foo 2013-01-01 00:00:04
... ... ... ...
995 -0.220893 foo 2013-01-01 00:16:35
996  0.492996 foo 2013-01-01 00:16:36
997 -0.461625 foo 2013-01-01 00:16:37
998  1.361779 foo 2013-01-01 00:16:38
999 -1.197988 foo 2013-01-01 00:16:39
[1000 rows x 3 columns]

Inferring compression type from the extension:

In [336]: df.to_pickle("data.pkl.xz", compression="infer")
In [337]: rt = pd.read_pickle("data.pkl.xz", compression="infer")
In [338]: rt
Out[338]:
   A         B         C
0 -0.288267  foo 2013-01-01 00:00:00
1 -0.084905  foo 2013-01-01 00:00:01
2  0.004772  foo 2013-01-01 00:00:02
3  1.382989  foo 2013-01-01 00:00:03
4  0.343635  foo 2013-01-01 00:00:04
... ... ... ...
995 -0.220893 foo 2013-01-01 00:16:35
996  0.492996 foo 2013-01-01 00:16:36
997 -0.461625 foo 2013-01-01 00:16:37
998  1.361779 foo 2013-01-01 00:16:38
999 -1.197988 foo 2013-01-01 00:16:39
[1000 rows x 3 columns]
The default is to ‘infer’:

```python
In [339]: df.to_pickle("data.pkl.gz")
In [340]: rt = pd.read_pickle("data.pkl.gz")
In [341]: rt
Out[341]:
   A     B     C
0 -0.288  foo 2013-01-01 00:00:00
1 -0.084  foo 2013-01-01 00:00:01
2  0.005  foo 2013-01-01 00:00:02
3  1.383  foo 2013-01-01 00:00:03
4  0.343  foo 2013-01-01 00:00:04
... ... ... ...
995 -0.221  foo 2013-01-01 00:16:35
996  0.493  foo 2013-01-01 00:16:36
997 -0.462  foo 2013-01-01 00:16:37
998  1.362  foo 2013-01-01 00:16:38
999 -1.198  foo 2013-01-01 00:16:39
[1000 rows x 3 columns]
```

```python
In [342]: df["A"].to_pickle("s1.pkl.bz2")
In [343]: rt = pd.read_pickle("s1.pkl.bz2")
In [344]: rt
Out[344]:
   A
0 -0.288
1 -0.084
2  0.005
3  1.383
4  0.343
... ...
995 -0.221
996  0.493
997 -0.462
998  1.362
999 -1.198
Name: A, Length: 1000, dtype: float64
```

Passing options to the compression protocol in order to speed up compression:

```python
In [345]: df.to_pickle(
                  .....:       "data.pkl.gz",
                  .....:       compression={"method": "gzip", 'compresslevel': 1}
                  .....: )
```

2.4. IO tools (text, CSV, HDF5, ...)
2.4.9 msgpack

Pandas support for msgpack has been removed in version 1.0.0. It is recommended to use pyarrow for on-the-wire transmission of pandas objects.

Example pyarrow usage:

```python
>>> import pandas as pd
>>> import pyarrow as pa

>>> df = pd.DataFrame({'A': [1, 2, 3]})
>>> context = pa.default_serialization_context()
>>> df_bytestring = context.serialize(df).to_buffer().to_pybytes()
```

For documentation on pyarrow, see here.

2.4.10 HDF5 (PyTables)

HDFStore is a dict-like object which reads and writes pandas using the high performance HDF5 format using the excellent PyTables library. See the cookbook for some advanced strategies.

**Warning:** Pandas uses PyTables for reading and writing HDF5 files, which allows serializing object-dtype data with pickle. Loading pickled data received from untrusted sources can be unsafe.

See: https://docs.python.org/3/library/pickle.html for more.

In [346]: store = pd.HDFStore('store.h5')

In [347]: print(store)
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5

Objects can be written to the file just like adding key-value pairs to a dict:

In [348]: index = pd.date_range('1/1/2000', periods=8)


In [350]: df = pd.DataFrame(np.random.randn(8, 3), index=index,
.....:
column=[‘A’, ‘B’, ‘C’])
.....:

# store.put(‘s’, s) is an equivalent method
In [351]: store[‘s’] = s

In [352]: store[‘df’] = df

In [353]: store
Out[353]:
<class ‘pandas.io.pytables.HDFStore’>
File path: store.h5

In a current or later Python session, you can retrieve stored objects:

# store.get(‘df’) is an equivalent method
In [354]: store[‘df’]
Out[345]:

<table>
<thead>
<tr>
<th>Date</th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01</td>
<td>1.334065</td>
<td>0.521036</td>
<td>0.930384</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>-1.613932</td>
<td>1.088104</td>
<td>-0.632963</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>-0.585314</td>
<td>-0.275038</td>
<td>-0.937512</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>0.632369</td>
<td>-1.249657</td>
<td>0.975593</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>1.060617</td>
<td>-0.143682</td>
<td>0.218423</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>3.050329</td>
<td>1.317933</td>
<td>-0.963725</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>-0.539452</td>
<td>-0.771133</td>
<td>0.023751</td>
</tr>
<tr>
<td>2000-01-08</td>
<td>0.649464</td>
<td>-1.736427</td>
<td>0.197288</td>
</tr>
</tbody>
</table>

# dotted (attribute) access provides get as well
In [355]: store.df
Out[355]:

<table>
<thead>
<tr>
<th>Date</th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01</td>
<td>1.334065</td>
<td>0.521036</td>
<td>0.930384</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>-1.613932</td>
<td>1.088104</td>
<td>-0.632963</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>-0.585314</td>
<td>-0.275038</td>
<td>-0.937512</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>0.632369</td>
<td>-1.249657</td>
<td>0.975593</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>1.060617</td>
<td>-0.143682</td>
<td>0.218423</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>3.050329</td>
<td>1.317933</td>
<td>-0.963725</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>-0.539452</td>
<td>-0.771133</td>
<td>0.023751</td>
</tr>
<tr>
<td>2000-01-08</td>
<td>0.649464</td>
<td>-1.736427</td>
<td>0.197288</td>
</tr>
</tbody>
</table>

Deletion of the object specified by the key:

# store.remove('df') is an equivalent method
In [356]: del store['df']
In [357]: store
Out[357]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5

Closing a Store and using a context manager:

In [358]: store.close()
In [359]: store
Out[359]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
In [360]: store.is_open
Out[360]: False

# Working with, and automatically closing the store using a context manager
In [361]: with pd.HDFStore('store.h5') as store:
      ...:     store.keys()
      ...:
Read/write API

HDFStore supports a top-level API using read_hdf for reading and to_hdf for writing, similar to how read_csv and to_csv work.

```python
In [362]: df_t1 = pd.DataFrame({'A': list(range(5)), 'B': list(range(5)))

In [363]: df_t1.to_hdf('store_t1.h5', 'table', append=True)

In [364]: pd.read_hdf('store_t1.h5', 'table', where='index>2')
Out[364]:
   A  B
0  0  0
1  1  1
2  2  2
3  3  3
4  4  4
```

HDFStore will by default not drop rows that are all missing. This behavior can be changed by setting dropna=True.

```python
In [365]: df_with_missing = pd.DataFrame({'col1': [0, np.nan, 2], 'col2': [1, np.nan, np.nan]})

In [366]: df_with_missing
Out[366]:
   col1  col2
0    0.0  1.0
1   NaN   NaN
2    2.0   NaN

In [367]: df_with_missing.to_hdf('file.h5', 'df_with_missing', format='table', mode='w')

In [368]: pd.read_hdf('file.h5', 'df_with_missing')
Out[368]:
   col1  col2
0    0.0  1.0
1   NaN   NaN
2    2.0   NaN

In [369]: df_with_missing.to_hdf('file.h5', 'df_with_missing', format='table', mode='w', dropna=True)

In [370]: pd.read_hdf('file.h5', 'df_with_missing')
Out[370]:
   col1  col2
0    0.0  1.0
1   NaN   NaN
2    2.0   NaN
```
Fixed format

The examples above show storing using `put`, which write the HDF5 to PyTables in a fixed array format, called the fixed format. These types of stores are **not** appendable once written (though you can simply remove them and rewrite). Nor are they queryable; they must be retrieved in their entirety. They also do not support dataframes with non-unique column names. The fixed format stores offer very fast writing and slightly faster reading than table stores. This format is specified by default when using `put` or `to_hdf` or by `format='fixed'` or `format='f'`.

**Warning:** A fixed format will raise a `TypeError` if you try to retrieve using a `where`:

```
>>> pd.DataFrame(np.random.randn(10, 2)).to_hdf('test_fixed.h5', 'df')
>>> pd.read_hdf('test_fixed.h5', 'df', where='index>5')
TypeError: cannot pass a where specification when reading a fixed format.
```

Table format

HDFStore supports another PyTables format on disk, the table format. Conceptually a table is shaped very much like a DataFrame, with rows and columns. A table may be appended to in the same or other sessions. In addition, delete and query type operations are supported. This format is specified by `format='table'` or `format='t'` to append or `put` or `to_hdf`.

This format can be set as an option as well `pd.set_option('io.hdf.default_format','table')` to enable `put/append/to_hdf` to by default store in the table format.

```python
In [371]: store = pd.HDFStore('store.h5')
In [372]: df1 = df[0:4]
In [373]: df2 = df[4:]

# append data (creates a table automatically)
In [374]: store.append('df', df1)
In [375]: store.append('df', df2)

In [376]: store
Out[376]: <class 'pandas.io.pytables.HDFStore'>
File path: store.h5

# select the entire object
In [377]: store.select('df')
Out[377]:
   A      B      C
0  2000-01-01 1.334065  0.521036  0.930384
1  2000-01-02 -1.613932  1.088104 -0.632963
2  2000-01-03 -0.585314 -0.275038 -0.937512
3  2000-01-04  0.632369 -1.249657  0.975593
4  2000-01-05  1.060617 -0.143682  0.218423
5  2000-01-06  3.050329  1.317933 -0.963725
6  2000-01-07 -0.539452 -0.771133  0.023751
7  2000-01-08  0.649464 -1.736427  0.197288

# the type of stored data
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

In [378]: store.root.df._v_attrs.pandas_type
Out[378]: 'frame_table'

**Note:** You can also create a table by passing format='table' or format='t' to a put operation.

### Hierarchical keys

Keys to a store can be specified as a string. These can be in a hierarchical path-name like format (e.g. `foo/bar/bah`), which will generate a hierarchy of sub-stores (or Groups in PyTables parlance). Keys can be specified without the leading '/' and are always absolute (e.g. 'foo' refers to '/foo'). Removal operations can remove everything in the sub-store and below, so be careful.

In [379]: store.put('foo/bar/bah', df)
In [380]: store.append('food/orange', df)
In [381]: store.append('food/apple', df)
In [382]: store
Out[382]: <class 'pandas.io.pytables.HDFStore'>
File path: store.h5

# a list of keys are returned
In [383]: store.keys()
Out[383]: ['/df', '/food/apple', '/food/orange', '/foo/bar/bah']

# remove all nodes under this level
In [384]: store.remove('food')

In [385]: store
Out[385]: <class 'pandas.io.pytables.HDFStore'>
File path: store.h5

You can walk through the group hierarchy using the `walk` method which will yield a tuple for each group key along with the relative keys of its contents.

New in version 0.24.0.

In [386]: for (path, subgroups, subkeys) in store.walk():
       ....:     for subgroup in subgroups:
       ....:         print('GROUP: {}:'.format(path), subgroup)
       ....:     for subkey in subkeys:
       ....:         key = '/'.join([path, subkey])
       ....:         print('KEY: {}:'.format(key))
       ....:         print(store.get(key))
GROUP: /foo
KEY: /df

A  B  C
--- --- ---
2000-01-01 1.334065 0.521036 0.930384
2000-01-02 -1.613932 1.088104 -0.632963
GROUP: /foo/bar
KEY: /foo/bar/bah

<table>
<thead>
<tr>
<th>Date</th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01</td>
<td>1.334065</td>
<td>0.521036</td>
<td>0.930384</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>-1.613932</td>
<td>1.088104</td>
<td>-0.632963</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>-0.585314</td>
<td>-0.275038</td>
<td>-0.937512</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>0.632369</td>
<td>-1.249657</td>
<td>0.975593</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>1.060617</td>
<td>-0.143682</td>
<td>0.218423</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>3.050329</td>
<td>1.317933</td>
<td>-0.963725</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>-0.539452</td>
<td>-0.771133</td>
<td>0.023751</td>
</tr>
<tr>
<td>2000-01-08</td>
<td>0.649464</td>
<td>-1.736427</td>
<td>0.197288</td>
</tr>
</tbody>
</table>

**Warning:** Hierarchical keys cannot be retrieved as dotted (attribute) access as described above for items stored under the root node.

```
In [8]: store.foo.bar.bah
AttributeError: 'HDFStore' object has no attribute 'foo'
```

# you can directly access the actual PyTables node but using the root node
```
In [9]: store.root.foo.bar.bah
```

```
/foo/bar/bah (Group) ''
    children := ['block0_items' (Array), 'block0_values' (Array), 'axis0' (Array), ...
                  'axis1' (Array)]
```

Instead, use explicit string based keys:

```
In [387]: store['foo/bar/bah']
```

```
Out[387]:
```

<table>
<thead>
<tr>
<th>Date</th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01</td>
<td>1.334065</td>
<td>0.521036</td>
<td>0.930384</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>-1.613932</td>
<td>1.088104</td>
<td>-0.632963</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>-0.585314</td>
<td>-0.275038</td>
<td>-0.937512</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>0.632369</td>
<td>-1.249657</td>
<td>0.975593</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>1.060617</td>
<td>-0.143682</td>
<td>0.218423</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>3.050329</td>
<td>1.317933</td>
<td>-0.963725</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>-0.539452</td>
<td>-0.771133</td>
<td>0.023751</td>
</tr>
<tr>
<td>2000-01-08</td>
<td>0.649464</td>
<td>-1.736427</td>
<td>0.197288</td>
</tr>
</tbody>
</table>

2.4. IO tools (text, CSV, HDF5, …)
Storing types

Storing mixed types in a table

Storing mixed-dtype data is supported. Strings are stored as a fixed-width using the maximum size of the appended column. Subsequent attempts at appending longer strings will raise a `ValueError`.

Passing `min_itemsize=dict(values=size)` as a parameter to `append` will set a larger minimum for the string columns. Storing floats, strings, ints, bools, `datetime64` are currently supported. For string columns, passing `nan_rep='nan'` to `append` will change the default `nan` representation on disk (which converts to/from `np.nan`), this defaults to `nan`.

```python
In [388]: df_mixed = pd.DataFrame({'A': np.random.randn(8),
                              'B': np.random.randn(8),
                              'C': np.array(np.random.randn(8), dtype='float32'),
                              'string': 'string',
                              'int': 1,
                              'bool': True,
                              'datetime64': pd.Timestamp('20010102')},
                              index=list(range(8)))

In [389]: df_mixed.loc[df_mixed.index[3:5], ['A', 'B', 'string', 'datetime64']] = np.nan

In [390]: store.append('df_mixed', df_mixed, min_itemsize=dict(values=50))

In [391]: df_mixed1 = store.select('df_mixed')

In [392]: df_mixed1
Out[392]:
     A      B     C    string   int   bool  datetime64
0  0.852727  0.463819  NaN         NaN  1.0   True    2001-01-02
1  1.236988  0.221252  NaN         NaN  1.0   True    2001-01-02
2  1.464930  0.146262  NaN         NaN  1.0   True    2001-01-02
3  1.282735  0.839473  NaN         NaN  1.0   True    2001-01-02
4  1.171605  0.793644  NaN         NaN  1.0   True    2001-01-02
5 -0.116008  0.743946  NaN         NaN  1.0   True    2001-01-02
6  1.994519  0.229933  NaN         NaN  1.0   True    2001-01-02
7 -0.050987  0.377756  NaN         NaN  1.0   True    2001-01-02

In [393]: df_mixed1.dtypes.value_counts()
Out[393]:
float64       2
datetime64[ns] 1
int64         1
bool          1
float32       1
object        1
dtype: int64
```

# we have provided a minimum string column size

```python
In [394]: store.root.df_mixed.table
Out[394]:
/df_mixed/table (Table(8,)) ''

description := {
```
(continues on next page)
Storing MultiIndex DataFrames

Storing MultiIndex DataFrames as tables is very similar to storing/selecting from homogeneous index DataFrames.

```python
In [395]: index = pd.MultiIndex(levels=[[['foo', 'bar', 'baz', 'qux'],
       ['one', 'two', 'three']],
       codes=[[0, 0, 0, 1, 1, 2, 2, 3, 3, 3],
       [0, 1, 2, 0, 1, 1, 2, 0, 1, 2]],
       names=['foo', 'bar'])

In [396]: df_mi = pd.DataFrame(np.random.randn(10, 3), index=index,
                                   columns=['A', 'B', 'C'])

In [397]: df_mi
Out[397]:
            A         B         C
foo bar
foo one  0.667450  0.169405 -1.358046
two -0.105563  0.492195  0.076693
three  0.213685 -0.285283 -1.210529
bar one -1.408386  0.941577 -0.342447
two  0.222031  0.052607  2.093214
baz two  1.064908  1.778161 -0.913867
three -0.030004 -0.399846 -1.234765
qux one  0.081323 -0.268494  0.168016
two -0.898283 -0.218499  1.408028
three -1.267828 -0.689263  0.520995

In [398]: store.append('df_mi', df_mi)

In [399]: store.select('df_mi')
Out[399]:
            A         B         C
foo bar
foo one  0.667450  0.169405 -1.358046
two -0.105563  0.492195  0.076693
three  0.213685 -0.285283 -1.210529
bar one -1.408386  0.941577 -0.342447
two  0.222031  0.052607  2.093214
```
### Querying

#### Querying a table

`select` and `delete` operations have an optional criterion that can be specified to select/delete only a subset of the data. This allows one to have a very large on-disk table and retrieve only a portion of the data.

A query is specified using the `Term` class under the hood, as a boolean expression.

- `index` and `columns` are supported indexers of DataFrames.
- If `data_columns` are specified, these can be used as additional indexers.
- Level name in a MultiIndex, with default name `level_0`, `level_1`, ... if not provided.

Valid comparison operators are:

```
=, ==, !=, >, >=, <, <=
```

Valid boolean expressions are combined with:

```
|: or
\&: and
\(: for grouping
```

These rules are similar to how boolean expressions are used in pandas for indexing.

**Note:**

- `=` will be automatically expanded to the comparison operator `==`
- ~ is the not operator, but can only be used in very limited circumstances
- If a list/tuple of expressions is passed they will be combined via \&

The following are valid expressions:

```
'index >= date'
"columns = ['A', 'D']"
```
• "columns in ['A', 'D']"
• 'columns = A'
• 'columns == A'
• "~(columns = ['A', 'B'])"
• 'index > df.index[3] & string = "bar"'
• '(index > df.index[3] & index <= df.index[6]) | string = "bar"'
• "ts >= Timestamp('2012-02-01')"
• "major_axis>=20130101"

The indexers are on the left-hand side of the sub-expression:
columns, major_axis, ts

The right-hand side of the sub-expression (after a comparison operator) can be:
• functions that will be evaluated, e.g. Timestamp('2012-02-01')
• strings, e.g. "bar"
• date-like, e.g. 20130101, or "20130101"
• lists, e.g. "['A', 'B']"
• variables that are defined in the local names space, e.g. date

Note: Passing a string to a query by interpolating it into the query expression is not recommended. Simply assign the string of interest to a variable and use that variable in an expression. For example, do this

```python
string = "HolyMoly"
store.select('df', 'index == string')
```

instead of this

```python
string = "HolyMoly"
store.select('df', f'index == {string}')
```

The latter will not work and will raise a SyntaxError. Note that there’s a single quote followed by a double quote in the string variable.

If you must interpolate, use the \"%r\" format specifier

```python
store.select('df', 'index == %r % string)
```

which will quote string.

Here are some examples:

```python
In [401]: dfq = pd.DataFrame(np.random.randn(10, 4), columns=list('ABCD'),
                        index=pd.date_range('20130101', periods=10))
```
```python
...:
```
```python
In [402]: store.append('dfq', dfq, format='table', data_columns=True)
```

Use boolean expressions, with in-line function evaluation.
In [403]: store.select('dfq', "index>pd.Timestamp('20130104') & columns=['A', 'B']")
Out[403]:
   A      B
2013-01-05 -1.083889  0.811865
2013-01-06 -0.402227  1.618922
2013-01-07  0.948196  0.183573
2013-01-08 -1.043530 -0.708145
2013-01-09  0.813949  1.508891
2013-01-10  1.176488 -1.246093

Use inline column reference.

In [404]: store.select('dfq', where="A>0 or C>0")
Out[404]:
   A  B  C     D
2013-01-01  0.620028 0.159416 -0.263043 -0.639244
2013-01-04 -0.536722 1.005707  0.296917  0.139796
2013-01-05 -1.083889 0.811865  1.648435 -0.164377
2013-01-07  0.948196 0.183573  0.145277  0.308146
2013-01-08 -1.043530 -0.708145  1.430905 -0.850136
2013-01-09  0.813949 1.508891 -1.556154  0.187597
2013-01-10  1.176488 -1.246093 -0.002726 -0.444249

The columns keyword can be supplied to select a list of columns to be returned, this is equivalent to passing a 'columns=list_of_columns_to_filter':

In [405]: store.select('df', "columns=['A', 'B']")
Out[405]:
   A      B
2000-01-01  1.334065  0.521036
2000-01-02 -1.613932  1.088104
2000-01-03 -0.585314 -0.275038
2000-01-04  0.632369 -1.249657
2000-01-05  1.060617 -0.143682
2000-01-06  3.050329  1.317933
2000-01-07 -0.539452 -0.771133
2000-01-08  0.649464 -1.736427

start and stop parameters can be specified to limit the total search space. These are in terms of the total number of rows in a table.

**Note:** select will raise a ValueError if the query expression has an unknown variable reference. Usually this means that you are trying to select on a column that is not a data_column.

select will raise a SyntaxError if the query expression is not valid.
Query `timedelta64[ns]`

You can store and query using the `timedelta64[ns]` type. Terms can be specified in the format: `<float>(<unit>)`, where float may be signed (and fractional), and unit can be D, s, ms, us, ns for the timedelta. Here’s an example:

```python
In [406]: from datetime import timedelta
In [407]: dftd = pd.DataFrame({
                        'A': pd.Timestamp('20130101'),
                        'B': [pd.Timestamp('20130101') + timedelta(days=i, seconds=10) for i in range(10)]})
In [408]: dftd['C'] = dftd['A'] - dftd['B']

In [409]: dftd
Out[409]:
          A                B                C
0 2013-01-01  00:00:10 -1 days 23:59:50
1 2013-01-01  00:00:10 -2 days 23:59:50
2 2013-01-01  00:00:10 -3 days 23:59:50
3 2013-01-01  00:00:10 -4 days 23:59:50
4 2013-01-01  00:00:10 -5 days 23:59:50
5 2013-01-01  00:00:10 -6 days 23:59:50
6 2013-01-01  00:00:10 -7 days 23:59:50
7 2013-01-01  00:00:10 -8 days 23:59:50
8 2013-01-01  00:00:10 -9 days 23:59:50
9 2013-01-01  00:00:10 -10 days 23:59:50

In [410]: store.append('dftd', dftd, data_columns=True)
In [411]: store.select('dftd', "C<-'-3.5D'")
Out[411]:
          A                B                C
4 2013-01-01  00:00:10 -5 days 23:59:50
5 2013-01-01  00:00:10 -6 days 23:59:50
6 2013-01-01  00:00:10 -7 days 23:59:50
7 2013-01-01  00:00:10 -8 days 23:59:50
8 2013-01-01  00:00:10 -9 days 23:59:50
9 2013-01-01  00:00:10 -10 days 23:59:50

In [412]: store.append('dftd', dftd, data_columns=True)
In [413]: store.select('dftd', "C<-'-3.5D'")
Out[413]:
          A                B                C
4 2013-01-01  00:00:10 -5 days 23:59:50
5 2013-01-01  00:00:10 -6 days 23:59:50
6 2013-01-01  00:00:10 -7 days 23:59:50
7 2013-01-01  00:00:10 -8 days 23:59:50
8 2013-01-01  00:00:10 -9 days 23:59:50
9 2013-01-01  00:00:10 -10 days 23:59:50

Query MultiIndex

Selecting from a MultiIndex can be achieved by using the name of the level.

```python
In [412]: df_mi.index.names
Out[412]: FrozenList(['foo', 'bar'])

In [413]: store.select('df_mi', "foo=baz and bar=two")
Out[413]:
        A        B        C
foo bar  1.064908  1.778161 -0.913867
baz two  1.064908  1.778161 -0.913867
```

If the MultiIndex levels names are None, the levels are automatically made available via the level_n keyword.
with n the level of the MultiIndex you want to select from.

```python
In [414]: index = pd.MultiIndex(
    ....:     levels=["foo", "bar", "baz", "qux"], ["one", "two", "three"],
    ....:     codes=[[0, 0, 0, 1, 1, 2, 2, 3, 3, 3], [0, 1, 2, 0, 1, 1, 2, 0, 1, 2]],
    ....: )

In [415]: df_mi_2 = pd.DataFrame(np.random.randn(10, 3),
    ....:     index=index, columns=["A", "B", "C"])

In [416]: df_mi_2
Out[416]:
       A       B       C
foo one  0.8568  1.4917  0.0013
  two    0.7018 -1.0979  0.1026
  three  0.6617  0.4435  0.5593
bar one  0.4591 -1.2226  0.5533
  two    0.7811  0.8262  0.5300
baz two  0.2961  1.3668  0.0737
  three -0.9949  0.7553  2.1197
qux one  2.6282 -0.0895 -0.1336
  two   -0.3379  0.6430  0.4211
  three  0.6043  1.0534  1.1090

In [417]: store.append("df_mi_2", df_mi_2)

# the levels are automatically included as data columns with keyword level_n
In [418]: store.select("df_mi_2", "level_0=foo and level_1=two")
Out[418]:
       A       B       C
foo two  0.7018 -1.0979  0.1026

Indexing

You can create/modify an index for a table with `create_table_index` after data is already in the table (after and append/put operation). Creating a table index is highly encouraged. This will speed your queries a great deal when you use a select with the indexed dimension as the where.

Note: Indexes are automagically created on the indexables and any data columns you specify. This behavior can be turned off by passing `index=False` to `append`.

# we have automagically already created an index (in the first section)
In [419]: i = store.root.df.table.cols.index.index

In [420]: i.optlevel, i.kind
Out[420]: (6, 'medium')

# change an index by passing new parameters
In [421]: store.create_table_index('df', optlevel=9, kind='full')

In [422]: i = store.root.df.table.cols.index.index
```

(continues on next page)
Oftentimes when appending large amounts of data to a store, it is useful to turn off index creation for each append, then recreate at the end.

```
In [424]: df_1 = pd.DataFrame(np.random.randn(10, 2), columns=list('AB'))
In [425]: df_2 = pd.DataFrame(np.random.randn(10, 2), columns=list('AB'))
In [426]: st = pd.HDFStore('appends.h5', mode='w')
In [427]: st.append('df', df_1, data_columns=['B'], index=False)
In [428]: st.append('df', df_2, data_columns=['B'], index=False)
In [429]: st.get_storer('df').table
```

```
Out[429]:
/df/table (Table(20,)) ''
    description := {
        "index": Int64Col(shape=(), dflt=0, pos=0),
        "values_block_0": Float64Col(shape=(1,), dflt=0.0, pos=1),
        "B": Float64Col(shape=(), dflt=0.0, pos=2)}
    byteorder := 'little'
    chunkshape := (2730,)
```

Then create the index when finished appending.

```
In [430]: st.create_table_index('df', columns=['B'], optlevel=9, kind='full')
In [431]: st.get_storer('df').table
```

```
Out[431]:
/df/table (Table(20,)) ''
    description := {
        "index": Int64Col(shape=(), dflt=0, pos=0),
        "values_block_0": Float64Col(shape=(1,), dflt=0.0, pos=1),
        "B": Float64Col(shape=(), dflt=0.0, pos=2)}
    byteorder := 'little'
    chunkshape := (2730,)
    autoindex := True
    colindexes := {
        "B": Index(9, full, shuffle, zlib(1)).is_csi=True}
```

See here for how to create a completely-sorted-index (CSI) on an existing store.
Query via data columns

You can designate (and index) certain columns that you want to be able to perform queries (other than the indexable columns, which you can always query). For instance say you want to perform this common operation, on-disk, and return just the frame that matches this query. You can specify data_columns = True to force all columns to be data_columns.

```python
In [433]: df_dc = df.copy()
In [434]: df_dc['string'] = 'foo'
In [435]: df_dc.loc[df_dc.index[4:6], 'string'] = np.nan
In [436]: df_dc.loc[df_dc.index[7:9], 'string'] = 'bar'
In [437]: df_dc['string2'] = 'cool'
In [438]: df_dc.loc[df_dc.index[1:3], ['B', 'C']] = 1.0
```

```latex
\begin{verbatim}
Out[439]:
\begin{tabular}{cccccc}
  A & B & C & string & string2 \\
  \hline
  2000-01-01 & 1.334065 & 0.521036 & 0.930384 & foo & cool \\
  2000-01-02 & -1.613932 & 1.000000 & 1.000000 & foo & cool \\
  2000-01-03 & -0.585314 & 1.000000 & 1.000000 & foo & cool \\
  2000-01-04 & 0.632369 & -1.249657 & 0.975593 & foo & cool \\
  2000-01-05 & 1.060617 & -0.143682 & 0.218423 & NaN & cool \\
  2000-01-06 & 3.050329 & 1.317933 & -0.963725 & NaN & cool \\
  2000-01-07 & -0.539452 & -0.771133 & 0.023751 & foo & cool \\
  2000-01-08 & 0.649464 & -1.736427 & 0.197288 & bar & cool \\
\end{tabular}
\end{verbatim}
```

# on-disk operations

```python
In [440]: store.append('df_dc', df_dc, data_columns=['B', 'C', 'string', 'string2'])
```

```python
In [441]: store.select('df_dc', where='B > 0')
```

```latex
\begin{verbatim}
Out[441]:
\begin{tabular}{cccccc}
  A & B & C & string & string2 \\
  \hline
  2000-01-01 & 1.334065 & 0.521036 & 0.930384 & foo & cool \\
  2000-01-02 & -1.613932 & 1.000000 & 1.000000 & foo & cool \\
  2000-01-03 & -0.585314 & 1.000000 & 1.000000 & foo & cool \\
  2000-01-06 & 3.050329 & 1.317933 & -0.963725 & NaN & cool \\
\end{tabular}
\end{verbatim}
```

# getting creative

```python
In [442]: store.select('df_dc', 'B > 0 & C > 0 & string == foo')
```

```latex
\begin{verbatim}
Out[442]:
\begin{tabular}{cccccc}
  A & B & C & string & string2 \\
  \hline
  2000-01-01 & 1.334065 & 0.521036 & 0.930384 & foo & cool \\
  2000-01-02 & -1.613932 & 1.000000 & 1.000000 & foo & cool \\
  2000-01-03 & -0.585314 & 1.000000 & 1.000000 & foo & cool \\
  2000-01-06 & 3.050329 & 1.317933 & -0.963725 & NaN & cool \\
\end{tabular}
\end{verbatim}
```

# this is in-memory version of this type of selection

```python
In [443]: df_dc[(df_dc.B > 0) & (df_dc.C > 0) & (df_dc.string == 'foo')]
```

```latex
\begin{verbatim}
Out[443]:
\begin{tabular}{cccccc}
  A & B & C & string & string2 \\
  \hline
  2000-01-01 & 1.334065 & 0.521036 & 0.930384 & foo & cool \\
  2000-01-02 & -1.613932 & 1.000000 & 1.000000 & foo & cool \\
  2000-01-03 & -0.585314 & 1.000000 & 1.000000 & foo & cool \\
\end{tabular}
\end{verbatim}
```

(continues on next page)
# we have automagically created this index and the B/C/string/string2 columns

In [444]: store.root.df_dc.table

Out[444]:
/df_dc/table (Table(8,)) ''

description := {
    "index": Int64Col(shape=(), dflt=0, pos=0),
    "values_block_0": Float64Col(shape=(1,), dflt=0.0, pos=1),
    "B": Float64Col(shape=(), dflt=0.0, pos=2),
    "C": Float64Col(shape=(), dflt=0.0, pos=3),
    "string": StringCol(itemsize=3, shape=(), dflt=b'', pos=4),
    "string2": StringCol(itemsize=4, shape=(), dflt=b'', pos=5)
}
yteorder := 'little'
cunkshape := (1680,)
autoindex := True
colindexes := {
    "index": Index(6, medium, shuffle, zlib(1)).is_csi=False,
    "B": Index(6, medium, shuffle, zlib(1)).is_csi=False,
    "C": Index(6, medium, shuffle, zlib(1)).is_csi=False,
    "string": Index(6, medium, shuffle, zlib(1)).is_csi=False,
    "string2": Index(6, medium, shuffle, zlib(1)).is_csi=False
}

There is some performance degradation by making lots of columns into data columns, so it is up to the user to designate these. In addition, you cannot change data columns (nor indexables) after the first append/put operation (Of course you can simply read in the data and create a new table!).

**Iterator**

You can pass iterator=True or chunksize=number_in_a_chunk to select and select_as_multiple to return an iterator on the results. The default is 50,000 rows returned in a chunk.

In [445]: for df in store.select('df', chunksize=3):
   .....:   print(df)
   .....:
   A   B   C
2000-01-01 1.334065 0.521036 0.930384
2000-01-02 -1.613932 1.088104 -0.632963
2000-01-03 -0.585314 -0.275038 -0.937512
   A   B   C
2000-01-04 0.632369 -1.249657 0.975593
2000-01-05 1.060617 -0.143682 0.218423
2000-01-06 3.050329 1.317933 -0.963725
   A   B   C
2000-01-07 -0.539452 -0.771133 0.023751
2000-01-08 0.649464 -1.736427 0.197288

**Note:** You can also use the iterator with read_hdf which will open, then automatically close the store when finished iterating.

for df in pd.read_hdf('store.h5', 'df', chunksize=3):
   print(df)
Note, that the chunksize keyword applies to the source rows. So if you are doing a query, then the chunksize will subdivide the total rows in the table and the query applied, returning an iterator on potentially unequal sized chunks.

Here is a recipe for generating a query and using it to create equal sized return chunks.

```python
In [446]: dfeq = pd.DataFrame({'number': np.arange(1, 11)})
In [447]: dfeq
Out[447]:
   number
0     1
1     2
2     3
3     4
4     5
5     6
6     7
7     8
8     9
9    10
In [448]: store.append('dfeq', dfeq, data_columns=['number'])
In [449]: def chunks(l, n):
   .....:     return [l[i:i + n] for i in range(0, len(l), n)]
   .....:
In [450]: evens = [2, 4, 6, 8, 10]
In [451]: coordinates = store.select_as_coordinates('dfeq', 'number=evens')
In [452]: for c in chunks(coordinates, 2):
   .....:     print(store.select('dfeq', where=c))
   .....:
   number
   1     2
   3     4
   5     6
   7     8
   9    10
```

Advanced queries

Select a single column

To retrieve a single indexable or data column, use the method `select_column`. This will, for example, enable you to get the index very quickly. These return a `Series` of the result, indexed by the row number. These do not currently accept the `where` selector.

```python
In [453]: store.select_column('df_dc', 'index')
Out[453]:
0 2000-01-01
1 2000-01-02
2 2000-01-03
```
Selecting coordinates

Sometimes you want to get the coordinates (a.k.a the index locations) of your query. This returns an `Int64Index` of the resulting locations. These coordinates can also be passed to subsequent `where` operations.

```python
In [455]: df_coord = pd.DataFrame(np.random.randn(1000, 2),
                   index=pd.date_range('20000101', periods=1000))

In [456]: store.append('df_coord', df_coord)

In [457]: c = store.select_as_coordinates('df_coord', 'index > 20020101')

In [458]: c
Out[458]:
Int64Index([732, 733, 734, 735, 736, 737, 738, 739, 740, 741, ...
         990, 991, 992, 993, 994, 995, 996, 997, 998, 999],
       dtype='int64', length=268)

In [459]: store.select('df_coord', where=c)
Out[459]:
     0     1
2002-01-02 -0.165548  0.646989
2002-01-03  0.782753 -0.123409
2002-01-04 -0.391932 -0.740915
2002-01-05  1.211070 -0.668715
2002-01-06  0.341987 -0.685867
...     ...     ...
2002-09-22  1.788110 -0.405908
2002-09-23 -0.801912  0.768460
2002-09-24  0.466284 -0.457411
2002-09-25 -0.364060  0.785367
2002-09-26 -1.463093  1.187315
[268 rows x 2 columns]
```
Selecting using a where mask

Sometime your query can involve creating a list of rows to select. Usually this mask would be a resulting index from an indexing operation. This example selects the months of a datetimeindex which are 5.

```python
In [460]: df_mask = pd.DataFrame(np.random.randn(1000, 2),
                      index=pd.date_range('20000101', periods=1000))

In [461]: store.append('df_mask', df_mask)

In [462]: c = store.select_column('df_mask', 'index')

In [463]: where = c[pd.DatetimeIndex(c).month == 5].index

In [464]: store.select('df_mask', where=where)
```

```
Out[464]:
     0       1
2000-05-01  1.735883 -2.615261
2000-05-02  0.422173  2.425154
2000-05-03  0.632453 -0.165640
2000-05-04 -1.017207 -0.005696
2000-05-05  0.299606  0.070606
...     ...     ...
2002-05-27  0.234503  1.199126
2002-05-28 -3.021833 -1.016828
2002-05-29  0.522794  0.063465
2002-05-30 -1.653736  0.031709
2002-05-31 -0.968402 -0.393583
[93 rows x 2 columns]
```

Storer object

If you want to inspect the stored object, retrieve via `get_storer`. You could use this programmatically to say get the number of rows in an object.

```python
In [465]: store.get_storer('df_dc').nrows
Out[465]: 8
```

Multiple table queries

The methods `append_to_multiple` and `select_as_multiple` can perform appending/selecting from multiple tables at once. The idea is to have one table (call it the selector table) that you index most/all of the columns, and perform your queries. The other table(s) are data tables with an index matching the selector table’s index. You can then perform a very fast query on the selector table, yet get lots of data back. This method is similar to having a very wide table, but enables more efficient queries.

The `append_to_multiple` method splits a given single DataFrame into multiple tables according to `d`, a dictionary that maps the table names to a list of ‘columns’ you want in that table. If `None` is used in place of a list, that table will have the remaining unspecified columns of the given DataFrame. The argument `selector` defines which table is the selector table (which you can make queries from). The argument `dropna` will drop rows from the input DataFrame to ensure tables are synchronized. This means that if a row for one of the tables being written to is entirely `np.NaN`, that row will be dropped from all tables.
If `dropna` is `False`, **THE USER IS RESPONSIBLE FOR SYNCHRONIZING THE TABLES.** Remember that entirely `np.Nan` rows are not written to the HDFStore, so if you choose to call `dropna=False`, some tables may have more rows than others, and therefore `select_as_multiple` may not work or it may return unexpected results.

```python
In [466]: df_mt = pd.DataFrame(np.random.randn(8, 6),
                  index=pd.date_range('1/1/2000', periods=8),
                  columns=['A', 'B', 'C', 'D', 'E', 'F'])

In [467]: df_mt['foo'] = 'bar'

In [468]: df_mt.loc[df_mt.index[1], ('A', 'B')] = np.nan

# you can also create the tables individually
In [469]: store.append_to_multiple({'df1_mt': ['A', 'B'], 'df2_mt': None},
                          df_mt, selector='df1_mt')

In [470]: store
Out[470]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5

# individual tables were created
In [471]: store.select('df1_mt')
Out[471]:
A  B
2000-01-01 1.251079 -0.362628
2000-01-02 NaN NaN
2000-01-03 0.719421 -0.448886
2000-01-04 1.140998 -0.877922
2000-01-05 1.043605 1.798494
2000-01-06 -0.467812 -0.027965
2000-01-07 0.150568 0.754820
2000-01-08 -0.596306 -0.910022

In [472]: store.select('df2_mt')
Out[472]:
C  D  E  F  foo
2000-01-01 1.602451 -0.221229 0.712403 0.465927 bar
2000-01-02 -0.525571 0.851566 -0.681308 -0.549386 bar
2000-01-03 -0.044171 1.396628 1.041242 -1.588171 bar
2000-01-04 0.463351 -0.861042 -2.192841 -1.025263 bar
2000-01-05 -1.954845 -1.712882 -0.204377 -1.608953 bar
2000-01-06 1.601542 -0.417884 -2.757922 -0.307713 bar
2000-01-07 -1.935461 1.007668 0.079529 -1.459471 bar
2000-01-08 -1.057072 -0.864360 -1.124870 1.732966 bar

# as a multiple
In [473]: store.select_as_multiple(['df1_mt', 'df2_mt'], where=['A>0', 'B>0'],
                               selector='df1_mt')
```

```
Delete from a table

You can delete from a table selectively by specifying a `where`. In deleting rows, it is important to understand the `PyTables` deletes rows by erasing the rows, then `moving` the following data. Thus deleting can potentially be a very expensive operation depending on the orientation of your data. To get optimal performance, it’s worthwhile to have the dimension you are deleting be the first of the `indexables`.

Data is ordered (on the disk) in terms of the `indexables`. Here’s a simple use case. You store panel-type data, with dates in the `major_axis` and ids in the `minor_axis`. The data is then interleaved like this:

- `date_1`
  - id_1
  - id_2
  - ...
  - id_n
- `date_2`
  - id_1
  - ...
  - id_n

It should be clear that a delete operation on the `major_axis` will be fairly quick, as one chunk is removed, then the following data moved. On the other hand a delete operation on the `minor_axis` will be very expensive. In this case it would almost certainly be faster to rewrite the table using a `where` that selects all but the missing data.

**Warning:** Please note that HDF5 **DOES NOT RECLAIM SPACE** in the h5 files automatically. Thus, repeatedly deleting (or removing nodes) and adding again, **WILL TEND TO INCREASE THE FILE SIZE**.

To *repack and clean* the file, use `ptrepack`.

Notes & caveats

Compression

`PyTables` allows the stored data to be compressed. This applies to all kinds of stores, not just tables. Two parameters are used to control compression: `complevel` and `complib`.

- `complevel` specifies if and how hard data is to be compressed. `complevel=0` and `complevel=None` disables compression and `0<complevel<10` enables compression.

- `complib` specifies which compression library to use. If nothing is specified the default library `zlib` is used. A compression library usually optimizes for either good compression rates or speed and the results will depend on the type of data. Which type of compression to choose depends on your specific needs and data. The list of supported compression libraries:
  - `zlib`: The default compression library. A classic in terms of compression, achieves good compression rates but is somewhat slow.
  - `lzo`: Fast compression and decompression.
  - `bzip2`: Good compression rates.
- **blosc:** Fast compression and decompression.

  Support for alternative blosc compressors:

  - `blosc:blosclz` This is the default compressor for `blosc`
  - `blosc:lz4`: A compact, very popular and fast compressor.
  - `blosc:lz4hc`: A tweaked version of LZ4, produces better compression ratios at the expense of speed.
  - `blosc:snappy`: A popular compressor used in many places.
  - `blosc:zlib`: A classic; somewhat slower than the previous ones, but achieving better compression ratios.
  - `blosc:zstd`: An extremely well balanced codec; it provides the best compression ratios among the others above, and at reasonably fast speed.

  If `complib` is defined as something other than the listed libraries a `ValueError` exception is issued.

  **Note:** If the library specified with the `complib` option is missing on your platform, compression defaults to `zlib` without further ado.

Enable compression for all objects within the file:

```python
store_compressed = pd.HDFStore('store_compressed.h5', complevel=9,  
complib='blosc:blosclz')
```

Or on-the-fly compression (this only applies to tables) in stores where compression is not enabled:

```python
store.append('df', df, complib='zlib', complevel=5)
```

**ptrepack**

PyTables offers better write performance when tables are compressed after they are written, as opposed to turning on compression at the very beginning. You can use the supplied PyTables utility `ptrepack`. In addition, `ptrepack` can change compression levels after the fact.

```
ptrepack --chunkshape=auto --propindexes --complevel=9 --complib=blosc in.h5 out.h5
```

Furthermore `ptrepack in.h5 out.h5` will repack the file to allow you to reuse previously deleted space. Alternatively, one can simply remove the file and write again, or use the `copy` method.

**Caveats**

**Warning:** `HDFStore` is not thread-safe for writing. The underlying PyTables only supports concurrent reads (via threading or processes). If you need reading and writing at the same time, you need to serialize these operations in a single thread in a single process. You will corrupt your data otherwise. See the (GH2397) for more information.

- If you use locks to manage write access between multiple processes, you may want to use `fsync()` before releasing write locks. For convenience you can use `store.flush(fsync=True)` to do this for you.
- Once a table is created columns (DataFrame) are fixed; only exactly the same columns can be appended.
pandas: powerful Python data analysis toolkit, Release 1.1.1

- Be aware that timezones (e.g., `pytz.timezone('US/Eastern')`) are not necessarily equal across timezone versions. So if data is localized to a specific timezone in the HDFStore using one version of a timezone library and that data is updated with another version, the data will be converted to UTC since these timezones are not considered equal. Either use the same version of timezone library or use `tz_convert` with the updated timezone definition.

**Warning:** PyTables will show a `NaturalNameWarning` if a column name cannot be used as an attribute selector. Natural identifiers contain only letters, numbers, and underscores, and may not begin with a number. Other identifiers cannot be used in a `where` clause and are generally a bad idea.

### DataTypes

HDFStore will map an object dtypes to the PyTables underlying dtype. This means the following types are known to work:

<table>
<thead>
<tr>
<th>Type</th>
<th>Represents missing values</th>
</tr>
</thead>
<tbody>
<tr>
<td>floating</td>
<td><code>float64</code>, <code>float32</code>, <code>float16</code></td>
</tr>
<tr>
<td>integer</td>
<td><code>int64</code>, <code>int32</code>, <code>int8</code>, <code>uint64</code>, <code>uint32</code>, <code>uint8</code></td>
</tr>
<tr>
<td>boolean</td>
<td></td>
</tr>
<tr>
<td>datetime64[ns]</td>
<td></td>
</tr>
<tr>
<td>timedelta64[ns]</td>
<td></td>
</tr>
<tr>
<td>categorical</td>
<td>see the section below</td>
</tr>
<tr>
<td>object</td>
<td><code>strings</code></td>
</tr>
</tbody>
</table>

Unicode columns are not supported, and **WILL FAIL**.

### Categorical data

You can write data that contains category dtypes to a HDFStore. Queries work the same as if it was an object array. However, the category dtyped data is stored in a more efficient manner.

```
In [474]: dfcat = pd.DataFrame({'A': pd.Series(list('aabbcdba')).astype('category'),
                           'B': np.random.randn(8)})
.....:

In [475]: dfcat
Out[475]:
    A    B
0  a  0.477849
1  a  0.283128
2  b  2.045700
3  b -2.045700
4  c  0.423113
5  d  2.314361
6  b -0.033100
7  a -0.965461

In [476]: dfcat.dtypes
Out[476]:
    A    category
    B    float64
```

(continues on next page)
d_type: object

In [477]: cstore = pd.HDFStore('cats.h5', mode='w')

In [478]: cstore.append('dfcat', dfcat, format='table', data_columns=['A'])

In [479]: result = cstore.select('dfcat', where="A in ['b', 'c']")

In [480]: result
Out[480]:
   A   B
0  b -2.045700
1  b -0.338206
2  c -0.423113
3  b -0.033100

In [481]: result.dtypes
Out[481]:
A  category
B  float64
dtype: object

String columns

min_itemsize

The underlying implementation of HDFStore uses a fixed column width (itemsize) for string columns. A string column itemsize is calculated as the maximum of the length of data (for that column) that is passed to the HDFStore, in the first append. Subsequent appends, may introduce a string for a column larger than the column can hold, an Exception will be raised (otherwise you could have a silent truncation of these columns, leading to loss of information). In the future we may relax this and allow a user-specified truncation to occur.

Pass min_itemsize on the first table creation to a-priori specify the minimum length of a particular string column. min_itemsize can be an integer, or a dict mapping a column name to an integer. You can pass values as a key to allow all indexables or data_columns to have this min_itemsize.

Passing a min_itemsize dict will cause all passed columns to be created as data_columns automatically.

Note: If you are not passing any data_columns, then the min_itemsize will be the maximum of the length of any string passed.

In [482]: dfs = pd.DataFrame({'A': 'foo', 'B': 'bar'}, index=list(range(5)))

In [483]: dfs
Out[483]:
   A   B
0  foo  bar
1  foo  bar
2  foo  bar
3  foo  bar
4  foo  bar

# A and B have a size of 30
In [484]: store.append('dfs', dfs, min_itemsize=30)

In [485]: store.get_storer('dfs').table
Out[485]:
/dfs/table (Table(5,)) ''
    description := {
        "index": Int64Col(shape=(), dflt=0, pos=0),
        "values_block_0": StringCol(itemsize=30, shape=(2,), dflt=b'', pos=1)}
    byteorder := 'little'
    chunkshape := (963,)
    autoindex := True
    colindexes := {
        "index": Index(6, medium, shuffle, zlib(1)).is_csi=False}
# A is created as a data_column with a size of 30
# B is size is calculated
In [486]: store.append('dfs2', dfs, min_itemsize={'A': 30})

In [487]: store.get_storer('dfs2').table
Out[487]:
/dfs2/table (Table(5,)) ''
    description := {
        "index": Int64Col(shape=(), dflt=0, pos=0),
        "values_block_0": StringCol(itemsize=3, shape=(1,), dflt=b'', pos=1),
        "A": StringCol(itemsize=30, shape=(), dflt=b'', pos=2)}
    byteorder := 'little'
    chunkshape := (1598,)
    autoindex := True
    colindexes := {
        "index": Index(6, medium, shuffle, zlib(1)).is_csi=False,
        "A": Index(6, medium, shuffle, zlib(1)).is_csi=False}

nan_rep

String columns will serialize a np.nan (a missing value) with the nan_rep string representation. This defaults to the string value nan. You could inadvertently turn an actual nan value into a missing value.

In [488]: dfss = pd.DataFrame({'A': ['foo', 'bar', 'nan']})

In [489]: dfss
Out[489]:
     A
   0 foo
   1 bar
   2 nan

In [490]: store.append('dfss', dfss)

In [491]: store.select('dfss')
Out[491]:
     A
   0  foo
   1  bar
   2  NaN

# here you need to specify a different nan rep
In [492]: store.append('dfss2', dfss, nan_rep='_nan_')
External compatibility

HDFStore writes table format objects in specific formats suitable for producing loss-less round trips to pandas objects. For external compatibility, HDFStore can read native PyTables format tables.

It is possible to write an HDFStore object that can easily be imported into R using the rhdf5 library (Package website). Create a table format store like this:

```
In [494]: df_for_r = pd.DataFrame({"first": np.random.rand(100),
                            ......: "second": np.random.rand(100),
                            ......: "class": np.random.randint(0, 2, (100, ))},
                            ......: index=range(100))
```

In R this file can be read into a data.frame object using the rhdf5 library. The following example function reads the corresponding column names and data values from the values and assembles them into a data.frame:

```
# Load values and column names for all datasets from corresponding nodes and
# insert them into one data.frame object.
library(rhdf5)
loadhdf5data <- function(h5File) {
  listing <- h5ls(h5File)
  # Find all data nodes, values are stored in *_values and corresponding column
  # titles in *_items
  data_nodes <- grep("_values", listing$name)
  name_nodes <- grep("_items", listing$name)
  # Load all data nodes, possibly nested, back into a list.
  list <- rapply(h5File, function(x) h5get(x, data_nodes$name), recursive=TRUE)
  # (continues on next page)
```

2.4. IO tools (text, CSV, HDF5, …)
data_paths = paste(listing$group[data_nodes], listing$name[data_nodes], sep = "/")
name_paths = paste(listing$group[name_nodes], listing$name[name_nodes], sep = "/")
columns = list()
for (idx in seq(data_paths)) {
  # NOTE: matrices returned by h5read have to be transposed to obtain
  # required Fortran order!
  data <- data.frame(t(h5read(h5File, data_paths[idx])))
  names <- t(h5read(h5File, name_paths[idx]))
  entry <- data.frame(data)
  colnames(entry) <- names
  columns <- append(columns, entry)
}
data <- data.frame(columns)
return(data)
}

Now you can import the DataFrame into R:

```r
> data = loadhdf5data("transfer.hdf5")
> head(data)
   first  second  class
 1 0.4170 0.3266 0
 2 0.7203 0.5270 0
 3 0.0001 0.8859 1
 4 0.3023 0.3573 1
 5 0.1467 0.9085 1
 6 0.0923 0.6234 1
```

**Note:** The R function lists the entire HDF5 file’s contents and assembles the data.frame object from all matching nodes, so use this only as a starting point if you have stored multiple DataFrame objects to a single HDF5 file.

**Performance**

- **tables** format come with a writing performance penalty as compared to fixed stores. The benefit is the ability to append/delete and query (potentially very large amounts of data). Write times are generally longer as compared with regular stores. Query times can be quite fast, especially on an indexed axis.
- You can pass `chunksize=<int>` to `append`, specifying the write chunksize (default is 50000). This will significantly lower your memory usage on writing.
- You can pass `expectedrows=<int>` to the first `append`, to set the TOTAL number of rows that PyTables will expect. This will optimize read/write performance.
- Duplicate rows can be written to tables, but are filtered out in selection (with the last items being selected; thus a table is unique on major, minor pairs)
- A PerformanceWarning will be raised if you are attempting to store types that will be pickled by PyTables (rather than stored as endemic types). See Here for more information and some solutions.
2.4.11 Feather

Feather provides binary columnar serialization for data frames. It is designed to make reading and writing data frames efficient, and to make sharing data across data analysis languages easy.

Feather is designed to faithfully serialize and de-serialize DataFrames, supporting all of the pandas dtypes, including extension dtypes such as categorical and datetime with tz.

Several caveats:

- The format will NOT write an Index, or MultiIndex for the DataFrame and will raise an error if a non-default one is provided. You can .reset_index() to store the index or .reset_index(drop=True) to ignore it.
- Duplicate column names and non-string columns names are not supported
- Actual Python objects in object dtype columns are not supported. These will raise a helpful error message on an attempt at serialization.

See the Full Documentation.

```
In [499]: df = pd.DataFrame({'a': list('abc'),
                      'b': list(range(1, 4)),
                      'c': np.arange(3, 6).astype('uint8'),
                      'd': np.arange(4.0, 7.0, dtype='float64'),
                      'e': [True, False, True],
                      'f': pd.Categorical(list('abc')),
                      'g': pd.date_range('20130101', periods=3),
                      'h': pd.date_range('20130101', periods=3, tz='US/Eastern'),
                      'i': pd.date_range('20130101', periods=3, freq='ns')})

In [500]: df
Out[500]:
   a  b  c  d  e  f   g      h       i
0  a  1  3  4.0  True  a 2013-01-01 2013-01-01 00:00:00-05:00 2013-01-01 00:00:00.
   000000000
1  b  2  4  5.0  False  b 2013-01-02 2013-01-02 00:00:00-05:00 2013-01-01 00:00:00.
   000000001
2  c  3  5  6.0  True  c 2013-01-03 2013-01-03 00:00:00-05:00 2013-01-01 00:00:00.
   000000002
```

```
In [501]: df.dtypes
Out[501]:
a    object
b   int64
c  uint8
d   float64
e    bool
f  category
g  datetime64[ns]
h  datetime64[ns, US/Eastern]
i  datetime64[ns]
dtype: object
```

Write to a feather file.
Read from a feather file.

```python
In [503]: result = pd.read_feather('example.feather')

In [504]: result
Out[504]:
   a  b  c  d  e  f  g  h
0  a  1  3  4.0  True  a  2013-01-01 2013-01-01 00:00:00-05:00 2013-01-01 00:00:00.
1  b  2  4  5.0  False  b  2013-01-02 2013-01-02 00:00:00-05:00 2013-01-01 00:00:00.
2  c  3  5  6.0  True  c  2013-01-03 2013-01-03 00:00:00-05:00 2013-01-01 00:00:00.
```

# we preserve dtypes

```python
In [505]: result.dtypes
Out[505]:
   a    object
   b    int64
   c    uint8
   d    float64
   e      bool
   f  category
g  datetime64[ns]
h  datetime64[ns, US/Eastern]
i  datetime64[ns]
dtype: object
```

2.4.12 Parquet

Apache Parquet provides a partitioned binary columnar serialization for data frames. It is designed to make reading and writing data frames efficient, and to make sharing data across data analysis languages easy. Parquet can use a variety of compression techniques to shrink the file size as much as possible while still maintaining good read performance.

Parquet is designed to faithfully serialize and de-serialize DataFrame's, supporting all of the pandas dtypes, including extension dtypes such as datetime with tz.

Several caveats.

- Duplicate column names and non-string columns names are not supported.
- The pyarrow engine always writes the index to the output, but fastparquet only writes non-default indexes. This extra column can cause problems for non-Pandas consumers that are not expecting it. You can force including or omitting indexes with the index argument, regardless of the underlying engine.
- Index level names, if specified, must be strings.
- In the pyarrow engine, categorical dtypes for non-string types can be serialized to parquet, but will de-serialize as their primitive dtype.
- The pyarrow engine preserves the ordered flag of categorical dtypes with string types. fastparquet does not preserve the ordered flag.
- Non supported types include Interval and actual Python object types. These will raise a helpful error message on an attempt at serialization. Period type is supported with pyarrow >= 0.16.0.
• The **pyarrow** engine preserves extension data types such as the nullable integer and string data type (requiring pyarrow >= 0.16.0, and requiring the extension type to implement the needed protocols, see the [extension types documentation](https://arrow.apache.org/docs/python/reference/extension-data-types.html)).

You can specify an engine to direct the serialization. This can be one of **pyarrow**, or **fastparquet**, or **auto**. If the engine is NOT specified, then the `pd.options.io.parquet.engine` option is checked; if this is also auto, then pyarrow is tried, and falling back to fastparquet.

See the documentation for **pyarrow** and **fastparquet**.

**Note:** These engines are very similar and should read/write nearly identical parquet format files. Currently **pyarrow** does not support timedelta data, **fastparquet**>=0.1.4 supports timezone aware datetimes. These libraries differ by having different underlying dependencies (fastparquet by using numba, while pyarrow uses a c-library).

```python
In [506]: df = pd.DataFrame({'a': list('abc'),
                   'b': list(range(1, 4)),
                   'c': np.arange(3, 6).astype('u1'),
                   'd': np.arange(4.0, 7.0, dtype='float64'),
                   'e': [True, False, True],
                   'f': pd.date_range('20130101', periods=3),
                   'g': pd.date_range('20130101', periods=3, tz='US/Eastern'),
                   'h': pd.Categorical(list('abc')),
                   'i': pd.Categorical(list('abc'), ordered=True))
```

```python
In [507]: df
Out[507]:
     a  b  c  d   e       f                  g     h     i
0  a  1  3  4.0 True 2013-01-01 00:00:00-05:00  a  a
1  b  2  4  5.0  False 2013-01-02 00:00:00-05:00  b  b
2  c  3  5  6.0 True 2013-01-03 00:00:00-05:00  c  c
```

```python
In [508]: df.dtypes
Out[508]:
     a     b     c    d    e     f    g     h    i
object    int64   uint8  float64   bool  datetime64[ns]  category  category
```

Write to a parquet file.

```python
In [509]: df.to_parquet('example_pa.parquet', engine='pyarrow')
```

```python
In [510]: df.to_parquet('example_fp.parquet', engine='fastparquet')
```

Read from a parquet file.

```python
In [511]: result = pd.read_parquet('example_fp.parquet', engine='fastparquet')
```
In [512]: result = pd.read_parquet('example_pa.parquet', engine='pyarrow')

In [513]: result.dtypes
Out[513]:
a object
b int64
c uint8
d float64
e bool
f datetime64[ns]
g datetime64[ns, US/Eastern]
h category
i category
dtype: object

Read only certain columns of a parquet file.

In [514]: result = pd.read_parquet('example_fp.parquet',
                      engine='fastparquet', columns=['a', 'b'])

In [515]: result = pd.read_parquet('example_pa.parquet',
                      engine='pyarrow', columns=['a', 'b'])

In [516]: result.dtypes
Out[516]:
a object
b int64
dtype: object

Handling indexes

Serializing a DataFrame to parquet may include the implicit index as one or more columns in the output file. Thus, this code:

In [517]: df = pd.DataFrame({'a': [1, 2], 'b': [3, 4]})
In [518]: df.to_parquet('test.parquet', engine='pyarrow')

creates a parquet file with three columns if you use pyarrow for serialization: a, b, and __index_level_0__. If you’re using fastparquet, the index may or may not be written to the file.

This unexpected extra column causes some databases like Amazon Redshift to reject the file, because that column doesn’t exist in the target table.

If you want to omit a dataframe’s indexes when writing, pass index=False to to_parquet():

In [519]: df.to_parquet('test.parquet', index=False)

This creates a parquet file with just the two expected columns, a and b. If your DataFrame has a custom index, you won’t get it back when you load this file into a DataFrame.

Passing index=True will always write the index, even if that’s not the underlying engine’s default behavior.
Partitioning Parquet files

New in version 0.24.0.

Parquet supports partitioning of data based on the values of one or more columns.

In [520]: df = pd.DataFrame({'a': [0, 0, 1, 1], 'b': [0, 1, 0, 1]})
In [521]: df.to_parquet(path='test', engine='pyarrow',
                             partition_cols=['a'], compression=None)

The path specifies the parent directory to which data will be saved. The partition_cols are the column names by which the dataset will be partitioned. Columns are partitioned in the order they are given. The partition splits are determined by the unique values in the partition columns. The above example creates a partitioned dataset that may look like:

```
<table>
<thead>
<tr>
<th>a</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
</tr>
<tr>
<td>b0bac803e32dc42ae83fddfd029cbdebc.parquet</td>
</tr>
<tr>
<td>...</td>
</tr>
<tr>
<td>a=1</td>
</tr>
<tr>
<td>e6ab24a4f45147b49b54a662f0c412a3.parquet</td>
</tr>
<tr>
<td>...</td>
</tr>
</tbody>
</table>
```

2.4.13 ORC

New in version 1.0.0.

Similar to the parquet format, the ORC Format is a binary columnar serialization for data frames. It is designed to make reading data frames efficient. Pandas provides only a reader for the ORC format, read_orc(). This requires the pyarrow library.

2.4.14 SQL queries

The pandas.io.sql module provides a collection of query wrappers to both facilitate data retrieval and to reduce dependency on DB-specific API. Database abstraction is provided by SQLAlchemy if installed. In addition you will need a driver library for your database. Examples of such drivers are psycopg2 for PostgreSQL or pymysql for MySQL. For SQLite this is included in Python’s standard library by default. You can find an overview of supported drivers for each SQL dialect in the SQLAlchemy docs.

If SQLAlchemy is not installed, a fallback is only provided for sqlite (and for mysql for backwards compatibility, but this is deprecated and will be removed in a future version). This mode requires a Python database adapter which respect the Python DB-API.

See also some cookbook examples for some advanced strategies.

The key functions are:

- `read_sql_table()`: Read SQL database table into a DataFrame.
- `read_sql_query()`: Read SQL query into a DataFrame.
- `read_sql()`: Read SQL query or database table into a DataFrame.
- `DataFrame.to_sql(name, con[, schema, ...])`: Write records stored in a DataFrame to a SQL database.

Note: The function `read_sql()` is a convenience wrapper around `read_sql_table()` and...
**pandas: powerful Python data analysis toolkit, Release 1.1.1**

`read_sql_query()` (and for backward compatibility) and will delegate to specific function depending on the provided input (database table name or sql query). Table names do not need to be quoted if they have special characters.

In the following example, we use the SQLite SQL database engine. You can use a temporary SQLite database where data are stored in “memory”.

To connect with SQLAlchemy you use the `create_engine()` function to create an engine object from database URI. You only need to create the engine once per database you are connecting to. For more information on `create_engine()` and the URI formatting, see the examples below and the SQLAlchemy documentation.

```python
In [522]: from sqlalchemy import create_engine

# Create your engine.
In [523]: engine = create_engine('sqlite:////:memory:)
```

If you want to manage your own connections you can pass one of those instead:

```python
with engine.connect() as conn, conn.begin():
    data = pd.read_sql_table('data', conn)
```

**Writing DataFrames**

Assuming the following data is in a DataFrame `data`, we can insert it into the database using `to_sql()`.

<table>
<thead>
<tr>
<th>id</th>
<th>Date</th>
<th>Col_1</th>
<th>Col_2</th>
<th>Col_3</th>
</tr>
</thead>
<tbody>
<tr>
<td>26</td>
<td>2012-10-18</td>
<td>X</td>
<td>25.7</td>
<td>True</td>
</tr>
<tr>
<td>42</td>
<td>2012-10-19</td>
<td>Y</td>
<td>-12.4</td>
<td>False</td>
</tr>
<tr>
<td>63</td>
<td>2012-10-20</td>
<td>Z</td>
<td>5.73</td>
<td>True</td>
</tr>
</tbody>
</table>

```python
In [524]: data
Out[524]:
   id   Date Col_1  Col_2  Col_3
0  26  2010-10-18  X   27.5  True
1  42  2010-10-19  Y  -12.5 False
2  63  2010-10-20  Z   5.73 True
```

```python
In [525]: data.to_sql('data', engine)
```

With some databases, writing large DataFrames can result in errors due to packet size limitations being exceeded. This can be avoided by setting the `chunksize` parameter when calling `to_sql`. For example, the following writes `data` to the database in batches of 1000 rows at a time:
pandas: powerful Python data analysis toolkit, Release 1.1.1

```python
In [526]: data.to_sql('data_chunked', engine, chunksize=1000)
```

### SQL data types

`to_sql()` will try to map your data to an appropriate SQL data type based on the dtype of the data. When you have columns of dtype `object`, pandas will try to infer the data type.

You can always override the default type by specifying the desired SQL type of any of the columns by using the `dtype` argument. This argument needs a dictionary mapping column names to SQLAlchemy types (or strings for the sqlite3 fallback mode). For example, specifying to use the sqlalchemy `String` type instead of the default `Text` type for string columns:

```python
In [527]: from sqlalchemy.types import String
In [528]: data.to_sql('data_dtype', engine, dtype={'Col_1': String})
```

**Note:** Due to the limited support for timedelta’s in the different database flavors, columns with type `timedelta64` will be written as integer values as nanoseconds to the database and a warning will be raised.

**Note:** Columns of `category` dtype will be converted to the dense representation as you would get with `np.asarray(categorical)` (e.g. for string categories this gives an array of strings). Because of this, reading the database table back in does **not** generate a categorical.

### Datetime data types

Using SQLAlchemy, `to_sql()` is capable of writing datetime data that is timezone naive or timezone aware. However, the resulting data stored in the database ultimately depends on the supported data type for datetime data of the database system being used.

The following table lists supported data types for datetime data for some common databases. Other database dialects may have different data types for datetime data.

<table>
<thead>
<tr>
<th>Database</th>
<th>SQL Datetime Types</th>
<th>Timezone Support</th>
</tr>
</thead>
<tbody>
<tr>
<td>SQLite</td>
<td>TEXT</td>
<td>No</td>
</tr>
<tr>
<td>MySQL</td>
<td>TIMESTAMP or DATETIME</td>
<td>No</td>
</tr>
<tr>
<td>PostgreSQL</td>
<td>TIMESTAMP or TIMESTAMP WITH TIME ZONE</td>
<td>Yes</td>
</tr>
</tbody>
</table>

When writing timezone aware data to databases that do not support timezones, the data will be written as timezone naive timestamps that are in local time with respect to the timezone.

`read_sql_table()` is also capable of reading datetime data that is timezone aware or naive. When reading `TIMESTAMP WITH TIME ZONE` types, pandas will convert the data to UTC.

2.4. IO tools (text, CSV, HDF5, …)
Insertion method

New in version 0.24.0.

The parameter `method` controls the SQL insertion clause used. Possible values are:

- None: Uses standard SQL `INSERT` clause (one per row).
- 'multi': Pass multiple values in a single `INSERT` clause. It uses a special SQL syntax not supported by all backends. This usually provides better performance for analytic databases like Presto and Redshift, but has worse performance for traditional SQL backend if the table contains many columns. For more information check the SQLAlchemy documentation.
- callable with signature `pd_table, conn, keys, data_iter`: This can be used to implement a more performant insertion method based on specific backend dialect features.

Example of a callable using PostgreSQL COPY clause:

```python
# Alternative to to_sql() *method* for DBs that support COPY FROM
import csv
from io import StringIO

def psql_insert_copy(table, conn, keys, data_iter):
    """
    Execute SQL statement inserting data
    """
    Parameters
    ---------
    table : pandas.io.sql.SQLTable
    conn : sqlalchemy.engine.Engine or sqlalchemy.engine.Connection
    keys : list of str
        Column names
    data_iter : Iterable that iterates the values to be inserted
    """

    # gets a DBAPI connection that can provide a cursor
dbapi_conn = conn.connection
    with dbapi_conn.cursor() as cur:
        s_buf = StringIO()
        writer = csv.writer(s_buf)
        writer.writerows(data_iter)
        s_buf.seek(0)

        columns = ', '.join('"{}"'.format(k) for k in keys)
        if table.schema:
            table_name = '{},{}'.format(table.schema, table.name)
        else:
            table_name = table.name

        sql = 'COPY {} ({}) FROM STDIN WITH CSV'.format(
            table_name, columns)
        cur.copy_expert(sql=sql, file=s_buf)
```
Reading tables

`read_sql_table()` will read a database table given the table name and optionally a subset of columns to read.

**Note:** In order to use `read_sql_table()`, you must have the SQLAlchemy optional dependency installed.

```
In [529]: pd.read_sql_table('data', engine)
Out[529]:
   index  id    Date  Col_1  Col_2  Col_3
0      0   26 2010-10-18    X  27.50   True
1      1   42 2010-10-19    Y -12.50   False
2      2   63 2010-10-20    Z   5.73   True
```

**Note:** Note that pandas infers column dtypes from query outputs, and not by looking up data types in the physical database schema. For example, assume `userid` is an integer column in a table. Then, intuitively, `select userid ...` will return integer-valued series, while `select cast(userid as text) ...` will return object-valued (str) series. Accordingly, if the query output is empty, then all resulting columns will be returned as object-valued (since they are most general). If you foresee that your query will sometimes generate an empty result, you may want to explicitly typecast afterwards to ensure dtype integrity.

You can also specify the name of the column as the DataFrame index, and specify a subset of columns to be read.

```
In [530]: pd.read_sql_table('data', engine, index_col='id')
Out[530]:
   index  Date  Col_1  Col_2  Col_3
id 0 2010-10-18    X  27.50   True
  1 2010-10-19    Y -12.50   False
  2 2010-10-20    Z   5.73   True
```

And you can explicitly force columns to be parsed as dates:

```
In [531]: pd.read_sql_table('data', engine, columns=['Col_1', 'Col_2'])
Out[531]:
     Col_1  Col_2
0      X  27.50
1      Y -12.50
2      Z   5.73
```

If needed you can explicitly specify a format string, or a dict of arguments to pass to `pandas.to_datetime()`:

```
pd.read_sql_table('data', engine, parse_dates={'Date': '%Y-%m-%d'})
pd.read_sql_table('data', engine, 
                  parse_dates={'Date': {'format': '%Y-%m-%d %H:%M:%S'}})
```

You can check if a table exists using `has_table()`
Schema support

Reading from and writing to different schema’s is supported through the `schema` keyword in the `read_sql_table()` and `to_sql()` functions. Note however that this depends on the database flavor (sqlite does not have schema’s). For example:

```python
df.to_sql('table', engine, schema='other_schema')
pd.read_sql_table('table', engine, schema='other_schema')
```

Querying

You can query using raw SQL in the `read_sql_query()` function. In this case you must use the SQL variant appropriate for your database. When using SQLAlchemy, you can also pass SQLAlchemy Expression language constructs, which are database-agnostic.

```python
In [533]: pd.read_sql_query('SELECT * FROM data', engine)
Out[533]:
    id  Date       Col_1       Col_2       Col_3
0   0  2010-10-18 00:00:00.000000 0.0000000000  27.500000  1
1   1  2010-10-19 00:00:00.000000 0.0000000000 -12.500000  0
2   2  2010-10-20 00:00:00.000000 0.0000000000   5.730000  1
```

Of course, you can specify a more “complex” query.

```python
In [534]: pd.read_sql_query("SELECT id, Col_1, Col_2 FROM data WHERE id = 42;", engine)
Out[534]:
    id  Col_1  Col_2
0  42  -0.092732 -0.156246 -12.500000
```

The `read_sql_query()` function supports a `chunksize` argument. Specifying this will return an iterator through chunks of the query result:

```python
In [535]: df = pd.DataFrame(np.random.randn(20, 3), columns=list('abc'))
In [536]: df.to_sql('data_chunks', engine, index=False)
In [537]: for chunk in pd.read_sql_query("SELECT * FROM data_chunks", engine, chunksize=5):
    print(chunk)
```

```
   a    b    c
0  0.092961 -0.674003 1.104153
1 -0.092732 -0.156246 -0.585167
2 -0.358119 -0.862331 -1.672907
3  0.550313 -1.507513 -0.617232
4  0.650576  1.033221  0.492464
   a    b    c
0 -1.627786 -0.692062 1.039548
1 -1.802313 -0.890905 -0.881794
2  0.630492  0.016739  0.014500
3 -0.438358  0.647275 -0.052075
4  0.673137  1.227539  0.203534
   a    b    c
0  0.861658  0.867852 -0.465016
```

(continues on next page)
You can also run a plain query without creating a DataFrame with `execute()`. This is useful for queries that don’t return values, such as INSERT. This is functionally equivalent to calling `execute` on the SQLAlchemy engine or `db` connection object. Again, you must use the SQL syntax variant appropriate for your database.

```python
from pandas.io import sql
sql.execute('SELECT * FROM table_name', engine)
sql.execute('INSERT INTO table_name VALUES(?, ?, ?)', engine,
            params=[('id', 1, 12.2, True)])
```

### Engine connection examples

To connect with SQLAlchemy you use the `create_engine()` function to create an engine object from database URI. You only need to create the engine once per database you are connecting to.

```python
from sqlalchemy import create_engine
engine = create_engine('postgresql://scott:tiger@localhost:5432/mydatabase')
engine = create_engine('mysql+mysqldb://scott:tiger@localhost/foo')
engine = create_engine('oracle://scott:tiger@127.0.0.1:1521/sidname')
engine = create_engine('mssql+pyodbc://mydsn')

# sqlite://<nohostname>/<path>
# where <path> is relative:
engine = create_engine('sqlite:///foo.db')

# or absolute, starting with a slash:
engine = create_engine('sqlite:///absolute/path/to/foo.db')
```

For more information see the examples the SQLAlchemy documentation.
Advanced SQLAlchemy queries

You can use SQLAlchemy constructs to describe your query.

Use `sqlalchemy.text()` to specify query parameters in a backend-neutral way

```python
In [538]: import sqlalchemy as sa

In [539]: pd.read_sql(sa.text('SELECT * FROM data where Col_1=:col1'),
               engine, params={'col1': 'X'})

Out[539]:
     index id     Date Col_1 Col_2     Col_3
0        0  26 2010-10-18 00:00:00.000000 X  27.5   1
```

If you have an SQLAlchemy description of your database you can express where conditions using SQLAlchemy expressions

```python
In [540]: metadata = sa.MetaData()

In [541]: data_table = sa.Table('data', metadata,
                          sa.Column('index', sa.Integer),
                          sa.Column('Date', sa.DateTime),
                          sa.Column('Col_1', sa.String),
                          sa.Column('Col_2', sa.Float),
                          sa.Column('Col_3', sa.Boolean),
                          )

In [542]: pd.read_sql(sa.select([data_table]).where(data_table.c.Col_3.is_(True)),
               engine)
Out[542]:
Empty DataFrame
Columns: [index, Date, Col_1, Col_2, Col_3]
Index: []
```

You can combine SQLAlchemy expressions with parameters passed to `read_sql()` using `sqlalchemy.bindparam()`

```python
In [543]: import datetime as dt

In [544]: expr = sa.select([data_table]).where(data_table.c.Date > sa.bindparam('date'))

In [545]: pd.read_sql(expr, engine, params={'date': dt.datetime(2010, 10, 18)})
Out[545]:
     index Date Col_1 Col_2     Col_3
0       1 2010-10-19 Y -12.50   False
1       2 2010-10-20 Z  5.73   True
```
**Sqlite fallback**

The use of sqlite is supported without using SQLAlchemy. This mode requires a Python database adapter which respect the Python DB-API.

You can create connections like so:

```python
import sqlite3
con = sqlite3.connect(':memory:)
```

And then issue the following queries:

```python
data.to_sql('data', con)
pd.read_sql_query("SELECT * FROM data", con)
```

### 2.4.15 Google BigQuery

**Warning:** Starting in 0.20.0, pandas has split off Google BigQuery support into the separate package pandas-gbq. You can pip install pandas-gbq to get it.

The pandas-gbq package provides functionality to read/write from Google BigQuery. pandas integrates with this external package. If pandas-gbq is installed, you can use the pandas methods `pd.read_gbq` and `DataFrame.to_gbq`, which will call the respective functions from pandas-gbq.

Full documentation can be found here.

### 2.4.16 Stata format

**Writing to stata format**

The method `to_stata()` will write a DataFrame into a .dta file. The format version of this file is always 115 (Stata 12).

In [546]: df = pd.DataFrame(np.random.randn(10, 2), columns=list('AB'))
In [547]: df.to_stata('stata.dta')

*Stata* data files have limited data type support: only strings with 244 or fewer characters, `int8`, `int16`, `int32`, `float32` and `float64` can be stored in .dta files. Additionally, *Stata* reserves certain values to represent missing data. Exporting a non-missing value that is outside of the permitted range in Stata for a particular data type will retype the variable to the next larger size. For example, `int8` values are restricted to lie between -127 and 100 in Stata, and so variables with values above 100 will trigger a conversion to `int16`. NaN values in floating points data types are stored as the basic missing data type (. in *Stata*).

**Note:** It is not possible to export missing data values for integer data types.

The *Stata* writer gracefully handles other data types including `int64`, `bool`, `uint8`, `uint16`, `uint32` by casting to the smallest supported type that can represent the data. For example, data with a type of `uint8` will be cast to `int8` if all values are less than 100 (the upper bound for non-missing `int8` data in *Stata*), or, if values are outside of this range, the variable is cast to `int16`. 

2.4. IO tools (text, CSV, HDF5, …) 339
Warning: Conversion from int64 to float64 may result in a loss of precision if int64 values are larger than 2**53.

Warning: StataWriter and to_stata() only support fixed width strings containing up to 244 characters, a limitation imposed by the version 115 dta file format. Attempting to write Stata dta files with strings longer than 244 characters raises a ValueError.

Reading from Stata format

The top-level function read_stata will read a dta file and return either a DataFrame or a StataReader that can be used to read the file incrementally.

In [548]: pd.read_stata('stata.dta')
Out[548]:
   index    A       B
0     0  0.608228  1.064810
1     1 -0.780506 -2.736887
2     2  0.143539  1.170191
3     3 -1.573076  0.075792
4     4 -1.722223 -0.774650
5     5  0.803627  0.221665
6     6  0.584637  0.147264
7     7  1.057825 -0.284136
8     8  0.912395  1.552808
9     9  0.189376 -0.109830

Specifying a chunksize yields a StataReader instance that can be used to read chunksize lines from the file at a time. The StataReader object can be used as an iterator.

In [549]: reader = pd.read_stata('stata.dta', chunksize=3)

In [550]: for df in reader:
      .....:     print(df.shape)
      .....:
(3, 3)
(3, 3)
(3, 3)
(1, 3)

For more fine-grained control, use iterator=True and specify chunksize with each call to read().

In [551]: reader = pd.read_stata('stata.dta', iterator=True)

In [552]: chunk1 = reader.read(5)

In [553]: chunk2 = reader.read(5)

Currently the index is retrieved as a column.

The parameter convert_categoricals indicates whether value labels should be read and used to create a Categorical variable from them. Value labels can also be retrieved by the function value_labels, which requires read() to be called before use.
The parameter `convert_missing` indicates whether missing value representations in Stata should be preserved. If `False` (the default), missing values are represented as `np.nan`. If `True`, missing values are represented using `StataMissingValue` objects, and columns containing missing values will have `object` data type.

**Note:** `read_stata()` and `StataReader` support .dta formats 113-115 (Stata 10-12), 117 (Stata 13), and 118 (Stata 14).

**Note:** Setting `preserve_dtypes=False` will upcast to the standard pandas data types: `int64` for all integer types and `float64` for floating point data. By default, the Stata data types are preserved when importing.

### Categorical data

Categorical data can be exported to Stata data files as value labeled data. The exported data consists of the underlying category codes as integer data values and the categories as value labels. Stata does not have an explicit equivalent to a `Categorical` and information about whether the variable is ordered is lost when exporting.

**Warning:** Stata only supports string value labels, and so `str` is called on the categories when exporting data. Exporting Categorical variables with non-string categories produces a warning, and can result a loss of information if the `str` representations of the categories are not unique.

Labeled data can similarly be imported from Stata data files as Categorical variables using the keyword argument `convert_categoricals` (True by default). The keyword argument `order_categoricals` (True by default) determines whether imported Categorical variables are ordered.

**Note:** When importing categorical data, the values of the variables in the Stata data file are not preserved since Categorical variables always use integer data types between -1 and n-1 where n is the number of categories. If the original values in the Stata data file are required, these can be imported by setting `convert_categoricals=False`, which will import original data (but not the variable labels). The original values can be matched to the imported categorical data since there is a simple mapping between the original Stata data values and the category codes of imported Categorical variables: missing values are assigned code -1, and the smallest original value is assigned 0, the second smallest is assigned 1 and so on until the largest original value is assigned the code n-1.

**Note:** Stata supports partially labeled series. These series have value labels for some but not all data values. Importing a partially labeled series will produce a Categorical with string categories for the values that are labeled and numeric categories for values with no label.
2.4.17 SAS formats

The top-level function `read_sas()` can read (but not write) SAS xport (.XPT) and (since v0.18.0) SAS7BDAT (.sas7bdat) format files.

SAS files only contain two value types: ASCII text and floating point values (usually 8 bytes but sometimes truncated). For xport files, there is no automatic type conversion to integers, dates, or categoricals. For SAS7BDAT files, the format codes may allow date variables to be automatically converted to dates. By default the whole file is read and returned as a DataFrame.

Specify a `chunksize` or use `iterator=True` to obtain reader objects (XportReader or SAS7BDATReader) for incrementally reading the file. The reader objects also have attributes that contain additional information about the file and its variables.

Read a SAS7BDAT file:

```python
df = pd.read_sas('sas_data.sas7bdat')
```

Obtain an iterator and read an XPORT file 100,000 lines at a time:

```python
def do_something(chunk):
    pass

rdr = pd.read_sas('sas_xport.xpt', chunk=100000)
for chunk in rdr:
    do_something(chunk)
```

The specification for the xport file format is available from the SAS web site.

No official documentation is available for the SAS7BDAT format.

2.4.18 SPSS formats

New in version 0.25.0.

The top-level function `read_spss()` can read (but not write) SPSS sav (.sav) and zsav (.zsav) format files.

SPSS files contain column names. By default the whole file is read, categorical columns are converted into `pd.Categorical`, and a DataFrame with all columns is returned.

Specify the `usecols` parameter to obtain a subset of columns. Specify `convert_categoricals=False` to avoid converting categorical columns into `pd.Categorical`.

Read an SPSS file:

```python
df = pd.read_spss('spss_data.sav')
```

Extract a subset of columns contained in `usecols` from an SPSS file and avoid converting categorical columns into `pd.Categorical`:

```python
df = pd.read_spss('spss_data.sav', usecols=['foo', 'bar'], convert_categoricals=False)
```

More information about the `sav` and `zsav` file format is available here.
2.4.19 Other file formats

pandas itself only supports IO with a limited set of file formats that map cleanly to its tabular data model. For reading and writing other file formats into and from pandas, we recommend these packages from the broader community.

**netCDF**

xarray provides data structures inspired by the pandas DataFrame for working with multi-dimensional datasets, with a focus on the netCDF file format and easy conversion to and from pandas.

2.4.20 Performance considerations

This is an informal comparison of various IO methods, using pandas 0.24.2. Timings are machine dependent and small differences should be ignored.

```
In [1]: sz = 1000000

In [3]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000000 entries, 0 to 999999
Data columns (total 2 columns):
   A 1000000 non-null float64
   B 1000000 non-null int64
dtypes: float64(1), int64(1)
memory usage: 15.3 MB
```

Given the next test set:

```
import numpy as np
import os

sz = 1000000

sz = 1000000
np.random.seed(42)

def test_sql_write(df):
    if os.path.exists('test.sql'):
        os.remove('test.sql')
    sql_db = sqlite3.connect('test.sql')
    df.to_sql(name='test_table', con=sql_db)
    sql_db.close()

def test_sql_read():
    sql_db = sqlite3.connect('test.sql')
    pd.read_sql_query("select * from test_table", sql_db)
    sql_db.close()

def test_hdf_fixed_write(df):
    df.to_hdf('test_fixed.hdf', 'test', mode='w')
```

(continues on next page)
When writing, the top-three functions in terms of speed are `test_feather_write`, `test_hdf_fixed_write` and `test_hdf_fixed_write_compress`.

```
in [4]: %timeit test_sql_write(df)  # (continues on next page)```

(continued from previous page)
In [5]: ```%timeit test_hdf_fixed_write(df)
19.4 ms ± 560 µs per loop (mean ± std. dev. of 7 runs, 1 loop each)```

In [6]: ```%timeit test_hdf_fixed_write_compress(df)
19.6 ms ± 308 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)```

In [7]: ```%timeit test_hdf_table_write(df)
449 ms ± 5.61 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)```

In [8]: ```%timeit test_hdf_table_write_compress(df)
448 ms ± 11.9 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)```

In [9]: ```%timeit test_csv_write(df)
3.66 s ± 26.2 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)```

In [10]: ```%timeit test_feather_write(df)
9.75 ms ± 117 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)```

In [11]: ```%timeit test_pickle_write(df)
30.1 ms ± 229 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)```

In [12]: ```%timeit test_pickle_write_compress(df)
4.29 s ± 15.9 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)```

In [13]: ```%timeit test_parquet_write(df)
67.6 ms ± 706 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)```

When reading, the top three are `test_feather_read`, `test_pickle_read` and `test_hdf_fixed_read`.

In [14]: ```%timeit test_sql_read()
1.77 s ± 17.7 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)```

In [15]: ```%timeit test_hdf_fixed_read()
19.4 ms ± 436 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)```

In [16]: ```%timeit test_hdf_fixed_read_compress()```

In [17]: ```%timeit test_hdf_table_read()
38.6 ms ± 857 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)```

In [18]: ```%timeit test_hdf_table_read_compress()```

In [19]: ```%timeit test_csv_read()
452 ms ± 9.04 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)```

In [20]: ```%timeit test_feather_read()
12.4 ms ± 99.7 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)```

In [21]: ```%timeit test_pickle_read()
18.4 ms ± 191 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)```

In [22]: ```%timeit test_pickle_read_compress()```

(continues on next page)
For this test case `test.pkl.compress`, `test.parquet` and `test.feather` took the least space on disk. Space on disk (in bytes)

<table>
<thead>
<tr>
<th>Filename</th>
<th>Size</th>
<th>Date</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>test.csv</td>
<td>29519500 B</td>
<td>Oct 10 06:45</td>
<td>test.csv</td>
</tr>
<tr>
<td>test.feather</td>
<td>16000248 B</td>
<td>Oct 10 06:45</td>
<td>test.feather</td>
</tr>
<tr>
<td>test.parquet</td>
<td>8281983 B</td>
<td>Oct 10 06:49</td>
<td>test.parquet</td>
</tr>
<tr>
<td>test.pkl</td>
<td>16000857 B</td>
<td>Oct 10 06:47</td>
<td>test.pkl</td>
</tr>
<tr>
<td>test.pkl.compress</td>
<td>7552144 B</td>
<td>Oct 10 06:48</td>
<td>test.pkl.compress</td>
</tr>
<tr>
<td>test.sql</td>
<td>34816000 B</td>
<td>Oct 10 06:42</td>
<td>test.sql</td>
</tr>
<tr>
<td>test_fixed.hdf</td>
<td>24009288 B</td>
<td>Oct 10 06:43</td>
<td>test_fixed.hdf</td>
</tr>
<tr>
<td>test_fixed_compress.hdf</td>
<td>24009288 B</td>
<td>Oct 10 06:43</td>
<td>test_fixed_compress.hdf</td>
</tr>
<tr>
<td>test_table.hdf</td>
<td>24458940 B</td>
<td>Oct 10 06:44</td>
<td>test_table.hdf</td>
</tr>
<tr>
<td>test_table_compress.hdf</td>
<td>24458940 B</td>
<td>Oct 10 06:44</td>
<td>test_table_compress.hdf</td>
</tr>
</tbody>
</table>

2.5 Indexing and selecting data

The axis labeling information in pandas objects serves many purposes:

- Identifies data (i.e. provides metadata) using known indicators, important for analysis, visualization, and interactive console display.
- Enables automatic and explicit data alignment.
- Allows intuitive getting and setting of subsets of the data set.

In this section, we will focus on the final point: namely, how to slice, dice, and generally get and set subsets of pandas objects. The primary focus will be on Series and DataFrame as they have received more development attention in this area.

**Note:** The Python and NumPy indexing operators `[]` and attribute operator `. provide quick and easy access to pandas data structures across a wide range of use cases. This makes interactive work intuitive, as there’s little new to learn if you already know how to deal with Python dictionaries and NumPy arrays. However, since the type of the data to be accessed isn’t known in advance, directly using standard operators has some optimization limits. For production code, we recommended that you take advantage of the optimized pandas data access methods exposed in this chapter.

**Warning:** Whether a copy or a reference is returned for a setting operation, may depend on the context. This is sometimes called chained assignment and should be avoided. See Returning a View versus Copy.

See the `MultiIndex / Advanced Indexing` for MultiIndex and more advanced indexing documentation. See the `cookbook` for some advanced strategies.
2.5.1 Different choices for indexing

Object selection has had a number of user-requested additions in order to support more explicit location based indexing. Pandas now supports three types of multi-axis indexing.

- **.loc** is primarily label based, but may also be used with a boolean array. `.loc` will raise `KeyError` when the items are not found. Allowed inputs are:
  - A single label, e.g. 5 or 'a' (Note that 5 is interpreted as a label of the index. This use is not an integer position along the index.).
  - A list or array of labels ['a', 'b', 'c'].
  - A slice object with labels 'a':'f' (Note that contrary to usual python slices, both the start and the stop are included, when present in the index! See Slicing with labels and Endpoints are inclusive.)
  - A boolean array (any NA values will be treated as False).
  - A callable function with one argument (the calling Series or DataFrame) and that returns valid output for indexing (one of the above).

See more at Selection by Label.

- **.iloc** is primarily integer position based (from 0 to length-1 of the axis), but may also be used with a boolean array. `.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except slice indexers which allow out-of-bounds indexing. (this conforms with Python/NumPy slice semantics). Allowed inputs are:
  - An integer e.g. 5.
  - A list or array of integers [4, 3, 0].
  - A slice object with ints 1:7.
  - A boolean array (any NA values will be treated as False).
  - A callable function with one argument (the calling Series or DataFrame) and that returns valid output for indexing (one of the above).

See more at Selection by Position, Advanced Indexing and Advanced Hierarchical.

- **.loc**, **.iloc**, and also [] indexing can accept a callable as indexer. See more at Selection By Callable.

Getting values from an object with multi-axes selection uses the following notation (using `.loc` as an example, but the following applies to `.iloc` as well). Any of the axes accessors may be the null slice :. Axes left out of the specification are assumed to be :, e.g. `p.loc['a']` is equivalent to `p.loc['a', :, :]`.

<table>
<thead>
<tr>
<th>Object Type</th>
<th>Indexers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series</td>
<td><code>s.loc[indexer]</code></td>
</tr>
<tr>
<td>DataFrame</td>
<td><code>df.loc[row_indexer, column_indexer]</code></td>
</tr>
</tbody>
</table>

2.5.2 Basics

As mentioned when introducing the data structures in the last section, the primary function of indexing with [] (a.k.a. `__getitem__` for those familiar with implementing class behavior in Python) is selecting out lower-dimensional slices. The following table shows return type values when indexing pandas objects with []:

<table>
<thead>
<tr>
<th>Object Type</th>
<th>Selection</th>
<th>Return Value Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series</td>
<td><code>series[label]</code></td>
<td>scalar value</td>
</tr>
<tr>
<td>DataFrame</td>
<td><code>frame[colname]</code></td>
<td>Series corresponding to colname</td>
</tr>
</tbody>
</table>
Here we construct a simple time series data set to use for illustrating the indexing functionality:

```python
In [1]: dates = pd.date_range('1/1/2000', periods=8)

In [2]: df = pd.DataFrame(np.random.randn(8, 4),
...:                   index=dates, columns=['A', 'B', 'C', 'D'])

In [3]: df
Out[3]:
   A          B          C          D
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632
2000-01-02  1.212112 -0.173215  0.119209 -1.044236
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804
2000-01-04  0.721555 -0.706771 -1.039575  0.271860
2000-01-05 -0.424972  0.567020  0.276232 -1.087401
2000-01-06 -0.673690  0.113648 -1.478427  0.524988
2000-01-07  0.404705  0.577046 -1.715002 -1.039268
2000-01-08 -0.370647 -1.157892 -1.344312  0.844885
```

**Note:** None of the indexing functionality is time series specific unless specifically stated.

Thus, as per above, we have the most basic indexing using []:

```python
In [4]: s = df['A']

In [5]: s[dates[5]]
Out[5]: -0.6736897080883706
```

You can pass a list of columns to [] to select columns in that order. If a column is not contained in the DataFrame, an exception will be raised. Multiple columns can also be set in this manner:

```python
In [6]: df
Out[6]:
   A          B          C          D
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632
2000-01-02  1.212112 -0.173215  0.119209 -1.044236
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804
2000-01-04  0.721555 -0.706771 -1.039575  0.271860
2000-01-05 -0.424972  0.567020  0.276232 -1.087401
2000-01-06 -0.673690  0.113648 -1.478427  0.524988
2000-01-07  0.404705  0.577046 -1.715002 -1.039268
2000-01-08 -0.370647 -1.157892 -1.344312  0.844885

In [7]: df[['B', 'A']] = df[['A', 'B']]

In [8]: df
Out[8]:
   A          B          C          D
2000-01-01 -0.282863  0.469112 -1.509059 -1.135632
2000-01-02 -0.173215  1.212112  0.119209 -1.044236
2000-01-03 -2.104569 -0.861849 -0.494929  1.071804
2000-01-04 -0.706771  0.721555 -1.039575  0.271860
2000-01-05  0.567020 -0.424972  0.276232 -1.087401
2000-01-06  0.113648 -0.673690 -1.478427  0.524988
2000-01-07  0.577046  0.404705 -1.715002 -1.039268
```

(continues on next page)
2000-01-08  -1.157892  -0.370647  -1.344312  0.844885

You may find this useful for applying a transform (in-place) to a subset of the columns.

**Warning:** pandas aligns all AXES when setting Series and DataFrame from .loc, and .iloc. This will **not** modify df because the column alignment is before value assignment.

```
In [9]: df[['A', 'B']]
Out [9]:
          A       B
2000-01-01 -0.282863  0.469112
2000-01-02 -0.173215  1.212112
2000-01-03 -2.104569 -0.861849
2000-01-04 -0.706771  0.721555
2000-01-05  0.567020 -0.424972
2000-01-06  0.113648 -0.673690
2000-01-07  0.577046  0.404705
2000-01-08 -1.157892 -0.370647

In [10]: df.loc[:, ['B', 'A']] = df[['A', 'B']]

In [11]: df[['A', 'B']]
Out [11]:
          A       B
2000-01-01 -0.282863  0.469112
2000-01-02 -0.173215  1.212112
2000-01-03 -2.104569 -0.861849
2000-01-04 -0.706771  0.721555
2000-01-05  0.567020 -0.424972
2000-01-06  0.113648 -0.673690
2000-01-07  0.577046  0.404705
2000-01-08 -1.157892 -0.370647

The correct way to swap column values is by using raw values:

```
In [12]: df.loc[:, ['B', 'A']] = df[['A', 'B']].to_numpy()

In [13]: df[['A', 'B']]
Out [13]:
          A       B
2000-01-01  0.469112 -0.282863
2000-01-02  1.212112 -0.173215
2000-01-03 -0.861849 -2.104569
2000-01-04  0.721555 -0.706771
2000-01-05 -0.424972  0.567020
2000-01-06  0.113648 -0.673690
2000-01-07  0.577046  0.404705
2000-01-08 -0.370647 -1.157892
```
2.5.3 Attribute access

You may access an index on a Series or column on a DataFrame directly as an attribute:

```
In [14]: sa = pd.Series([1, 2, 3], index=list('abc'))
In [15]: dfa = df.copy()

In [16]: sa.b
Out[16]: 2

In [17]: dfa.A
Out[17]:
2000-01-01  0.469112
2000-01-02  1.212112
2000-01-03 -0.861849
2000-01-04  0.721555
2000-01-05 -0.424972
2000-01-06 -0.673690
2000-01-07  0.404705
2000-01-08 -0.370647
Freq: D, Name: A, dtype: float64

In [18]: sa.a = 5
In [19]: sa
Out[19]:
a  5  
b  2  
c  3  
dtype: int64

In [20]: dfa.A = list(range(len(dfa.index)))  # ok if A already exists
In [21]: dfa
Out[21]:
          A   B   C   D
2000-01-01 0 -0.282863 -1.509059 -1.135632
2000-01-02 1 -0.173215  0.119209 -1.044236
2000-01-03 2 -2.104569 -0.494929  1.071804
2000-01-04 3 -0.706771 -1.039575  0.271860
2000-01-05 4  0.567020  0.276232 -1.087401
2000-01-06 5  0.113648 -1.478427  0.524988
2000-01-07 6  0.577046 -1.715002 -1.039268
2000-01-08 7 -1.157892 -1.344312  0.844885

In [22]: dfa['A'] = list(range(len(dfa.index)))  # use this form to create a new column
In [23]: dfa
Out[23]:
          A   B   C   D
2000-01-01 0 -0.282863 -1.509059 -1.135632
2000-01-02 1 -0.173215  0.119209 -1.044236
2000-01-03 2 -2.104569 -0.494929  1.071804
2000-01-04 3 -0.706771 -1.039575  0.271860
2000-01-05 4  0.567020  0.276232 -1.087401
2000-01-06 5  0.113648 -1.478427  0.524988
2000-01-07 6  0.577046 -1.715002 -1.039268
2000-01-08 7 -1.157892 -1.344312  0.844885
```

(continues on next page)
Warning:

- You can use this access only if the index element is a valid Python identifier, e.g. s.1 is not allowed. See here for an explanation of valid identifiers.
- The attribute will not be available if it conflicts with an existing method name, e.g. s.min is not allowed, but s['min'] is possible.
- Similarly, the attribute will not be available if it conflicts with any of the following list: index, major_axis, minor_axis, items.
- In any of these cases, standard indexing will still work, e.g. s['1'], s['min'], and s['index'] will access the corresponding element or column.

If you are using the IPython environment, you may also use tab-completion to see these accessible attributes.

You can also assign a dict to a row of a DataFrame:

```
In [24]: x = pd.DataFrame({'x': [1, 2, 3], 'y': [3, 4, 5]})
In [25]: x.iloc[1] = {'x': 9, 'y': 99}
In [26]: x
```

<table>
<thead>
<tr>
<th></th>
<th>x</th>
<th>y</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>1</td>
<td>9</td>
<td>99</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>5</td>
</tr>
</tbody>
</table>

You can use attribute access to modify an existing element of a Series or column of a DataFrame, but be careful; if you try to use attribute access to create a new column, it creates a new attribute rather than a new column. In 0.21.0 and later, this will raise a UserWarning:

```
In [1]: df = pd.DataFrame({'one': [1., 2., 3.]})
In [2]: df.two = [4, 5, 6]
UserWarning: Pandas doesn't allow Series to be assigned into nonexistent columns - see https://pandas.pydata.org/pandas-docs/stable/indexing.html#attribute_access
In [3]: df
Out[3]:
   one
0  1.0
1  2.0
2  3.0
```

2.5. Indexing and selecting data
2.5.4 Slicing ranges

The most robust and consistent way of slicing ranges along arbitrary axes is described in the Selection by Position section detailing the .iloc method. For now, we explain the semantics of slicing using the [ ] operator.

With Series, the syntax works exactly as with an ndarray, returning a slice of the values and the corresponding labels:

```
In [27]: s[:5]
Out[27]:
2000-01-01  0.469112
2000-01-02  1.212112
2000-01-03 -0.861849
2000-01-04  0.721555
2000-01-05 -0.424972
Freq: D, Name: A, dtype: float64
```

```
In [28]: s[::2]
Out[28]:
2000-01-01  0.469112
2000-01-03 -0.861849
2000-01-05 -0.424972
2000-01-07  0.404705
Freq: 2D, Name: A, dtype: float64
```

```
In [29]: s[::-1]
Out[29]:
2000-01-08 -0.370647
2000-01-07  0.404705
2000-01-06 -0.673690
2000-01-05 -0.424972
2000-01-04  0.721555
2000-01-03 -0.861849
2000-01-02  1.212112
2000-01-01  0.469112
Freq: -1D, Name: A, dtype: float64
```

Note that setting works as well:

```
In [30]: s2 = s.copy()
In [31]: s2[:5] = 0
In [32]: s2
Out[32]:
2000-01-01  0.000000
2000-01-02  0.000000
2000-01-03  0.000000
2000-01-04  0.000000
2000-01-05  0.000000
2000-01-06 -0.673690
2000-01-07  0.404705
2000-01-08 -0.370647
Freq: D, Name: A, dtype: float64
```

With DataFrame, slicing inside of [ ] slices the rows. This is provided largely as a convenience since it is such a common operation.
In [33]: df[:3]
Out[33]:
      A       B      C          D
2000-01-01 -0.282863 -1.509059 -1.135632
2000-01-02 -0.173215 -0.119209 -1.044236
2000-01-03 -1.045690 -0.494929  1.071804

In [34]: df[::-1]
Out[34]:
      A       B      C          D
2000-01-08 -1.343121 -1.578922  0.844885
2000-01-07 -1.039268 -1.478427  0.524988
2000-01-06 -1.478427  0.113648  0.524988
2000-01-05 -0.874010  0.276232  1.071804
2000-01-04 -1.044236  0.271860 -1.044236
2000-01-03  1.071804 -0.494929 -1.044236
2000-01-02  0.119209 -0.173215 -1.044236
2000-01-01 -1.135632 -0.282863 -1.509059

2.5.5 Selection by label

**Warning:** Whether a copy or a reference is returned for a setting operation, may depend on the context. This is sometimes called chained assignment and should be avoided. See *Returning a View versus Copy*.

**Warning:** .loc is strict when you present slicers that are not compatible (or convertible) with the index type. For example using integers in a DatetimeIndex. These will raise a TypeError.

In [35]: df1 = pd.DataFrame(np.random.randn(5, 4),
                        columns=list('ABCD'),
                        index=pd.date_range('20130101', periods=5))

In [36]: df1
Out[36]:
     A       B       C       D
2013-01-01 1.075770 -0.109050 1.643563 -1.469388
2013-01-02 0.357021 -0.674600 -1.776904 -0.968914
2013-01-03 -1.294524  0.413738  0.276662 -0.472035
2013-01-04 -0.013960 -0.362543 -0.006154 -0.923061
2013-01-05  0.895717  0.805244 -1.206412  2.565646

In [4]: df1.loc[2:3]
TypeError: cannot do slice indexing on <class 'pandas.tseries.index.DatetimeIndex'> with these indexers [2] of <type 'int'>

String likes in slicing can be convertible to the type of the index and lead to natural slicing.

In [37]: df1.loc['20130102':'20130104']
Out[37]:
     A       B       C       D
2013-01-02 0.357021 -0.674600 -1.776904 -0.968914
2013-01-03 -1.294524  0.413738  0.276662 -0.472035
2013-01-04 -0.013960 -0.362543 -0.006154 -0.923061

2.5. Indexing and selecting data
Warning: Starting in 0.21.0, pandas will show a FutureWarning if indexing with a list with missing labels. In the future this will raise a KeyError. See list-like Using loc with missing keys in a list is Deprecated.

pandas provides a suite of methods in order to have purely label based indexing. This is a strict inclusion based protocol. Every label asked for must be in the index, or a KeyError will be raised. When slicing, both the start bound AND the stop bound are included, if present in the index. Integers are valid labels, but they refer to the label and not the position.

The .loc attribute is the primary access method. The following are valid inputs:

- A single label, e.g. 5 or 'a' (Note that 5 is interpreted as a label of the index. This use is not an integer position along the index.).
- A list or array of labels ['a', 'b', 'c'].
- A slice object with labels 'a':'f' (Note that contrary to usual python slices, both the start and the stop are included, when present in the index! See Slicing with labels.
- A boolean array.
- A callable, see Selection By Callable.

```
In [38]: s1 = pd.Series(np.random.randn(6), index=list('abcdef'))

In [39]: s1
Out[39]:
      a  1.431256
      b  1.340309
      c -1.170299
      d -0.226169
      e  0.410835
      f  0.813850
      dtype: float64

In [40]: s1.loc['c':]
Out[40]:
      c  -1.170299
      d  -0.226169
      e   0.410835
      f   0.813850
      dtype: float64

In [41]: s1.loc['b']
Out[41]: 1.3403088497993827
```

Note that setting works as well:

```
In [42]: s1.loc['c'] = 0

In [43]: s1
Out[43]:
      a  1.431256
      b  1.340309
      c  0.000000
      d  0.000000
      e  0.000000
      f  0.000000
      dtype: float64
```

(continues on next page)
With a DataFrame:

```python
In [44]: df1 = pd.DataFrame(np.random.randn(6, 4),
                         index=list('abcdef'),
                         columns=list('ABCD'))
```

```python
In [45]: df1
Out[45]:
     A      B      C      D
a  0.132  -0.827  -0.076  -1.188
b  1.130  -1.437  -1.414   1.608
c  1.024   0.569   0.876  -2.211
d  0.974  -2.007  -0.410  -0.079
e  0.546  -1.219  -1.227   0.769
f  1.281  -0.728  -0.121  -0.098
```

Accessing via label slices:

```python
In [46]: df1.loc[['a', 'b', 'd'], :]
Out[46]:
     A      B      C      D
a  0.132  -0.827  -0.076  -1.188
b  1.130  -1.437  -1.414   1.608
d  0.974  -2.007  -0.410  -0.079
e  0.546  -1.219  -1.227   0.769
f  1.281  -0.728  -0.121  -0.098
```

For getting a cross section using a label (equivalent to `df.xs('a')`):

```python
In [47]: df1.loc['a']
Out[47]:
     A      B      C      D
Name: a, dtype: float64
```

For getting values with a boolean array:

```python
In [48]: df1.loc['a'] > 0
Out[48]:
     A   True
     B   False
     C   False
     D   False
Name: a, dtype: bool
```

2.5. Indexing and selecting data
In [50]: df1.loc[:, df1['a'] > 0]
Out[50]:
    A
a  0.132003
b  1.130127
c  1.024180
d  0.974466
e  0.545952
f -1.281247

NA values in a boolean array propagate as False:

Changed in version 1.0.2: mask = pd.array([True, False, True, False, pd.NA, False], dtype="boolean") mask df1[mask]

For getting a value explicitly:

# this is also equivalent to `df1.at['a','A']`
In [51]: df1['a', 'A']
Out[51]:
    0
0  0.132003

Slicing with labels

When using .loc with slices, if both the start and the stop labels are present in the index, then elements located between the two (including them) are returned:

In [52]: s = pd.Series(list('abcde'), index=[0, 3, 2, 5, 4])

In [53]: s.loc[3:5]
Out[53]:
     3     b
     2     c
     5     d
dtype: object

If at least one of the two is absent, but the index is sorted, and can be compared against start and stop labels, then slicing will still work as expected, by selecting labels which rank between the two:

In [54]: s.sort_index()
Out[54]:
    0     a
    2     c
    3     b
    4     e
    5     d
dtype: object

In [55]: s.sort_index().loc[1:6]
Out[55]:
    2     c
    3     b
    4     e
    5     d
dtype: object
However, if at least one of the two is absent and the index is not sorted, an error will be raised (since doing otherwise would be computationally expensive, as well as potentially ambiguous for mixed type indexes). For instance, in the above example, `s.loc[1:6]` would raise `KeyError`.

For the rationale behind this behavior, see *Endpoints are inclusive*.

### 2.5.6 Selection by position

**Warning:** Whether a copy or a reference is returned for a setting operation, may depend on the context. This is sometimes called *chained assignment* and should be avoided. See *Returning a View versus Copy*.

Pandas provides a suite of methods in order to get **purely integer based indexing**. The semantics follow closely Python and NumPy slicing. These are 0-based indexing. When slicing, the start bound is *included*, while the upper bound is *excluded*. Trying to use a non-integer, even a valid label will raise an `IndexError`.

The `.iloc` attribute is the primary access method. The following are valid inputs:

- An integer e.g. 5.
- A list or array of integers [4, 3, 0].
- A slice object with ints 1:7.
- A boolean array.
- A callable, see *Selection By Callable*.

```python
In [56]: s1 = pd.Series(np.random.randn(5), index=list(range(0, 10, 2)))
In [57]: s1
Out[57]:
0    0.695775
2    0.341734
4    0.959726
6   -1.110336
8   -0.619976
dtype: float64
In [58]: s1.iloc[:3]
Out[58]:
0    0.695775
2    0.341734
4    0.959726
dtype: float64
In [59]: s1.iloc[3]
Out[59]: -1.110336102891167
```

Note that setting works as well:

```python
In [60]: s1.iloc[:3] = 0
In [61]: s1
Out[61]:
0    0.000000
2    0.000000
4    0.000000
```

(continues on next page)
With a DataFrame:

```python
In [62]: df1 = pd.DataFrame(np.random.randn(6, 4),
                        index=list(range(0, 12, 2)),
                        columns=list(range(0, 8, 2)))

In [63]: df1
Out[63]:
         0     2     4     6
0  0.149748 -0.732339  0.687738  0.176444
2  0.403310 -0.154951  0.301624 -2.179861
4 -1.369849 -0.954208  1.462696 -1.743161
6 -0.826591 -0.345352  1.314232  0.690579
8  0.995761  2.396780  0.014871  3.357427
10 -0.317441 -1.236269  0.896171 -0.487602
```

Select via integer slicing:

```python
In [64]: df1.iloc[:3]
Out[64]:
         0     2     4     6
0  0.149748 -0.732339  0.687738  0.176444
2  0.403310 -0.154951  0.301624 -2.179861
4 -1.369849 -0.954208  1.462696 -1.743161

In [65]: df1.iloc[1:5, 2:4]
Out[65]:
         2     4
4  0.301624 -2.179861
6  1.462696 -1.743161
8  0.148711  3.357427

In [66]: df1.iloc[[1, 3, 5], [1, 3]]
Out[66]:
         1     3
2 -0.154951 -2.179861
6 -0.345352  0.690579
10 -1.236269 -0.487602

In [67]: df1.iloc[1:3, :]
Out[67]:
         0     2     4     6
2  0.403310 -0.154951  0.301624 -2.179861
4 -1.369849 -0.954208  1.462696 -1.743161

In [68]: df1.iloc[:, 1:3]
Out[68]:
         0     2     4
2  0.403310 -0.154951  0.301624 -2.179861
4 -1.369849 -0.954208  1.462696 -1.743161
```

(continues on next page)
# this is also equivalent to `df1.iat[1,1]`
In [69]: df1.iat[1, 1]
Out[69]: -0.1549507744249032

For getting a cross section using an integer position (equiv to `df.xs(1)`):

In [70]: df1.iloc[1]
Out[70]:
0    0.403310
2   -0.154951
4    0.301624
6   -2.179861
Name: 2, dtype: float64

Out of range slice indexes are handled gracefully just as in Python/Numpy.

# these are allowed in python/numpy.
In [71]: x = list('abcdef')

In [72]: x
Out[72]: ['a', 'b', 'c', 'd', 'e', 'f']

In [73]: x[4:10]
Out[73]: ['e', 'f']

In [74]: x[8:10]
Out[74]: []

In [75]: s = pd.Series(x)

In [76]: s
Out[76]:
0  a
1  b
2  c
3  d
4  e
5  f
dtype: object

In [77]: s.iloc[4:10]
Out[77]:
4  e
dtype: object

In [78]: s.iloc[8:10]
Out[78]: Series([], dtype: object)

Note that using slices that go out of bounds can result in an empty axis (e.g. an empty DataFrame being returned).

2.5. Indexing and selecting data
In [79]: df1 = pd.DataFrame(np.random.randn(5, 2), columns=list('AB'))

In [80]: df1
Out[80]:
   A      B
0 -0.082240 -2.182937
1  0.380396  0.084844
2  0.432390  1.519970
3 -0.493662  0.600178
4  0.274230  0.132885

In [81]: df1.iloc[:, 2:3]
Out[81]:
Empty DataFrame
Columns: []
Index: [0, 1, 2, 3, 4]

In [82]: df1.iloc[:, 1:3]
Out[82]:
   B
0 -2.182937
1  0.084844
2  1.519970
3  0.600178
4  0.132885

In [83]: df1.iloc[4:6]
Out[83]:
   A      B
4  0.27423  0.132885

A single indexer that is out of bounds will raise an `IndexError`. A list of indexers where any element is out of bounds will raise an `IndexError`.

>>> df1.iloc[[4, 5, 6]]
IndexError: positional indexers are out-of-bounds

>>> df1.iloc[:, 4]
IndexError: single positional indexer is out-of-bounds

2.5.7 Selection by callable

.loc, .iloc, and also [] indexing can accept a `callable` as indexer. The `callable` must be a function with one argument (the calling Series or DataFrame) that returns valid output for indexing.

In [84]: df1 = pd.DataFrame(np.random.randn(6, 4),
.....: index=list('abcdef'),
.....: columns=list('ABCD'))

In [85]: df1
Out[85]:
   A      B      C      D
0 -0.023688  2.410179  1.450520  0.206053
1 -0.251905 -2.213588  1.063327  1.266143
(continues on next page)
You can use callable indexing in Series.

In [90]: df1['A'].loc[lambda s: s > 0]
Out[90]:

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>c</td>
<td>0.299368</td>
</tr>
<tr>
<td>e</td>
<td>1.289997</td>
</tr>
</tbody>
</table>

You can use callable indexing in `Series`. Using these methods / indexers, you can chain data selection operations without using a temporary variable.

In [91]: bb = pd.read_csv('data/baseball.csv', index_col='id')

In [92]: (bb.groupby(['year', 'team']).sum()
       ....: .loc[lambda df: df['r'] > 100])

(continues on next page)
### 2.5.8 IX indexer is deprecated

**Warning:** Starting in 0.20.0, the `.ix` indexer is deprecated, in favor of the more strict `.iloc` and `.loc` indexers.

`.ix` offers a lot of magic on the inference of what the user wants to do. To wit, `.ix` can decide to index **positionally** OR via *labels* depending on the data type of the index. This has caused quite a bit of user confusion over the years.

The recommended methods of indexing are:

- `.loc` if you want to *label* index.
- `.iloc` if you want to *positionally* index.

```
In [93]: dfd = pd.DataFrame({'A': [1, 2, 3],
....:                     'B': [4, 5, 6]},
....:                     index=list('abc'))
....:

In [94]: dfd
Out[94]:
   A  B
  a  1  4
  b  2  5
  c  3  6

In [3]: dfd.ix[[0, 2], 'A']
Out[3]:
   a
0  1
1  3
Name: A, dtype: int64
```

Previous behavior, where you wish to get the 0th and the 2nd elements from the index in the ‘A’ column.
Using `.loc`. Here we will select the appropriate indexes from the index, then use label indexing.

```python
In [95]: dfd.loc[dfd.index[[0, 2]], 'A']
Out[95]:
   a  c
0  1  3
Name: A, dtype: int64
```

This can also be expressed using `.iloc`, by explicitly getting locations on the indexers, and using positional indexing to select things.

```python
In [96]: dfd.iloc[[0, 2], dfd.columns.get_loc('A')]
Out[96]:
   a  c
0  1  3
Name: A, dtype: int64
```

For getting multiple indexers, using `.get_indexer`:

```python
In [97]: dfd.iloc[[0, 2], dfd.columns.get_indexer(['A', 'B'])]
Out[97]:
   A  B
0  1  4
2  3  6
```

### 2.5.9 Indexing with list with missing labels is deprecated

**Warning:** Starting in 0.21.0, using `.loc` or `[]` with a list with one or more missing labels, is deprecated, in favor of `.reindex`.

In prior versions, using `.loc[list-of-labels]` would work as long as at least 1 of the keys was found (otherwise it would raise a `KeyError`). This behavior is deprecated and will show a warning message pointing to this section. The recommended alternative is to use `.reindex()`.

For example.

```python
In [98]: s = pd.Series([1, 2, 3])
In [99]: s
Out[99]:
0  1
1  2
2  3
dtype: int64
```

Selection with all keys found is unchanged.

```python
In [100]: s.loc[[1, 2]]
Out[100]:
   1  2
   2  3
dtype: int64
```

Previous behavior

2.5. Indexing and selecting data
In [4]: s.loc[[1, 2, 3]]
Out[4]:
1  2.0  
2  3.0  
3  NaN 
  dtype: float64

Current behavior

In [4]: s.loc[[1, 2, 3]]
Passing list-likes to .loc with any non-matching elements will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-reindex-
listlike

Out[4]:
1  2.0  
2  3.0  
3  NaN 
  dtype: float64

Reindexing

The idiomatic way to achieve selecting potentially not-found elements is via .reindex(). See also the section on
reindexing.

In [101]: s.reindex([1, 2, 3])
Out[101]:
1  2.0  
2  3.0  
3  NaN 
  dtype: float64

Alternatively, if you want to select only valid keys, the following is idiomatic and efficient; it is guaranteed to preserve
the dtype of the selection.

In [102]: labels = [1, 2, 3]

In [103]: s.loc[s.index.intersection(labels)]
Out[103]:
1  2  
2  3  
  dtype: int64

Having a duplicated index will raise for a .reindex():

In [104]: s = pd.Series(np.arange(4), index=['a', 'a', 'b', 'c'])

In [105]: labels = ['c', 'd']

In [17]: s.reindex(labels)
ValueError: cannot reindex from a duplicate axis

Generally, you can intersect the desired labels with the current axis, and then reindex.
However, this would still raise if your resulting index is duplicated.

```
In [42]: labels = ['a', 'd']
In [43]: s.loc[s.index.intersection(labels)].reindex(labels)
ValueError: cannot reindex from a duplicate axis
```

### 2.5.10 Selecting random samples

A random selection of rows or columns from a Series or DataFrame with the `sample()` method. The method will sample rows by default, and accepts a specific number of rows/columns to return, or a fraction of rows.

```
In [107]: s = pd.Series([0, 1, 2, 3, 4, 5])

# When no arguments are passed, returns 1 row.
In [108]: s.sample()
Out[108]:
   4  4
4  4

dtype: int64

# One may specify either a number of rows:
In [109]: s.sample(n=3)
Out[109]:
   0  0
   4  4
   1  1
4  4

dtype: int64

# Or a fraction of the rows:
In [110]: s.sample(frac=0.5)
Out[110]:
   5  5
   3  3
   1  1
5  5

dtype: int64
```

By default, `sample` will return each row at most once, but one can also sample with replacement using the `replace` option:

```
In [111]: s = pd.Series([0, 1, 2, 3, 4, 5])

# Without replacement (default):
In [112]: s.sample(n=6, replace=False)
Out[112]:
   0  0
   1  1
   5  5
   3  3
   2  2
   5  5
```

(continues on next page)
# With replacement:
In [113]: s.sample(n=6, replace=True)
Out[113]:
0 0
4 4
3 3
2 2
4 4
4 4
dtype: int64

By default, each row has an equal probability of being selected, but if you want rows to have different probabilities, you can pass the `sample` function sampling weights as `weights`. These weights can be a list, a NumPy array, or a Series, but they must be of the same length as the object you are sampling. Missing values will be treated as a weight of zero, and inf values are not allowed. If weights do not sum to 1, they will be re-normalized by dividing all weights by the sum of the weights. For example:

```
In [114]: s = pd.Series([0, 1, 2, 3, 4, 5])
In [115]: example_weights = [0, 0, 0.2, 0.2, 0.2, 0.4]
In [116]: s.sample(n=3, weights=example_weights)
Out[116]:
5 5
4 4
3 3
dtype: int64
```

# Weights will be re-normalized automatically
In [117]: example_weights2 = [0.5, 0, 0, 0, 0, 0]
In [118]: s.sample(n=1, weights=example_weights2)
Out[118]:
0 0
dtype: int64

When applied to a DataFrame, you can use a column of the DataFrame as sampling weights (provided you are sampling rows and not columns) by simply passing the name of the column as a string.

```
In [119]: df2 = pd.DataFrame({'col1': [9, 8, 7, 6],
                         'weight_column': [0.5, 0.4, 0.1, 0]})
In [120]: df2.sample(n=3, weights='weight_column')
Out[120]:
          col1  weight_column
1         8            0.4
0         9            0.5
2         7            0.1
```

`sample` also allows users to sample columns instead of rows using the `axis` argument.

```
In [121]: df3 = pd.DataFrame({'col1': [1, 2, 3], 'col2': [2, 3, 4]})
```
In [122]: df3.sample(n=1, axis=1)
Out[122]:
    col1
0  1
1  2
2  3

Finally, one can also set a seed for `sample`'s random number generator using the `random_state` argument, which will accept either an integer (as a seed) or a NumPy RandomState object.

In [123]: df4 = pd.DataFrame({'col1': [1, 2, 3], 'col2': [2, 3, 4]})

# With a given seed, the sample will always draw the same rows.
In [124]: df4.sample(n=2, random_state=2)
Out[124]:
     col1  col2
2   3    4
1   2    3

In [125]: df4.sample(n=2, random_state=2)
Out[125]:
     col1  col2
2   3    4
1   2    3

2.5.11 Setting with enlargement

The `.loc/[]` operations can perform enlargement when setting a non-existent key for that axis. In the `Series` case this is effectively an appending operation.

In [126]: se = pd.Series([1, 2, 3])

In [127]: se
Out[127]:
     0  1.0
     1  2.0
     2  3.0
     5  5.0

dtype: float64


In [129]: se
Out[129]:
     0  1.0
     1  2.0
     2  3.0
     5  5.0

dtype: float64

A `DataFrame` can be enlarged on either axis via `.loc`.

In [130]: dfi = pd.DataFrame(np.arange(6).reshape(3, 2),
   columns=['A', 'B'])
   .....:

(continues on next page)
In [131]: dfi
Out[131]:
    A  B
0  0  1
1  2  3
2  4  5

In [132]: dfi.loc[:, 'C'] = dfi.loc[:, 'A']

In [133]: dfi
Out[133]:
    A  B  C
0  0  1  0
1  2  3  2
2  4  5  4

This is like an *append* operation on the DataFrame.

In [134]: dfi.loc[3] = 5

In [135]: dfi
Out[135]:
    A  B  C
0  0  1  0
1  2  3  2
2  4  5  4
3  5  5  5

### 2.5.12 Fast scalar value getting and setting

Since indexing with [] must handle a lot of cases (single-label access, slicing, boolean indexing, etc.), it has a bit of overhead in order to figure out what you’re asking for. If you only want to access a scalar value, the fastest way is to use the *at* and *iat* methods, which are implemented on all of the data structures.

Similarly to *loc*, *at* provides *label* based scalar lookups, while, *iat* provides *integer* based lookups analogously to *iloc*

In [136]: s.iat[5]
Out[136]: 5

In [137]: df.at[dates[5], 'A']
Out[137]: -0.6736897080883706

In [138]: df.iat[3, 0]
Out[138]: 0.7215551622443669

You can also set using these same indexers.

In [139]: df.at[dates[5], 'E'] = 7

In [140]: df.iat[3, 0] = 7

*at* may enlarge the object in-place as above if the indexer is missing.
2.5.13 Boolean indexing

Another common operation is the use of boolean vectors to filter the data. The operators are: | for or, & for and, and ~ for not. These must be grouped by using parentheses, since by default Python will evaluate an expression such as df['A'] > 2 & df['B'] < 3 as df['A'] > (2 & df['B']) < 3, while the desired evaluation order is (df['A'] > 2) & (df['B'] < 3).

Using a boolean vector to index a Series works exactly as in a NumPy ndarray:

```python
In [143]: s = pd.Series(range(-3, 4))
```

```python
In [144]: s
```

```
Out[144]:
0   -3
1   -2
2   -1
3    0
4    1
5    2
6    3
dtype: int64
```

```python
In [145]: s[s > 0]
```

```
Out[145]:
4
5
6
dtype: int64
```

```python
In [146]: s[(s < -1) | (s > 0.5)]
```

```
Out[146]:
0   -3
1   -2
4    1
5    2
6    3
dtype: int64
```

```python
In [147]: s[~(s < 0)]
```

```
Out[147]:
3    0
```

(continues on next page)
You may select rows from a DataFrame using a boolean vector the same length as the DataFrame’s index (for example, something derived from one of the columns of the DataFrame):

```python
In [148]: df[df['A'] > 0]
Out[148]:
   A         B         C         D         E
0 2000-01-01  0.469112 -0.282863 -1.509059 -1.135632    NaN
1 2000-01-02  1.212112 -0.173215  0.119209 -1.044236    NaN
2 2000-01-04  7.000000 -0.706771 -1.039575  0.271860    NaN
3 2000-01-07  0.404705  0.577046 -1.715002 -1.039268    NaN
```

List comprehensions and the `map` method of Series can also be used to produce more complex criteria:

```python
In [149]: df2 = pd.DataFrame({'a': ['one', 'one', 'two', 'three', 'two', 'one', 'six'],
                      'b': ['x', 'y', 'y', 'x', 'y', 'x', 'x'],
                      'c': np.random.randn(7)})

# only want 'two' or 'three'
In [150]: criterion = df2['a'].map(lambda x: x.startswith('t'))
In [151]: df2[criterion]
Out[151]:
   a    b    c
2  two  0.041290
3  three  0.361719
4  two  -0.238075

# equivalent but slower
In [152]: df2[[x.startswith('t') for x in df2['a']]]
Out[152]:
   a     b     c
2  two  0.041290
3  three  0.361719
4  two  -0.238075

# Multiple criteria
In [153]: df2[criterion & (df2['b'] == 'x')]
Out[153]:
   a     b     c
2  two  0.041290
3  three  0.361719
```

With the choice methods `Selection by Label`, `Selection by Position`, and `Advanced Indexing` you may select along more than one axis using boolean vectors combined with other indexing expressions.

```python
In [154]: df2.loc[criterion & (df2['b'] == 'x'), 'b': 'c']
Out[154]:
   b     c
3  x  0.361719
```
2.5.14 Indexing with `isin`

Consider the `isin()` method of `Series`, which returns a boolean vector that is true wherever the `Series` elements exist in the passed list. This allows you to select rows where one or more columns have values you want:

```python
In [155]: s = pd.Series(np.arange(5), index=np.arange(5)[::-1], dtype='int64')
In [156]: s
Out[156]:
0 4
1 3
2 2
3 1
4 0
dtype: int64
In [157]: s.isin([2, 4, 6])
Out[157]:
4  False
3  False
2  True
1  False
0  True
dtype: bool
In [158]: s[s.isin([2, 4, 6])]
Out[158]:
2 2
0 4
dtype: int64
```

The same method is available for `Index` objects and is useful for the cases when you don’t know which of the sought labels are in fact present:

```python
In [159]: s[s.index.isin([2, 4, 6])]
Out[159]:
4 0
2 2
dtype: int64

# compare it to the following
In [160]: s.reindex([2, 4, 6])
Out[160]:
2 2.0
4 0.0
6 NaN
dtype: float64
```

In addition to that, `MultiIndex` allows selecting a separate level to use in the membership check:

```python
In [161]: s_mi = pd.Series(np.arange(6),
                   index=pd.MultiIndex.from_product([[0, 1], ['a', 'b', 'c']]))
   .....:

In [162]: s_mi
Out[162]:
0 a 0
```
DataFrame also has an \texttt{isin()} method. When calling \texttt{isin}, pass a set of values as either an array or dict. If values is an array, \texttt{isin} returns a DataFrame of booleans that is the same shape as the original DataFrame, with True wherever the element is in the sequence of values.

```python
In [165]: df = pd.DataFrame({'vals': [1, 2, 3, 4], 'ids': ['a', 'b', 'f', 'n'],
                      'ids2': ['a', 'n', 'c', 'n']})

In [166]: values = ['a', 'b', 1, 3]
In [167]: df.isin(values)
```

```python
Out[167]:
  vals  ids  ids2
0  True  True  True
1  False  True  False
2  True  False  False
3  False  False  False
```

Oftentimes you’ll want to match certain values with certain columns. Just make values a \texttt{dict} where the key is the column, and the value is a list of items you want to check for.

```python
In [168]: values = {'ids': ['a', 'b'], 'vals': [1, 3]}
In [169]: df.isin(values)
```

```python
Out[169]:
  vals  ids  ids2
0  True  True  True
1  False  True  False
2  True  False  False
3  False  False  False
```

Combine DataFrame’s \texttt{isin} with the \texttt{any()} and \texttt{all()} methods to quickly select subsets of your data that meet a given criteria. To select a row where each column meets its own criterion:

```python
In [170]: values = {'ids': ['a', 'b'], 'ids2': ['a', 'c'], 'vals': [1, 3]}
```

(continues on next page)
In [171]: row_mask = df.isin(values).all(1)

In [172]: df[row_mask]
Out[172]:
   vals  ids  ids2
0     1    a    a

2.5.15 The `where()` Method and Masking

Selecting values from a Series with a boolean vector generally returns a subset of the data. To guarantee that selection output has the same shape as the original data, you can use the `where` method in `Series` and `DataFrame`.

To return only the selected rows:

In [173]: s[s > 0]
Out[173]:
   3   1
   2   2
   1   3
   0   4
dtype: int64

To return a Series of the same shape as the original:

In [174]: s.where(s > 0)
Out[174]:
   4    NaN
   3    1.0
   2    2.0
   1    3.0
   0    4.0
dtype: float64

Selecting values from a DataFrame with a boolean criterion now also preserves input data shape. `where` is used under the hood as the implementation. The code below is equivalent to `df.where(df < 0)`.

In [175]: df[df < 0]
Out[175]:
     A          B          C          D
   2000-01-01 -2.104139 -1.309525 NaN        NaN
   2000-01-02 -0.352480 NaN -1.192319 NaN
   2000-01-03 -0.864883 NaN -0.227870 NaN
   2000-01-04 NaN -1.222082 NaN -1.233203
   2000-01-05 NaN -0.605656 -1.169184 NaN
   2000-01-06 NaN -0.948458 NaN -0.684718
   2000-01-07 -2.670153 -0.114722 NaN -0.048788
   2000-01-08 NaN NaN -0.048788 -0.808838

In addition, `where` takes an optional `other` argument for replacement of values where the condition is False, in the returned copy.

In [176]: df.where(df < 0, -df)
Out[176]:
     A          B          C          D
   2000-01-01 -2.104139 -1.309525 NaN        NaN
   2000-01-02 -0.352480 NaN -1.192319 NaN
   2000-01-03 -0.864883 NaN -0.227870 NaN
   2000-01-04 NaN -1.222082 NaN -1.233203
   2000-01-05 NaN -0.605656 -1.169184 NaN
   2000-01-06 NaN -0.948458 NaN -0.684718
   2000-01-07 -2.670153 -0.114722 NaN -0.048788
   2000-01-08 NaN NaN -0.048788 -0.808838
You may wish to set values based on some boolean criteria. This can be done intuitively like so:

```python
In [177]: s2 = s.copy()

In [178]: s2[s2 < 0] = 0

In [179]: s2
Out[179]:
    4    0
   -- --
 0  4
1  3
2  2
3  1

```

By default, `where` returns a modified copy of the data. There is an optional parameter `inplace` so that the original data can be modified without creating a copy:

```python
In [183]: df_orig = df.copy()

In [184]: df_orig.where(df > 0, -df, inplace=True)

In [185]: df_orig
Out[185]:
   A      B      C      D
0-01-01 2.10414 1.30952 0.48585 0.24517
0-01-02 0.35248 0.39039 1.19232 1.65582
0-01-03 0.86489 0.29967 0.22787 0.28106
0-01-04 0.84696 1.22208 0.60070 1.23320
0-01-05 0.66969 0.60566 1.16918 0.34242
0-01-06 0.86858 0.94846 2.29778 0.68472
0-01-07 2.67015 0.11472 0.16890 0.04805
0-01-08 0.80119 1.39207 0.04878 0.80884

```

(continues on next page)
Note: The signature for DataFrame.where() differs from numpy.where(). Roughly df1.where(m, df2) is equivalent to np.where(m, df1, df2).

```
In [186]: df.where(df < 0, -df) == np.where(df < 0, df, -df)
Out[186]:
   A  B  C  D
2000-01-01  True True True True
2000-01-02  True True True True
2000-01-03  True True True True
2000-01-04  True True True True
2000-01-05  True True True True
2000-01-06  True True True True
2000-01-07  True True True True
2000-01-08  True True True True
```

Alignment

Furthermore, where aligns the input boolean condition (ndarray or DataFrame), such that partial selection with setting is possible. This is analogous to partial setting via .loc (but on the contents rather than the axis labels).

```
In [187]: df2 = df.copy()
In [188]: df2[df2[1:4] > 0] = 3
In [189]: df2
Out[189]:
   A      B       C       D
2000-01-01 -2.104139 -2.104139 0.485855 0.245166
2000-01-02 -0.352480  0.390389 -0.352480  1.655824
2000-01-03 -0.864883  0.299674 -0.864883  0.281059
2000-01-04  3.000000 -1.222082  3.000000 -1.232033
2000-01-05  0.669692 -0.605656 -0.669692  0.342416
2000-01-06  0.868584 -0.948458 -0.948458 -0.684718
2000-01-07 -2.670153 -0.114722 -0.114722 -0.048048
2000-01-08  0.801196  1.392071  1.392071 -0.808838
```

Where can also accept axis and level parameters to align the input when performing the where.

```
In [190]: df2 = df.copy()
In [191]: df2.where(df2 > 0, df2['A'], axis='index')
Out[191]:
   A      B       C       D
2000-01-01 -2.104139 -2.104139 0.485855 0.245166
2000-01-02 -0.352480 -0.352480 -0.352480  1.655824
2000-01-03 -0.864883 -0.864883 -0.864883  0.846958
2000-01-04  3.000000  3.000000  3.000000  0.846958
2000-01-05  0.669692  0.669692  0.669692  0.342416
2000-01-06  0.868584  0.868584  0.868584 -0.684718
2000-01-07 -2.670153 -2.670153 -2.670153 -0.048048
2000-01-08  0.801196  1.392071  1.392071  0.801196
```
This is equivalent to (but faster than) the following.

```python
In [192]: df2 = df.copy()
In [193]: df.apply(lambda x, y: x.where(x > 0, y), y=df['A'])
Out[193]:
     A       B       C       D
2000-01-01 -2.104139 -2.104139   0.485855   0.245166
2000-01-02  0.352480  0.390389  -0.352480   1.655824
2000-01-03 -0.864883  0.299674  -0.864883   0.281059
2000-01-04  0.846958  0.846958   0.600705   0.846958
2000-01-05  0.669692  0.669692   0.669692   0.342416
2000-01-06  0.868584  0.868584   2.297780   0.868584
2000-01-07 -2.670153 -2.670153   0.168904  -2.670153
2000-01-08  0.801196  1.392071   0.801196   0.801196
```

`where` can accept a callable as condition and other arguments. The function must be with one argument (the calling Series or DataFrame) and that returns valid output as condition and other argument.

```python
In [194]: df3 = pd.DataFrame({
    ...:     'A': [1, 2, 3],
    ...:     'B': [4, 5, 6],
    ...:     'C': [7, 8, 9]
    ...: })
In [195]: df3.where(lambda x: x > 4, lambda x: x + 10)
Out[195]:
    A  B  C
0   11 14  7
1   12  5  8
2   13  6  9
```

**Mask**

`mask()` is the inverse boolean operation of `where`.

```python
In [196]: s.mask(s >= 0)
Out[196]:
    4  NaN
   3  NaN
   2  NaN
   1  NaN
   0  NaN
dtype: float64
In [197]: df.mask(df >= 0)
Out[197]:
     A       B       C       D
2000-01-01 -2.104139 -1.309525  NaN       NaN
2000-01-02  0.352480  NaN   -1.192319  NaN
2000-01-03 -0.864883  NaN   -0.227870  NaN
2000-01-04  NaN   -1.222082  NaN   -1.233203
2000-01-05  NaN   -0.605656  NaN   -1.169184
2000-01-06  NaN   -0.948458  NaN   -0.684718
2000-01-07 -2.670153  NaN   -0.048788  -0.808838
2000-01-08  NaN       NaN  -0.048788   0.808838
```
2.5.16 The query() Method

*DataFrame* objects have a `query()` method that allows selection using an expression.

You can get the value of the frame where column `b` has values between the values of columns `a` and `c`. For example:

```python
In [198]: n = 10
In [199]: df = pd.DataFrame(np.random.rand(n, 3), columns=list('abc'))
In [200]: df
Out[200]:
   a   b   c
0  0.438921  0.118680  0.863670
1  0.138138  0.577363  0.686602
2  0.595307  0.564592  0.520630
3  0.913052  0.926075  0.616184
4  0.078718  0.854477  0.898725
5  0.076404  0.523211  0.591538
6  0.792342  0.216974  0.564056
7  0.397890  0.454131  0.915716
8  0.074315  0.437913  0.019794
9  0.559209  0.502065  0.026437

# pure python
In [201]: df[(df['a'] < df['b']) & (df['b'] < df['c'])]
Out[201]:
   a   b   c
1  0.138138  0.577363  0.686602
4  0.078718  0.854477  0.898725
5  0.076404  0.523211  0.591538
7  0.397890  0.454131  0.915716

# query
In [202]: df.query('(a < b) & (b < c)')
Out[202]:
   a   b   c
1  0.138138  0.577363  0.686602
4  0.078718  0.854477  0.898725
5  0.076404  0.523211  0.591538
7  0.397890  0.454131  0.915716
```

Do the same thing but fall back on a named index if there is no column with the name `a`.

```python
In [203]: df = pd.DataFrame(np.random.randint(n / 2, size=(n, 2)), columns=list('bc'))
In [204]: df.index.name = 'a'
In [205]: df
Out[205]:
   b   c
a
0   4
1   1
2   3
3   4
4   3
5   0
```

(continues on next page)
If instead you don’t want to or cannot name your index, you can use the name `index` in your query expression:

```python
In [207]: df = pd.DataFrame(np.random.randint(n, size=(n, 2)), columns=list('bc'))
In [208]: df
Out[208]:
     b  c
0  3  1
1  3  0
2  5  6
3  5  2
4  7  4
5  0  1
6  2  5
7  0  1
8  6  0
9  7  9
In [209]: df.query('index < b < c')
Out[209]:
     b  c
2  5  6
```

**Note:** If the name of your index overlaps with a column name, the column name is given precedence. For example,

```python
In [210]: df = pd.DataFrame({'a': np.random.randint(5, size=5)})
In [211]: df.index.name = 'a'
In [212]: df.query('a > 2')  # uses the column 'a', not the index
Out[212]:
     a
a  1  3
3  3
```

You can still use the index in a query expression by using the special identifier `index`:

```python
In [213]: df.query('index > 2')
Out[213]:
     a
a  3  3
4  2
```
If for some reason you have a column named `index`, then you can refer to the index as `ilevel_0` as well, but at this point you should consider renaming your columns to something less ambiguous.

**MultiIndex** query() Syntax

You can also use the levels of a DataFrame with a `MultiIndex` as if they were columns in the frame:

```
In [214]: n = 10

In [215]: colors = np.random.choice(['red', 'green'], size=n)

In [216]: foods = np.random.choice(['eggs', 'ham'], size=n)

In [217]: colors
Out[217]:
array(['red', 'red', 'red', 'green', 'green', 'green', 'green', 'green', 'green', 'green'], dtype='<U5')

In [218]: foods
Out[218]:
array(['ham', 'ham', 'eggs', 'eggs', 'eggs', 'ham', 'ham', 'eggs', 'eggs', 'eggs'], dtype='<U4')

In [219]: index = pd.MultiIndex.from_arrays([colors, foods], names=['color', 'food'])

In [220]: df = pd.DataFrame(np.random.randn(n, 2), index=index)

In [221]: df
Out[221]:
   0       1
color food
red  ham  0.194889 -0.381994
    ham  0.318587  2.089075
    eggs -0.728293 -0.090255
green eggs -0.748199  1.318931
   ham  0.461007  0.542749
   eggs -0.305384 -0.479195
   ham  0.095031 -0.270099
   eggs -0.707140 -0.773882
   eggs  0.229453  0.304418

In [222]: df.query('color == "red"')
Out[222]:
   0       1
color food
red  ham  0.194889 -0.381994
    ham  0.318587  2.089075
    eggs -0.728293 -0.090255
```

If the levels of the `MultiIndex` are unnamed, you can refer to them using special names:

```
In [223]: df.index.names = [None, None]

In [224]: df
Out[224]:
   0       1
color food
red  ham  0.194889 -0.381994
    ham  0.318587  2.089075
    eggs -0.728293 -0.090255
```

(continues on next page)
In [225]: df.query('ilevel_0 == "red"')
Out[225]:
   0     1
red  ham  0.194889 -0.381994
   ham  0.318587  2.089075
   eggs -0.728293 -0.090255
green eggs -0.748199  1.318931
    eggs -2.029766  0.792652
    ham  0.461007 -0.542749
    ham -0.305384 -0.479195
    eggs  0.095031 -0.270099
    eggs -0.707140 -0.773882
    eggs  0.229453  0.304418

The convention is `ilevel_0`, which means “index level 0” for the 0th level of the index.

**query() Use Cases**

A use case for `query()` is when you have a collection of `DataFrame` objects that have a subset of column names (or index levels/names) in common. You can pass the same query to both frames without having to specify which frame you’re interested in querying.

In [226]: df = pd.DataFrame(np.random.rand(n, 3), columns=list('abc'))

In [227]: df
Out[227]:
   a   b   c
  0 0.224283 0.736107 0.139168
  1 0.302827 0.657803 0.713897
  2 0.611185 0.136624 0.984960
  3 0.195246 0.123436 0.627712
  4 0.618673 0.371660 0.047902
  5 0.480088 0.062993 0.185760
  6 0.568018 0.483467 0.445289
  7 0.309040 0.274580 0.587101
  8 0.258993 0.477769 0.370255
  9 0.550459 0.840870 0.304611

In [228]: df2 = pd.DataFrame(np.random.rand(n + 2, 3), columns=df.columns)

In [229]: df2
Out[229]:
   a   b   c
  0 0.357579 0.229800 0.596001
  1 0.309059 0.957923 0.965663
  2 0.123102 0.336914 0.318616
  3 0.526506 0.323321 0.860813
  4 0.518736 0.486514 0.384724
  5 0.190804 0.505723 0.614533
  6 0.891939 0.623977 0.676639
query()  Python versus pandas Syntax Comparison

Full numpy-like syntax:

```python
In [232]: df = pd.DataFrame(np.random.randint(10, size=(10, 3)), columns=list('abc'))
In [233]: df
Out[233]:
   a  b  c
0  7  8  9
1  1  0  7
2  2  7  2
3  6  2  2
4  2  6  3
5  3  8  2
6  1  7  2
7  5  1  5
8  9  8  0
9  1  5  0

In [234]: df.query('(a < b) & (b < c)')
Out[234]:
   a  b  c
0  7  8  9

In [235]: df[(df['a'] < df['b']) & (df['b'] < df['c'])]
Out[235]:
   a  b  c
0  7  8  9
```

Slightly nicer by removing the parentheses (by binding making comparison operators bind tighter than `&` and `|`).

```python
In [236]: df.query('a < b & b < c')
Out[236]:
   a  b  c
0  7  8  9
```

Use English instead of symbols:

```python
In [237]: df.query('a < b and b < c')
Out[237]:
   a  b  c
0  7  8  9
```

Pretty close to how you might write it on paper:
The **in** and **not in** operators

`query()` also supports special use of Python’s **in** and **not in** comparison operators, providing a succinct syntax for calling the `isin` method of a `Series` or `DataFrame`.

```python
# get all rows where columns "a" and "b" have overlapping values
In [239]: df = pd.DataFrame({'a': list('aabbccddeeff'),
                       'b': list('aaaabbbbcccc'),
                       'c': np.random.randint(5, size=12),
                       'd': np.random.randint(9, size=12))

In [240]: df
Out[240]:
     a   b   c   d
0  a   a   2   6
1  a   a   4   7
2  b   a   1   6
3  b   a   2   1
4  c   b   3   6
5  c   b   0   2
6  d   b   3   3
7  d   b   2   1
8  e   c   4   3
9  e   c   2   0
10 f   c   0   6
11 f   c   1   2

In [241]: df.query('a in b')
Out[241]:  
    a   b   c   d
0  a   a   2   6
1  a   a   4   7
2  b   a   1   6
3  b   a   2   1
4  c   b   3   6
5  c   b   0   2

# How you'd do it in pure Python
In [242]: df[df['a'].isin(df['b'])]
Out[242]:  
    a   b   c   d
0  a   a   2   6
1  a   a   4   7
2  b   a   1   6
3  b   a   2   1
4  c   b   3   6
5  c   b   0   2

In [243]: df.query('a not in b')
Out[243]:  
    a   b   c   d
0  a   a   2   6
1  a   a   4   7
2  b   a   1   6
3  b   a   2   1
4  c   b   3   6
5  c   b   0   2
```

(continues on next page)
You can combine this with other expressions for very succinct queries:

```python
# rows where cols a and b have overlapping values
# and col c's values are less than col d's
In [245]: df.query('a in b and c < d')
Out[245]:
   a  b  c  d
0  a  a  2  6
1  a  a  4  7
2  b  a  1  6
4  c  b  3  6
5  c  b  0  2

# pure Python
In [246]: df[df['b'].isin(df['a']) & (df['c'] < df['d'])]
Out[246]:
   a  b  c  d
0  a  a  2  6
1  a  a  4  7
2  b  a  1  6
4  c  b  3  6
5  c  b  0  2
10 f  c  0  6
11 f  c  1  2
```

Note: Note that **in** and **not in** are evaluated in Python, since **numexpr** has no equivalent of this operation. However, **only the in/not in expression itself** is evaluated in vanilla Python. For example, in the expression

```python
df.query('a in b + c + d')
```

**(b + c + d)** is evaluated by **numexpr** and **then** the **in** operation is evaluated in plain Python. In general, any operations that can be evaluated using **numexpr** will be.
Special use of the `==` operator with `list` objects

Comparing a list of values to a column using `==/!=` works similarly to `in/not in`.

```python
In [247]: df.query('b == ["a", "b", "c"]')
Out[247]:
   a  b  c  d
0  a  a  2  6
1  a  a  4  7
2  b  a  1  6
3  b  a  2  1
4  c  b  3  6
5  c  b  0  2
6  d  b  3  3
7  d  b  2  1
8  e  c  4  3
9  e  c  2  0
10 f  c  0  6
11 f  c  1  2
```

# pure Python

```python
In [248]: df[df['b'].isin(["a", "b", "c")])
Out[248]:
   a  b  c  d
0  a  a  2  6
1  a  a  4  7
2  b  a  1  6
3  b  a  2  1
4  c  b  3  6
5  c  b  0  2
6  d  b  3  3
7  d  b  2  1
8  e  c  4  3
9  e  c  2  0
10 f  c  0  6
11 f  c  1  2
```

```python
In [249]: df.query('c == [1, 2]')
Out[249]:
   a  b  c  d
0  a  a  2  6
1  a  a  4  7
2  b  a  1  6
3  b  a  2  1
7  d  b  2  1
9  e  c  2  0
11 f  c  1  2
```

```python
In [250]: df.query('c != [1, 2]')
Out[250]:
   a  b  c  d
1  a  a  4  7
4  c  b  3  6
5  c  b  0  2
6  d  b  3  3
8  e  c  4  3
10 f  c  0  6
```

# using `in/not in`

(continues on next page)
In [251]: df.query('1, 2 in c')
Out[251]:
   a  b  c  d
0  a  a  2  6
2  b  a  1  6
3  b  a  2  1
7  d  b  2  1
9  e  c  2  0
11 f  c  1  2

In [252]: df.query('1, 2 not in c')
Out[252]:
   a  b  c  d
1  a  a  4  7
4  c  b  3  6
5  c  b  0  2
6  d  b  3  3
8  e  c  4  3
10 f  c  0  6

# pure Python
In [253]: df[df['c'].isin([1, 2])]
Out[253]:
   a  b  c  d
0  a  a  2  6
2  b  a  1  6
3  b  a  2  1
7  d  b  2  1
9  e  c  2  0
11 f  c  1  2

Boolean operators

You can negate boolean expressions with the word `not` or the `~` operator.

In [254]: df = pd.DataFrame(np.random.rand(n, 3), columns=list('abc'))
In [255]: df['bools'] = np.random.rand(len(df)) > 0.5
In [256]: df.query('~bools')
Out[256]:
   a  b  c  bools
2 0.697753 0.212799 0.329209  False
7 0.275396 0.691034 0.826619  False
8 0.190649 0.558748 0.262467  False

In [257]: df.query('not bools')
Out[257]:
   a  b  c  bools
2 0.697753 0.212799 0.329209  False
7 0.275396 0.691034 0.826619  False
8 0.190649 0.558748 0.262467  False

In [258]: df.query('not bools') == df[~df['bools']]
Out[258]:
(continues on next page)
Of course, expressions can be arbitrarily complex too:

```python
# short query syntax
In [259]: shorter = df.query('a < b < c and (not bools) or bools > 2')

# equivalent in pure Python
In [260]: longer = df[(df['a'] < df['b'])
......:   & (df['b'] < df['c'])
......:   & (~df['bools'])
......:   | (df['bools'] > 2)]

In [261]: shorter
Out[261]:
   a       b       c     bools
 0  0.275396  0.691034  0.826619   False

In [262]: longer
Out[262]:
   a       b       c     bools
 0  0.275396  0.691034  0.826619   False

In [263]: shorter == longer
Out[263]:
   a       b       c     bools
 0  True    True    True    True
```

**Performance of `query()`**

`DataFrame.query()` using `numexpr` is slightly faster than Python for large frames.
Note: You will only see the performance benefits of using the `numexpr` engine with `DataFrame.query()` if your frame has more than approximately 200,000 rows.

This plot was created using a `DataFrame` with 3 columns each containing floating point values generated using `numpy.random.randn()`.

### 2.5.17 Duplicate data

If you want to identify and remove duplicate rows in a DataFrame, there are two methods that will help: `duplicated` and `drop_duplicates`. Each takes as an argument the columns to use to identify duplicated rows.

- `duplicated` returns a boolean vector whose length is the number of rows, and which indicates whether a row is duplicated.
- `drop_duplicates` removes duplicate rows.

By default, the first observed row of a duplicate set is considered unique, but each method has a `keep` parameter to specify targets to be kept.

- `keep='first'` (default): mark / drop duplicates except for the first occurrence.
- `keep='last'`: mark / drop duplicates except for the last occurrence.
- `keep=False`: mark / drop all duplicates.

```
In [264]: df2 = pd.DataFrame({'a': ['one', 'one', 'two', 'two', 'two', 'three', 'four ...
.....:   'b': ['x', 'y', 'x', 'y', 'x', 'x', 'x'],
.....:   'c': np.random.randn(7))})

In [265]: df2
Out[265]:
   a      b      c
0  one     x -1.067137
```

(continues on next page)
In [266]: df2.duplicated('a')
Out[266]:
0  False
1   True
2   False
3   True
4   True
5   False
6   False
dtype: bool

In [267]: df2.duplicated('a', keep='last')
Out[267]:
0   True
1   False
2   True
3   True
4   False
5   False
6   False
dtype: bool

In [268]: df2.duplicated('a', keep=False)
Out[268]:
0   True
1   True
2   True
3   True
4   True
5   False
6   False
dtype: bool

In [269]: df2.drop_duplicates('a')
Out[269]:
<table>
<thead>
<tr>
<th>a</th>
<th>b</th>
<th>c</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>one</td>
<td>-1.067137</td>
</tr>
<tr>
<td>2</td>
<td>two</td>
<td>-0.211056</td>
</tr>
<tr>
<td>5</td>
<td>three</td>
<td>-1.964475</td>
</tr>
<tr>
<td>6</td>
<td>four</td>
<td>1.298329</td>
</tr>
</tbody>
</table>

In [270]: df2.drop_duplicates('a', keep='last')
Out[270]:
<table>
<thead>
<tr>
<th>a</th>
<th>b</th>
<th>c</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>one</td>
<td>0.309500</td>
</tr>
<tr>
<td>4</td>
<td>two</td>
<td>-0.390820</td>
</tr>
<tr>
<td>5</td>
<td>three</td>
<td>-1.964475</td>
</tr>
<tr>
<td>6</td>
<td>four</td>
<td>1.298329</td>
</tr>
</tbody>
</table>

In [271]: df2.drop_duplicates('a', keep=False)
Also, you can pass a list of columns to identify duplications.

```
In [272]: df2.duplicated(['a', 'b'])
Out[272]:
0   False
1   False
2   False
3   False
4   True
5   False
6   False
dtype: bool
```

```
In [273]: df2.drop_duplicates(['a', 'b'])
Out[273]:
   a  b  c
0  one x -1.067137
1  one y  0.309500
2  two x -0.211056
3  two y -1.842023
5  three x -1.964475
6  four x  1.298329
```

To drop duplicates by index value, use `Index.duplicated` then perform slicing. The same set of options are available for the `keep` parameter.

```
In [274]: df3 = pd.DataFrame({'a': np.arange(6),
                          'b': np.random.randn(6)},
                          index=['a', 'a', 'b', 'c', 'b', 'a'])

In [275]: df3
Out[275]:
   a  b
a  0  1.440455
a  1  2.456086
b  2  1.038402
c  3 -0.894409
b  4  0.683536
a  5  3.082764

In [276]: df3.index.duplicated()
Out[276]: array([False,  True, False, False,  True,  True])

In [277]: df3[~df3.index.duplicated()]
Out[277]:
   a  b
a  0  1.440455
b  2  1.038402
c  3 -0.894409
```

(continues on next page)
In [278]: df3[~df3.index.duplicated(keep='last')]
Out[278]:
    a   b
  c  3  -0.894409
  b  4   0.683536
  a  5   3.082764

In [279]: df3[~df3.index.duplicated(keep=False)]
Out[279]:
    a   b
  c  3  -0.894409

2.5.18 Dictionary-like get () method

Each of Series or DataFrame have a get method which can return a default value.

In [280]: s = pd.Series([1, 2, 3], index=['a', 'b', 'c'])

In [281]: s.get('a')  # equivalent to s['a']
Out[281]: 1

In [282]: s.get('x', default=-1)
Out[282]: -1

2.5.19 The lookup() method

Sometimes you want to extract a set of values given a sequence of row labels and column labels, and the lookup method allows for this and returns a NumPy array. For instance:

In [283]: dflookup = pd.DataFrame(np.random.rand(20, 4), columns=['A', 'B', 'C', 'D'])

In [284]: dflookup.lookup(list(range(0, 10, 2)), ['B', 'C', 'A', 'B', 'D'])
Out[284]: array([0.3506, 0.4779, 0.4825, 0.9197, 0.5019])

2.5.20 Index objects

The pandas Index class and its subclasses can be viewed as implementing an ordered multiset. Duplicates are allowed. However, if you try to convert an Index object with duplicate entries into a set, an exception will be raised.

Index also provides the infrastructure necessary for lookups, data alignment, and reindexing. The easiest way to create an Index directly is to pass a list or other sequence to Index:

In [285]: index = pd.Index(['e', 'd', 'a', 'b'])

In [286]: index
Out[286]: Index(['e', 'd', 'a', 'b'], dtype='object')

In [287]: 'd' in index
Out[287]: True
You can also pass a name to be stored in the index:

```python
In [288]: index = pd.Index(['e', 'd', 'a', 'b'], name='something')
In [289]: index.name
Out[289]: 'something'
```

The name, if set, will be shown in the console display:

```python
In [290]: index = pd.Index(list(range(5)), name='rows')
In [291]: columns = pd.Index(['A', 'B', 'C'], name='cols')
In [292]: df = pd.DataFrame(np.random.randn(5, 3), index=index, columns=columns)
In [293]: df
Out[293]:
     A         B         C
rows
0  1.295989  0.185778  0.436259
1  0.678101  0.311369 -0.528378
2 -0.674808 -1.103529 -0.656157
3  1.889957  2.076651 -1.102192
4 -1.211795 -0.791746  0.634724
```

**Setting metadata**

Indexes are “mostly immutable”, but it is possible to set and change their metadata, like the index name (or, for MultiIndex, levels and codes).

You can use the `rename`, `set_names`, `set_levels`, and `set_codes` to set these attributes directly. They default to returning a copy; however, you can specify `inplace=True` to have the data change in place.

See `Advanced Indexing` for usage of MultiIndexes.

```python
In [295]: ind = pd.Index([1, 2, 3])
In [296]: ind.rename("apple")
Out[296]: Int64Index([1, 2, 3], dtype='int64', name='apple')
In [297]: ind.name = "bob"
```

(continues on next page)
set_names, set_levels, and set_codes also take an optional level argument

In [301]: index = pd.MultiIndex.from_product([range(3), ['one', 'two']], names=['first', 'second'])
Out[301]: MultiIndex([(0, 'one'),
(0, 'two'),
(1, 'one'),
(1, 'two'),
(2, 'one'),
(2, 'two')],
names=['first', 'second'])

In [302]: index.levels[1]
Out[302]: Index(['one', 'two'], dtype='object', name='second')

In [303]: index.set_levels(['a', 'b'], level=1)
Out[303]: MultiIndex([(0, 'a'),
(0, 'b'),
(1, 'a'),
(1, 'b'),
(2, 'a'),
(2, 'b')],
names=['first', 'second'])

Set operations on Index objects

The two main operations are union (|) and intersection (&). These can be directly called as instance methods or used via overloaded operators. Difference is provided via the .difference() method.

In [305]: a = pd.Index(['c', 'b', 'a'])
In [306]: b = pd.Index(['c', 'e', 'd'])
In [307]: a | b
Out[307]: Index(['a', 'b', 'c', 'd', 'e'], dtype='object')
In [308]: a & b
Out[308]: Index(['c'], dtype='object')
In [309]: a.difference(b)
Out[309]: Index(['a', 'b'], dtype='object')

Also available is the symmetric_difference (^) operation, which returns elements that appear in either idx1 or idx2, but not in both. This is equivalent to the Index created by idx1.difference(idx2).union(idx2.difference(idx1)), with duplicates dropped.

In [310]: idx1 = pd.Index([1, 2, 3, 4])
(continues on next page)
In [311]: idx2 = pd.Index([2, 3, 4, 5])
In [312]: idx1.symmetric_difference(idx2)
Out[312]: Int64Index([1, 5], dtype='int64')
In [313]: idx1 ^ idx2
Out[313]: Int64Index([1, 5], dtype='int64')

Note: The resulting index from a set operation will be sorted in ascending order.

When performing Index.union() between indexes with different dtypes, the indexes must be cast to a common dtype. Typically, though not always, this is object dtype. The exception is when performing a union between integer and float data. In this case, the integer values are converted to float.

In [314]: idx1 = pd.Index([0, 1, 2])
In [315]: idx2 = pd.Index([0.5, 1.5])
In [316]: idx1 | idx2
Out[316]: Float64Index([0.0, 0.5, 1.0, 1.5, 2.0], dtype='float64')

**Missing values**

Important: Even though Index can hold missing values (NaN), it should be avoided if you do not want any unexpected results. For example, some operations exclude missing values implicitly.

Index.fillna fills missing values with specified scalar value.

In [317]: idx1 = pd.Index([1, np.nan, 3, 4])
In [318]: idx1
Out[318]: Float64Index([1.0, nan, 3.0, 4.0], dtype='float64')
In [319]: idx1.fillna(2)
Out[319]: Float64Index([1.0, 2.0, 3.0, 4.0], dtype='float64')
In [320]: idx2 = pd.DatetimeIndex([pd.Timestamp('2011-01-01'),
                           pd.NaT,
                           pd.Timestamp('2011-01-03')])
In [321]: idx2
Out[321]: DatetimeIndex(['2011-01-01', 'NaT', '2011-01-03'], dtype='datetime64[ns]',freq=None)
In [322]: idx2.fillna(pd.Timestamp('2011-01-02'))
Out[322]: DatetimeIndex(['2011-01-01', '2011-01-02', '2011-01-03'], dtype='datetime64[ns]', freq=None)
2.5.21 Set / reset index

Occasionally you will load or create a data set into a DataFrame and want to add an index after you’ve already done so. There are a couple of different ways.

Set an index

DataFrame has a `set_index()` method which takes a column name (for a regular `Index`) or a list of column names (for a `MultiIndex`). To create a new, re-indexed DataFrame:

```
In [323]: data
Out[323]:
   a   b   c   d
0  bar one  z  1.0
1  bar two  y  2.0
2  foo one  x  3.0
3  foo two  w  4.0

In [324]: indexed1 = data.set_index('c')
In [325]: indexed1
Out[325]:
   a   b   d
   c
  z bar one  1.0
  y bar two  2.0
  x foo one  3.0
  w foo two  4.0

In [326]: indexed2 = data.set_index(['a', 'b'])
```

The `append` keyword option allow you to keep the existing index and append the given columns to a MultiIndex:

```
In [328]: frame = data.set_index('c', drop=False)
In [329]: frame = frame.set_index(['a', 'b'], append=True)
In [330]: frame
Out[330]:
   c   d
   a   b
   bar one  z  1.0
    two y  2.0
   foo one  x  3.0
    two w  4.0
```

Other options in `set_index` allow you not drop the index columns or to add the index in-place (without creating a new object):

```
In [331]: frame = data.set_index('c')
In [332]: frame.set_index(['a', 'b'], append=True, inplace=True)
In [333]: frame
Out[333]:
   c   d
   a   b
   bar one  z  1.0
    two y  2.0
   foo one  x  3.0
    two w  4.0
```
In [331]: data.set_index('c', drop=False)
Out[331]:
   a  b  c  d
  c
  z  bar one z 1.0
  y  bar two y 2.0
  x  foo one x 3.0
  w  foo two w 4.0

In [332]: data.set_index(['a', 'b'], inplace=True)
In [333]: data
Out[333]:
   c  d
  a  b
  bar one z 1.0
      two y 2.0
  foo one x 3.0
      two w 4.0

Reset the index

As a convenience, there is a new function on DataFrame called `reset_index()` which transfers the index values into the DataFrame’s columns and sets a simple integer index. This is the inverse operation of `set_index()`.

In [334]: data
Out[334]:
   c  d
  a  b
  bar one z 1.0
      two y 2.0
  foo one x 3.0
      two w 4.0

In [335]: data.reset_index()
Out[335]:
   a  b  c  d
   0 bar one z 1.0
   1 bar two y 2.0
   2 foo one x 3.0
   3 foo two w 4.0

The output is more similar to a SQL table or a record array. The names for the columns derived from the index are the ones stored in the `names` attribute.

You can use the `level` keyword to remove only a portion of the index:

In [336]: frame
Out[336]:
   c  d
  c a  b
  z bar one z 1.0
  y bar two y 2.0
  x foo one x 3.0
  w foo two w 4.0

(continues on next page)
reset_index takes an optional parameter drop which if true simply discards the index, instead of putting index values in the DataFrame’s columns.

Adding an ad hoc index

If you create an index yourself, you can just assign it to the index field:

```python
data.index = index
```

### 2.5.22 Returning a view versus a copy

When setting values in a pandas object, care must be taken to avoid what is called chained indexing. Here is an example.

```python
In [338]: dfmi = pd.DataFrame([list('abcd'),
                      ....: list('efgh'),
                      ....: list('ijkl'),
                      ....: list('mnop')],
                      ....: columns=pd.MultiIndex.from_product([['one', 'two'],
                      ....: ['first', 'second']]))

In [339]: dfmi
```

<table>
<thead>
<tr>
<th>first</th>
<th>second</th>
</tr>
</thead>
<tbody>
<tr>
<td>one</td>
<td>two</td>
</tr>
<tr>
<td>a</td>
<td>b</td>
</tr>
<tr>
<td>e</td>
<td>f</td>
</tr>
<tr>
<td>i</td>
<td>j</td>
</tr>
<tr>
<td>m</td>
<td>n</td>
</tr>
</tbody>
</table>

Compare these two access methods:

```python
In [340]: dfmi['one']['second']
Out[340]:
0   b
1   f
2   j
3   n
Name: second, dtype: object
```

```python
In [341]: dfmi.loc[:, ('one', 'second')]
Out[341]:
(continues on next page)"
These both yield the same results, so which should you use? It is instructive to understand the order of operations on these and why method 2 (.loc) is much preferred over method 1 (chained []).

dfmi['one'] selects the first level of the columns and returns a DataFrame that is singly-indexed. Then another Python operation dfmi_with_one['second'] selects the series indexed by 'second'. This is indicated by the variable dfmi_with_one because pandas sees these operations as separate events. e.g. separate calls to __getitem__, so it has to treat them as linear operations, they happen one after another.

Contrast this to df.loc[:, ('one', 'second')] which passes a nested tuple of (slice(None), ('one', 'second')) to a single call to __getitem__. This allows pandas to deal with this as a single entity. Furthermore this order of operations can be significantly faster, and allows one to index both axes if so desired.

Why does assignment fail when using chained indexing?

The problem in the previous section is just a performance issue. What’s up with the SettingWithCopy warning? We don’t usually throw warnings around when you do something that might cost a few extra milliseconds!

But it turns out that assigning to the product of chained indexing has inherently unpredictable results. To see this, think about how the Python interpreter executes this code:

```python
dfmi.loc[:, ('one', 'second')] = value
# becomes
dfmi.loc.__setitem__((slice(None), ('one', 'second')), value)
```

But this code is handled differently:

```python
dfmi['one']['second'] = value
# becomes
dfmi.__getitem__('one').__setitem__('second', value)
```

See that __getitem__ in there? Outside of simple cases, it’s very hard to predict whether it will return a view or a copy (it depends on the memory layout of the array, about which pandas makes no guarantees), and therefore whether the __setitem__ will modify dfmi or a temporary object that gets thrown out immediately afterward. That’s what SettingWithCopy is warning you about!

Note: You may be wondering whether we should be concerned about the loc property in the first example. But dfmi.loc is guaranteed to be dfmi itself with modified indexing behavior, so dfmi.loc.__getitem__ / dfmi.loc.__setitem__ operate on dfmi directly. Of course, dfmi.loc.__getitem__(idx) may be a view or a copy of dfmi.

Sometimes a SettingWithCopy warning will arise at times when there’s no obvious chained indexing going on. These are the bugs that SettingWithCopy is designed to catch! Pandas is probably trying to warn you that you’ve done this:

```python
def do_something(df):
    foo = df[['bar', 'baz']]  # Is foo a view? A copy? Nobody knows!
    # ... many lines here ...
```

(continues on next page)
# We don't know whether this will modify df or not!

```python
foo['quux'] = value
return foo
```

Yikes!

## Evaluation order matters

When you use chained indexing, the order and type of the indexing operation partially determine whether the result is a slice into the original object, or a copy of the slice.

Pandas has the SettingWithCopyWarning because assigning to a copy of a slice is frequently not intentional, but a mistake caused by chained indexing returning a copy where a slice was expected.

If you would like pandas to be more or less trusting about assignment to a chained indexing expression, you can set the `mode.chained_assignment` option to one of these values:

- 'warn', the default, means a SettingWithCopyWarning is printed.
- 'raise' means pandas will raise a SettingWithCopyException you have to deal with.
- None will suppress the warnings entirely.

In [342]: dfb = pd.DataFrame({'a': ['one', 'one', 'two', 'three', 'two', 'one', 'six'], 'c': np.arange(7)})

# This will show the SettingWithCopyWarning
# but the frame values will be set
In [343]: dfb['c'][dfb['a'].str.startswith('o')] = 42

This however is operating on a copy and will not work.

```python
>>> pd.set_option('mode.chained_assignment', 'warn')

>>> dfb[dfb['a'].str.startswith('o')]['c'] = 42
Traceback (most recent call last)
... SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_index,col_indexer] = value instead
```

A chained assignment can also crop up in setting in a mixed dtype frame.

**Note:** These setting rules apply to all of `.loc/.iloc`.

The following is the recommended access method using `.loc` for multiple items (using mask) and a single item using a fixed index:

In [344]: dfc = pd.DataFrame({'a': ['one', 'one', 'two', 'three', 'two', 'one', 'six'], 'c': np.arange(7)})

In [345]: dfd = dfc.copy()
# Setting multiple items using a mask

```
In [346]: mask = dfd['a'].str.startswith('o')

In [347]: dfd.loc[mask, 'c'] = 42

In [348]: dfd
```

```
Out[348]:
     a  c
0   one 42
1   one 42
2   two 2
3  three 3
4   two 4
5   one 42
6   six 6
```

# Setting a single item

```
In [349]: dfd = dfc.copy()

In [350]: dfd.loc[2, 'a'] = 11

In [351]: dfd
```

```
Out[351]:
     a  c
0   one 0
1   one 1
2   11 2
3  three 3
4   two 4
5   one 5
6   six 6
```

The following *can* work at times, but it is not guaranteed to, and therefore should be avoided:

```
In [352]: dfd = dfc.copy()

In [353]: dfd['a'][2] = 111

In [354]: dfd
```

```
Out[354]:
     a  c
0   one 0
1   one 1
2   111 2
3  three 3
4   two 4
5   one 5
6   six 6
```

Last, the subsequent example will **not** work at all, and so should be avoided:

```python
>>> pd.set_option('mode.chained_assignment','raise')

>>> dfd.loc[0]['a'] = 1111
Traceback (most recent call last)
...
SettingWithCopyException:
```

# 2.5. Indexing and selecting data
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_index,col_indexer] = value instead

Warning: The chained assignment warnings / exceptions are aiming to inform the user of a possibly invalid assignment. There may be false positives; situations where a chained assignment is inadvertently reported.

2.6 MultiIndex / advanced indexing

This section covers indexing with a MultiIndex and other advanced indexing features.
See the Indexing and Selecting Data for general indexing documentation.

Warning: Whether a copy or a reference is returned for a setting operation may depend on the context. This is sometimes called chained assignment and should be avoided. See Returning a View versus Copy.

See the cookbook for some advanced strategies.

2.6.1 Hierarchical indexing (MultiIndex)

Hierarchical / Multi-level indexing is very exciting as it opens the door to some quite sophisticated data analysis and manipulation, especially for working with higher dimensional data. In essence, it enables you to store and manipulate data with an arbitrary number of dimensions in lower dimensional data structures like Series (1d) and DataFrame (2d).

In this section, we will show what exactly we mean by “hierarchical” indexing and how it integrates with all of the pandas indexing functionality described above and in prior sections. Later, when discussing group by and pivoting and reshaping data, we’ll show non-trivial applications to illustrate how it aids in structuring data for analysis.

See the cookbook for some advanced strategies.

Changed in version 0.24.0: MultiIndex.labels has been renamed to MultiIndex.codes and MultiIndex.set_labels to MultiIndex.set_codes.

Creating a MultiIndex (hierarchical index) object

The MultiIndex object is the hierarchical analogue of the standard Index object which typically stores the axis labels in pandas objects. You can think of MultiIndex as an array of tuples where each tuple is unique. A MultiIndex can be created from a list of arrays (using MultiIndex.from_arrays()), an array of tuples (using MultiIndex.from_tuples()), a crossed set of iterables (using MultiIndex.from_product()), or a DataFrame (using MultiIndex.from_frame()). The Index constructor will attempt to return a MultiIndex when it is passed a list of tuples. The following examples demonstrate different ways to initialize MultiIndexes.

In [1]: arrays = [['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux'], ...
   ...:     ['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two']]
   ...
In [2]: tuples = list(zip(*arrays))

(continues on next page)
In [3]: tuples
Out[3]:
[('bar', 'one'),
 ('bar', 'two'),
 ('baz', 'one'),
 ('baz', 'two'),
 ('foo', 'one'),
 ('foo', 'two'),
 ('qux', 'one'),
 ('qux', 'two')]

In [4]: index = pd.MultiIndex.from_tuples(tuples, names=['first', 'second'])

In [5]: index
Out[5]:
MultiIndex([('bar', 'one'),
            ('bar', 'two'),
            ('baz', 'one'),
            ('baz', 'two'),
            ('foo', 'one'),
            ('foo', 'two'),
            ('qux', 'one'),
            ('qux', 'two')],
           names=['first', 'second'])

In [6]: s = pd.Series(np.random.randn(8), index=index)

In [7]: s
Out[7]:
first  second
bar   one   0.469112
      two  -0.282863
baz   one  -1.509059
      two  -1.135632
foo   one   1.212112
      two  -0.173215
qux   one   0.119209
      two  -1.044236
dtype: float64

When you want every pairing of the elements in two iterables, it can be easier to use the MultiIndex. from_product() method:

In [8]: iterables = [['bar', 'baz', 'foo', 'qux'], ['one', 'two']]  

In [9]: pd.MultiIndex.from_product(iterables, names=['first', 'second'])
Out[9]:
MultiIndex([('bar', 'one'),
            ('bar', 'two'),
            ('baz', 'one'),
            ('baz', 'two'),
            ('foo', 'one'),
            ('foo', 'two'),
            ('qux', 'one'),
            ('qux', 'two')],
           names=['first', 'second'])
You can also construct a MultiIndex from a DataFrame directly, using the method `MultiIndex.from_frame()`. This is a complementary method to `MultiIndex.to_frame()`.

New in version 0.24.0:

```
in [10]: df = pd.DataFrame([['bar', 'one'], ['bar', 'two'],  
                         ....:       ['foo', 'one'], ['foo', 'two']],  
                         ....:        columns=['first', 'second'])  

In [11]: pd.MultiIndex.from_frame(df)  
Out[11]:  
MultiIndex([('bar', 'one'),  
             ('bar', 'two'),  
             ('foo', 'one'),  
             ('foo', 'two')],  
           names=['first', 'second'])  
```

As a convenience, you can pass a list of arrays directly into `Series` or `DataFrame` to construct a MultiIndex automatically:

```
in [12]: arrays = [np.array(['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux']),  
               ....:       np.array(['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two'])]  

In [13]: s = pd.Series(np.random.randn(8), index=arrays)  

In [14]: s  
Out[14]:  
bar one -0.861849  
two -2.104569  
baz one -0.494929  
two 1.071804  
foo one 0.721555  
two -0.706771  
qux one -1.039575  
two 0.271860  
dtype: float64  

In [15]: df = pd.DataFrame(np.random.randn(8, 4), index=arrays)  

In [16]: df  
Out[16]:  
      0       1       2       3  
bar one 0.424972 0.567020 0.276232 -1.087401  
two -0.673690 0.113648 -1.478427 0.524988  
baz one 0.404705 0.577046 -1.715002 -1.039268  
two 1.071804 -1.157892 -1.344312 0.844885  
foo one 1.075770 -0.109050 1.643563 -1.469388  
two 0.357021 -0.674600 -1.776904 -0.968914  
qux one -1.294524 0.413738 0.276662 -0.472035  
two -0.013960 -0.362543 -0.006154 -0.923061  
```

All of the MultiIndex constructors accept a `names` argument which stores string names for the levels themselves. If no names are provided, None will be assigned:

```
in [17]: df.index.names  
Out[17]: FrozenList([None, None])  
```
This index can back any axis of a pandas object, and the number of levels of the index is up to you:

```python
In [18]: df = pd.DataFrame(np.random.randn(3, 8), index=['A', 'B', 'C'],
                     columns=index)
In [19]: df
Out[19]:
first bar baz foo qux
second one two one two one two one two
A   0.895717 0.805244 -1.206412 2.565646 1.431256 1.340309 -1.170299 -0.226169
B   0.410835 0.813850 0.132003 -0.827317 -0.076467 -1.187678 1.130127 -1.436737
C  -1.413681 1.607920 1.024180 0.569605 0.875906 -2.211372 0.974466 -2.006747
In [20]: pd.DataFrame(np.random.randn(6, 6), index=index[:6], columns=index[:6])
Out[20]:
first bar baz foo
second one two one two one two one two
first second
bar one -0.410001 -0.078638 0.545952 -1.219217 -1.226825 0.769804
   two -1.281247 -0.727707 -0.121306 -0.097883 0.695775 0.341734
baz one 0.959726 -1.110336 -0.619976 0.149748 -0.732339 0.687738
   two 0.176444 0.403310 -0.154951 0.301624 -2.179861 -1.369849
foo one -0.954208 1.462696 -1.743161 -0.826591 -0.345352 1.314232
   two 0.690579 0.995761 2.396780 0.014871 3.357427 -0.317441
```

We’ve “sparsified” the higher levels of the indexes to make the console output a bit easier on the eyes. Note that how the index is displayed can be controlled using the multi_sparse option in pandas.set_options():

```python
In [21]: with pd.option_context('display.multi_sparse', False):
   ....:     df
   ....:```

It’s worth keeping in mind that there’s nothing preventing you from using tuples as atomic labels on an axis:

```python
In [22]: pd.Series(np.random.randn(8), index=tuples)
Out[22]:
(bar, one) -1.236269
(bar, two)  0.896171
(baz, one) -0.487602
(baz, two) -0.082240
(foo, one) -2.182937
(foo, two)  0.380396
(qux, one)  0.084844
(qux, two)  0.432390
dtype: float64
```

The reason that the MultiIndex matters is that it can allow you to do grouping, selection, and reshaping operations as we will describe below and in subsequent areas of the documentation. As you will see in later sections, you can find yourself working with hierarchically-indexed data without creating a MultiIndex explicitly yourself. However, when loading data from a file, you may wish to generate your own MultiIndex when preparing the data set.

---

2.6. MultiIndex / advanced indexing
Reconstructing the level labels

The method `get_level_values()` will return a vector of the labels for each location at a particular level:

```python
In [23]: index.get_level_values(0)
Out[23]: Index(['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux'],
           dtype='object', name='first')

In [24]: index.get_level_values('second')
Out[24]: Index(['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two'],
             dtype='object', name='second')
```

Basic indexing on axis with Multiindex

One of the important features of hierarchical indexing is that you can select data by a “partial” label identifying a subgroup in the data. Partial selection “drops” levels of the hierarchical index in the result in a completely analogous way to selecting a column in a regular DataFrame:

```python
In [25]: df['bar']
Out[25]:
    second  one  two
   --      --  --
A  0.895717 0.805244
B  0.410835 0.813850
C -1.413681 1.607920

In [26]: df['bar', 'one']
Out[26]:
   A  0.895717
   B  0.410835
   C -1.413681
Name: (bar, one), dtype: float64

In [27]: df['bar']['one']
Out[27]:
   A  0.895717
   B  0.410835
   C -1.413681
Name: one, dtype: float64

In [28]: s['qux']
Out[28]:
   one  -1.039575
   two   0.271860
dtype: float64
```

See `Cross-section with hierarchical index` for how to select on a deeper level.
Defined levels

The MultiIndex keeps all the defined levels of an index, even if they are not actually used. When slicing an index, you may notice this. For example:

```python
In [29]: df.columns.levels  # original MultiIndex
Out[29]: FrozenList([['bar', 'baz', 'foo', 'qux'], ['one', 'two']])

In [30]: df[['foo','qux']].columns.levels  # sliced
Out[30]: FrozenList([['bar', 'baz', 'foo', 'qux'], ['one', 'two']])
```

This is done to avoid a recomputation of the levels in order to make slicing highly performant. If you want to see only the used levels, you can use the `get_level_values()` method.

```python
In [31]: df[['foo', 'qux']].columns.to_numpy()
Out[31]: array([('foo', 'one'), ('foo', 'two'), ('qux', 'one'), ('qux', 'two')],
          dtype=object)

# for a specific level
In [32]: df[['foo', 'qux']].columns.get_level_values(0)
Out[32]: Index(['foo', 'foo', 'qux', 'qux'], dtype='object', name='first')
```

To reconstruct the MultiIndex with only the used levels, the `remove_unused_levels()` method may be used.

```python
In [33]: new_mi = df[['foo', 'qux']].columns.remove_unused_levels()

In [34]: new_mi.levels
Out[34]: FrozenList([['foo', 'qux'], ['one', 'two']])
```

Data alignment and using reindex

Operations between differently-indexed objects having MultiIndex on the axes will work as you expect; data alignment will work the same as an Index of tuples:

```python
In [35]: s + s[:-2]
Out[35]:
    bar  one  -1.723698
        two  -4.209138
    baz  one  -0.989859
        two   2.143608
    foo  one   1.443110
        two  -1.413542
    qux  one     NaN
        two     NaN
    dtype: float64

In [36]: s + s[::2]
Out[36]:
    bar  one  -1.723698
        two     NaN
    baz  one  -0.989859
        two     NaN
    foo  one   1.443110
        two     NaN
    qux  one  -2.079150
```

(continues on next page)
The `reindex()` method of `Series/DataFrames` can be called with another `MultiIndex`, or even a list or array of tuples:

```
In [37]: s.reindex(index[:3])
Out[37]:
first  second
bar   one   -0.861849
       two   -2.104569
baz   one   -0.494929
dtype: float64
```

```
In [38]: s.reindex([('foo', 'two'), ('bar', 'one'), ('qux', 'one'), ('baz', 'one')])
Out[38]:
foo   two  -0.706771
bar   one  -0.861849
qux   one  -1.039575
baz   one  -0.494929
dtype: float64
```

### 2.6.2 Advanced indexing with hierarchical index

Syntactically integrating `MultiIndex` in advanced indexing with `.loc` is a bit challenging, but we've made every effort to do so. In general, `MultiIndex` keys take the form of tuples. For example, the following works as you would expect:

```
In [39]: df = df.T

In [40]: df
Out[40]:
      A   B   C
first second
bar   one  0.895717  0.410835 -1.413681
       two  0.805244  0.813850  1.607920
baz   one  1.206412  0.132003  1.024180
       two  2.565646 -0.827317  0.569605
foo   one  1.431256 -0.076467  0.875906
       two  1.340309 -1.187678 -2.211372
qux   one -1.170299  1.130127  0.974466
       two -0.226169 -1.436737 -2.006747

In [41]: df.loc[('bar', 'two')]
Out[41]:
   A  0.805244
   B  0.813850
   C  1.607920
Name: (bar, two), dtype: float64
```

Note that `df.loc['bar', 'two']` would also work in this example, but this shorthand notation can lead to ambiguity in general.

If you also want to index a specific column with `.loc`, you must use a tuple like this:
You don’t have to specify all levels of the MultiIndex by passing only the first elements of the tuple. For example, you can use “partial” indexing to get all elements with bar in the first level as follows:

```
In [43]: df.loc['bar']
Out[43]:
   A     B     C
second
one  0.895717  0.410835 -1.413681
two  0.805244  0.813850  1.607920
```

This is a shortcut for the slightly more verbose notation `df.loc[['bar',],]` (equivalent to `df.loc['bar',]` in this example).

“Partial” slicing also works quite nicely.

```
In [44]: df.loc['baz':'foo']
Out[44]:
   A     B     C
first second
baz one -1.206412  0.132003  1.024180
two  2.565646 -0.827317  0.569605
foo one  1.431256 -0.076467  0.875906
two  1.340309 -1.187678 -2.211372
```

You can slice with a ‘range’ of values, by providing a slice of tuples.

```
In [45]: df.loc[['baz', 'two'):('qux', 'one')]
Out[45]:
   A     B     C
first second
baz two  2.565646 -0.827317  0.569605
foo one  1.431256 -0.076467  0.875906
two  1.340309 -1.187678 -2.211372
qux one -1.170299  1.130127  0.974466
```

```
In [46]: df.loc[['baz', 'two'):'foo']
Out[46]:
   A     B     C
first second
baz two  2.565646 -0.827317  0.569605
foo one  1.431256 -0.076467  0.875906
two  1.340309 -1.187678 -2.211372
```

Passing a list of labels or tuples works similar to reindexing:

```
In [47]: df.loc[['bar', 'two'], ['qux', 'one'])
Out[47]:
   A     B     C
first second
bar two  0.805244  0.813850  1.607920
qux one -1.170299  1.130127  0.974466
```

**Note:** It is important to note that tuples and lists are not treated identically in pandas when it comes to indexing. Whereas a tuple is interpreted as one multi-level key, a list is used to specify several keys. Or in other words, tuples
go horizontally (traversing levels), lists go vertically (scanning levels).

Importantly, a list of tuples indexes several complete MultiIndex keys, whereas a tuple of lists refer to several values within a level:

```python
In [48]: s = pd.Series([1, 2, 3, 4, 5, 6],
     index=pd.MultiIndex.from_product([["A", "B"], ["c", "d", "e"]]))
In [49]: s.loc[(["A", "c"], ["B", "d")]
Out[49]:
A  c  1
B  d  5
dtype: int64
In [50]: s.loc(["A", "B"], ["c", "d"]])
Out[50]:
A  c  1
d  2
B  d  4
d  5
dtype: int64
```

**Using slicers**

You can slice a MultiIndex by providing multiple indexers.

You can provide any of the selectors as if you are indexing by label, see *Selection by Label*, including slices, lists of labels, labels, and boolean indexers.

You can use `slice(None)` to select all the contents of that level. You do not need to specify all the deeper levels, they will be implied as `slice(None)`.

As usual, both sides of the slicers are included as this is label indexing.

**Warning:** You should specify all axes in the `.loc` specifier, meaning the indexer for the index and for the columns. There are some ambiguous cases where the passed indexer could be mis-interpreted as indexing both axes, rather than into say the MultiIndex for the rows.

You should do this:
```python
df.loc[[slice('A1', 'A3'), ...], :]
```

You should not do this:
```python
df.loc[[slice('A1', 'A3'), ...]]
```

```python
In [51]: def mklbl(prefix, n):
      ....:     return "%s%s" % (prefix, i) for i in range(n)
      ....:
In [52]: miindex = pd.MultiIndex.from_product([mklbl('A', 4),
               mklbl('B', 2),
               mklbl('C', 4),
               mklbl('D', 2)])
(continues on next page)```
....:
In [53]: micolumns = pd.MultiIndex.from_tuples([('a', 'foo'), ('a', 'bar'),
                                             ('b', 'foo'), ('b', 'bah')],
                                             names=['lvl0', 'lvl1'])
....:

In [54]: dfmi = pd.DataFrame(np.arange(len(miindex) * len(micolumns)).reshape((len(miindex), len(micolumns))),
                             index=miindex, columns=micolumns).sort_index().sort_index(axis=1)

In [55]: dfmi
Out[55]:

<table>
<thead>
<tr>
<th></th>
<th>lvl0</th>
<th>lvl1</th>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>bar</td>
<td>foo</td>
</tr>
<tr>
<td>A0</td>
<td>B0</td>
<td>C0</td>
<td>D0</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>D1</td>
<td>5</td>
<td>4</td>
<td>7</td>
<td>6</td>
</tr>
<tr>
<td>C1</td>
<td>D0</td>
<td>9</td>
<td>8</td>
<td>11</td>
</tr>
<tr>
<td>D1</td>
<td>13</td>
<td>12</td>
<td>15</td>
<td>14</td>
</tr>
<tr>
<td>C2</td>
<td>D0</td>
<td>17</td>
<td>16</td>
<td>19</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>A3</td>
<td>B1</td>
<td>C1</td>
<td>D1</td>
<td>237</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>236</td>
<td>239</td>
</tr>
<tr>
<td>B1</td>
<td>C1</td>
<td>D0</td>
<td>241</td>
<td>240</td>
</tr>
<tr>
<td></td>
<td>241</td>
<td>240</td>
<td>242</td>
<td>240</td>
</tr>
<tr>
<td>D1</td>
<td>245</td>
<td>244</td>
<td>247</td>
<td>246</td>
</tr>
<tr>
<td>C3</td>
<td>D0</td>
<td>249</td>
<td>248</td>
<td>251</td>
</tr>
<tr>
<td>D1</td>
<td>253</td>
<td>252</td>
<td>255</td>
<td>254</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

[64 rows x 4 columns]

Basic MultiIndex slicing using slices, lists, and labels.

In [56]: dfmi.loc[(slice('A1', 'A3'), slice(None), ['C1', 'C3']), :]
Out[56]:

<table>
<thead>
<tr>
<th></th>
<th>lvl0</th>
<th>lvl1</th>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>bar</td>
<td>foo</td>
</tr>
<tr>
<td>A1</td>
<td>B0</td>
<td>C1</td>
<td>D0</td>
<td>73</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>72</td>
<td>75</td>
</tr>
<tr>
<td>D1</td>
<td>77</td>
<td>76</td>
<td>79</td>
<td>78</td>
</tr>
<tr>
<td>C3</td>
<td>D0</td>
<td>89</td>
<td>88</td>
<td>91</td>
</tr>
<tr>
<td>D1</td>
<td>93</td>
<td>92</td>
<td>95</td>
<td>94</td>
</tr>
<tr>
<td>B1</td>
<td>C1</td>
<td>D0</td>
<td>105</td>
<td>104</td>
</tr>
<tr>
<td></td>
<td>104</td>
<td>104</td>
<td>107</td>
<td>106</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>A3</td>
<td>B0</td>
<td>C3</td>
<td>D1</td>
<td>221</td>
</tr>
<tr>
<td></td>
<td>221</td>
<td>220</td>
<td>223</td>
<td>222</td>
</tr>
<tr>
<td>B1</td>
<td>C1</td>
<td>D0</td>
<td>233</td>
<td>232</td>
</tr>
<tr>
<td></td>
<td>233</td>
<td>232</td>
<td>235</td>
<td>234</td>
</tr>
<tr>
<td>D1</td>
<td>237</td>
<td>236</td>
<td>239</td>
<td>238</td>
</tr>
<tr>
<td>C3</td>
<td>D0</td>
<td>249</td>
<td>248</td>
<td>251</td>
</tr>
<tr>
<td>D1</td>
<td>253</td>
<td>252</td>
<td>255</td>
<td>254</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

[24 rows x 4 columns]

You can use pandas.IndexSlice to facilitate a more natural syntax using :., rather than using slice(None).

In [57]: idx = pd.IndexSlice

In [58]: dfmi.loc[idx[:, :, ['C1', 'C3']], idx[:, 'foo']]
Out[58]:

(continues on next page)
It is possible to perform quite complicated selections using this method on multiple axes at the same time.

```python
In [59]: dfmi.loc['A1', (slice(None), 'foo')]
Out[59]:
lvl0    a    b
lvl1   foo   foo
A0 B0 C1 D0  8  10
     D1  12  14
     C3 D0  24  26
     D1  28  30
     B1 C1 D0  40  42
...   ...   ...
A3 B0 C3 D1 220 222
B1 C1 D0 232 234
     D1 236 238
     C3 D0 248 250
     D1 252 254
[32 rows x 2 columns]
```

```python
In [60]: dfmi.loc[idx[:, :, ['C1', 'C3']], idx[:, 'foo']]
Out[60]:
lvl0    a    b
lvl1   foo   foo
A0 B0 C1 D0  8  10
     D1  12  14
     C3 D0  24  26
     D1  28  30
     B1 C1 D0  40  42
...   ...   ...
A3 B0 C3 D1 220 222
B1 C1 D0 232 234
     D1 236 238
     C3 D0 248 250
     D1 252 254
[32 rows x 2 columns]
```

Using a boolean indexer you can provide selection related to the values.
In [61]: mask = dfmi[('a', 'foo')] > 200

In [62]: dfmi.loc[idx[mask, :, ['C1', 'C3']], idx[:, 'foo']]
Out[62]:
lvl0  a  b
lvl1  foo  foo
A3  B0  C1  D1  204 206
    C3  D0  216 218
    D1  220 222
B1  C1  D0  232 234
    D1  236 238
C3  D0  248 250
    D1  252 254

You can also specify the axis argument to .loc to interpret the passed slicers on a single axis.

In [63]: dfmi.loc(axis=0)[:, :, ['C1', 'C3']]
Out[63]:
lvl0  a  b
lvl1  bar  foo  bah  foo
A0  B0  C1  D0  9  8  11  10
    D1  13 12  15  14
    C3  D0  25 24  27  26
    D1  29 28  31  30
B1  C1  D0  41 40  43  42
    ... ... ... ... ...
A3  B0  C3  D1  221 220 223 222
B1  C1  D0  233 232 235 234
    D1  237 236 239 238
C3  D0  249 248 251 250
    D1  253 252 255 254

[32 rows x 4 columns]

Furthermore, you can set the values using the following methods.

In [64]: df2 = dfmi.copy()

In [65]: df2.loc(axis=0)[:, :, ['C1', 'C3']] = -10

In [66]: df2
Out[66]:
lvl0  a  b
lvl1  bar  foo  bah  foo
A0  B0  C0  D0  1  0  3  2
    D1  5  4  7  6
    C1  D0  -10 -10 -10 -10
    D1  -10 -10 -10 -10
    C2  D0  17 16 19 18
    ... ... ... ... ...
A3  B1  C1  D1  -10 -10 -10 -10
    C2  D0  241 240 243 242
    D1  245 244 247 246
    C3  D0  -10 -10 -10 -10
    D1  -10 -10 -10 -10

[64 rows x 4 columns]
You can use a right-hand-side of an alignable object as well.

```
In [67]: df2 = dfmi.copy()

In [68]: df2.loc[idx[:, :, ['C1', 'C3']], :] = df2 * 1000

In [69]: df2
```

```
Out[69]:
      lvl0  a  b
     lvl1  bar  foo  bah  foo
   A0 B0  C0  D0  1  0  3  2
   D1  5  4  7  6
   C1 D0  9000  8000  11000  10000
   D1  13000  12000  15000  14000
   C2 D0  17  16  19  18
   ...  ...  ...  ...  ...
   A3 B1  C1 D1  237000  236000  239000  238000
   C2 D0  241  240  243  242
   D1  245  244  247  246
   C3 D0  249000  248000  251000  250000
   D1  253000  252000  255000  254000

[64 rows x 4 columns]
```

**Cross-section**

The `xs()` method of DataFrame additionally takes a level argument to make selecting data at a particular level of a MultiIndex easier.

```
In [70]: df
```

```
Out[70]:
     A       B       C
first second
bar one  0.895717  0.410835 -1.413681
two   0.805244  0.813850  1.607920
baz  one  -1.206412  0.132003  1.024180
two   2.565646 -0.827317  0.569605
foo  one   1.431256 -0.076467  0.875906
two   1.340309 -1.187678 -2.211372
qux one  -1.170299  1.130127  0.974466
two  -0.226169 -1.436737 -2.006747
```

```
In [71]: df.xs('one', level='second')
```

```
Out[71]:
     A       B       C
first
bar one  0.895717  0.410835 -1.413681
baz  one  -1.206412  0.132003  1.024180
foo  one   1.431256 -0.076467  0.875906
qux one  -1.170299  1.130127  0.974466
```

```
# using the slicers
In [72]: df.loc[(slice(None), 'one'), :]
```

```
Out[72]:
     A       B       C
first second
bar one  0.895717  0.410835 -1.413681
baz  one  -1.206412  0.132003  1.024180
foo  one   1.431256 -0.076467  0.875906
qux one  -1.170299  1.130127  0.974466
```

(continues on next page)
You can also select on the columns with `xs`, by providing the axis argument.

```python
In [73]: df = df.T

In [74]: df.xs('one', level='second', axis=1)
```

```markdown
<table>
<thead>
<tr>
<th>first</th>
<th>bar</th>
<th>baz</th>
<th>foo</th>
<th>qux</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.895717</td>
<td>-1.206412</td>
<td>1.431256</td>
<td>-1.170299</td>
</tr>
<tr>
<td>B</td>
<td>0.410835</td>
<td>0.132003</td>
<td>-0.076467</td>
<td>1.130127</td>
</tr>
<tr>
<td>C</td>
<td>-1.413681</td>
<td>1.024180</td>
<td>0.875906</td>
<td>0.974466</td>
</tr>
</tbody>
</table>
```

```python
# using the slicers
In [75]: df.loc[:, (slice(None), 'one')]
```

```markdown
<table>
<thead>
<tr>
<th>second one one one one</th>
</tr>
</thead>
<tbody>
<tr>
<td>A 0.895717 -1.206412 1.431256 -1.170299</td>
</tr>
<tr>
<td>B 0.410835 0.132003 -0.076467 1.130127</td>
</tr>
<tr>
<td>C -1.413681 1.024180 0.875906 0.974466</td>
</tr>
</tbody>
</table>
```

`xs` also allows selection with multiple keys.

```python
In [76]: df.xs(('one', 'bar'), level=('second', 'first'), axis=1)
```

```markdown
<table>
<thead>
<tr>
<th>first</th>
<th>bar</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.895717</td>
</tr>
<tr>
<td>B</td>
<td>0.410835</td>
</tr>
<tr>
<td>C</td>
<td>-1.413681</td>
</tr>
</tbody>
</table>
```

```python
# using the slicers
In [77]: df.loc[:, ('bar', 'one')]
```

```markdown
| A | 0.895717 |
| B | 0.410835 |
| C | -1.413681 |
```

You can pass `drop_level=False` to `xs` to retain the level that was selected.

```python
In [78]: df.xs('one', level='second', axis=1, drop_level=False)
```

```markdown
<table>
<thead>
<tr>
<th>first</th>
<th>bar</th>
<th>baz</th>
<th>foo</th>
<th>qux</th>
</tr>
</thead>
<tbody>
<tr>
<td>second one one one one</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>0.895717</td>
<td>-1.206412</td>
<td>1.431256</td>
<td>-1.170299</td>
</tr>
<tr>
<td>B</td>
<td>0.410835</td>
<td>0.132003</td>
<td>-0.076467</td>
<td>1.130127</td>
</tr>
<tr>
<td>C</td>
<td>-1.413681</td>
<td>1.024180</td>
<td>0.875906</td>
<td>0.974466</td>
</tr>
</tbody>
</table>
```

Compare the above with the result using `drop_level=True` (the default value).
Advanced reindexing and alignment

Using the parameter `level` in the `reindex()` and `align()` methods of pandas objects is useful to broadcast values across a level. For instance:

```python
In [80]: midx = pd.MultiIndex(levels=[['zero', 'one'], ['x', 'y']],
     ....:                     codes=[[1, 1, 0, 0], [1, 0, 1, 0]])

In [81]: df = pd.DataFrame(np.random.randn(4, 2), index=midx)

In [82]: df
Out[82]:
   0     1
one  y  1.519970 -0.493662
    x  0.600178  0.274230
zero y  0.132885 -0.023688
    x  2.410179  1.450520

In [83]: df2 = df.mean(level=0)

In [84]: df2
Out[84]:
   0     1
one  y  1.060074 -0.109716
    x  1.060074 -0.109716
zero y  1.271532  0.713416
    x  1.271532  0.713416

# aligning
In [86]: df_aligned, df2_aligned = df.align(df2, level=0)

In [87]: df_aligned
Out[87]:
   0     1
one  y  1.519970 -0.493662
    x  0.600178  0.274230
zero y  0.132885 -0.023688
    x  2.410179  1.450520

In [88]: df2_aligned
Out[88]:
   0     1
```

(continues on next page)
Swapping levels with `swaplevel`

The `swaplevel()` method can switch the order of two levels:

```python
In [89]: df[:5]
Out[89]:
       0     1
   one  y  1.519970 -0.493662
         x  0.600178  0.274230
   zero y  0.132885 -0.023688
          x  2.410179  1.450520

In [90]: df[:5].swaplevel(0, 1, axis=0)
Out[90]:
        0     1
   y one  1.519970 -0.493662
   x one  0.600178  0.274230
   y zero  0.132885 -0.023688
   x zero  2.410179  1.450520
```

Reordering levels with `reorder_levels`

The `reorder_levels()` method generalizes the `swaplevel` method, allowing you to permute the hierarchical index levels in one step:

```python
In [91]: df[:5].reorder_levels([1, 0], axis=0)
Out[91]:
        0     1
   y one  1.519970 -0.493662
   x one  0.600178  0.274230
   y zero  0.132885 -0.023688
   x zero  2.410179  1.450520
```

Renaming names of an Index or MultiIndex

The `rename()` method is used to rename the labels of a `MultiIndex`, and is typically used to rename the columns of a `DataFrame`. The `columns` argument of `rename` allows a dictionary to be specified that includes only the columns you wish to rename.

```python
In [92]: df.rename(columns={0: "col0", 1: "col1"})
Out[92]:
     col0   col1
   one  y  1.519970 -0.493662
         x  0.600178  0.274230
   zero y  0.132885 -0.023688
          x  2.410179  1.450520
```

This method can also be used to rename specific labels of the main index of the `DataFrame`.

2.6. MultiIndex / advanced indexing
The `rename_axis()` method is used to rename the name of a `Index` or `MultiIndex`. In particular, the names of the levels of a `MultiIndex` can be specified, which is useful if `reset_index()` is later used to move the values from the `MultiIndex` to a column.

```python
In [94]: df.rename_axis(index=['abc', 'def'])
Out[94]:
   0   1
abc def
one y 1.519970 -0.493662
   x 0.600178  0.274230
zero y 0.132885 -0.023688
   x 2.410179  1.450520
```

Note that the columns of a DataFrame are an index, so that using `rename_axis` with the `columns` argument will change the name of that index.

```python
In [95]: df.rename_axis(columns="Cols").columns
Out[95]:
RangeIndex(start=0, stop=2, step=1, name='Cols')
```

Both `rename` and `rename_axis` support specifying a dictionary, `Series` or a mapping function to map labels/names to new values.

When working with an `Index` object directly, rather than via a `DataFrame`, `Index.set_names()` can be used to change the names.

```python
In [96]: mi = pd.MultiIndex.from_product([1, 2], ['a', 'b'], names=['x', 'y'])
In [97]: mi.names
Out[97]: FrozenList(['x', 'y'])
In [98]: mi2 = mi.rename("new name", level=0)
In [99]: mi2
Out[99]:
MultiIndex([(1, 'a'),
            (1, 'b'),
            (2, 'a'),
            (2, 'b')],
           names=['new name', 'y'])
```

You cannot set the names of the `MultiIndex` via a level.

```python
In [100]: mi.levels[0].name = "name via level"
---------------------------------------------------------------------------
AttributeError                               Traceback (most recent call last)
<ipython-input-100-35d32a9a5218> in <module>
----> 1 mi.levels[0].name = "name via level"
/pandas-release/pandas/pandas/core/indexes/base.py in name(self, value)
```

(continues on next page)
if self._no_setting_name:
    # Used in MultiIndex.levels to avoid silently ignoring name updates.
    raise RuntimeError(
        "Cannot set name on a level of a MultiIndex. Use "
        "MultiIndex.set_names' instead."
    )

Use `Index.set_names()` instead.

### 2.6.3 Sorting a MultiIndex

For `MultiIndex`-ed objects to be indexed and sliced effectively, they need to be sorted. As with any index, you can use `sort_index()`.

```python
In [101]: import random

In [102]: random.shuffle(tuples)

In [103]: s = pd.Series(np.random.randn(8), index=pd.MultiIndex.from_tuples(tuples))

In [104]: s
Out[104]:
baz two 0.206053
qux one -0.251905
baz one -2.213588
foo two 1.063327
    one 1.266143
qux two 0.299368
bar two -0.863838
    one 0.408204
dtype: float64

In [105]: s.sort_index()
Out[105]:
bar one 0.408204
two -0.863838
baz one -2.213588
two 0.206053
foo one 1.266143
two 1.063327
qux one -0.251905
two 0.299368
dtype: float64

In [106]: s.sort_index(level=0)
Out[106]:
bar one 0.408204
two -0.863838
baz one -2.213588
two 0.206053
foo one 1.266143
two 1.063327
```

(continues on next page)
You may also pass a level name to `sort_index` if the `MultiIndex` levels are named.

```
In [108]: s.index.set_names(['L1', 'L2'], inplace=True)

In [109]: s.sort_index(level='L1')
Out[109]:
   L1  L2
   bar one  0.408204
          two -0.863838
   baz one -2.213588
          two  0.206053
   foo one  1.266143
          two  1.063327
   qux one -0.251905
          two  0.299368
dtype: float64

In [110]: s.sort_index(level='L2')
Out[110]:
   L1  L2
   bar one  0.408204
   baz one -2.213588
   foo one  1.266143
   qux one -0.251905
   bar two -0.863838
   baz two  0.206053
   foo two  1.063327
   qux two  0.299368
dtype: float64
```

On higher dimensional objects, you can sort any of the other axes by level if they have a `MultiIndex`:

```
In [111]: df.T.sort_index(level=1, axis=1)
Out[111]:
   one  zero  one  zero
        x    x    y    y
0  0.600178  2.410179  1.519970  0.132885
1  0.274230  1.450520  0.493662  0.023688
```

Indexing will work even if the data are not sorted, but will be rather inefficient (and show a `PerformanceWarning`). It will also return a copy of the data rather than a view:
In [112]: dfm = pd.DataFrame({'jim': [0, 0, 1, 1],
......:         'joe': ['x', 'x', 'z', 'y'],
......:         'jolie': np.random.rand(4))

In [113]: dfm = dfm.set_index(['jim', 'joe'])

In [114]: dfm
Out[114]:
<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>jolie</td>
</tr>
<tr>
<td>jim</td>
<td>joe</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>x</td>
<td>0.490671</td>
</tr>
<tr>
<td></td>
<td>x</td>
<td>0.120248</td>
</tr>
<tr>
<td>1</td>
<td>z</td>
<td>0.537020</td>
</tr>
<tr>
<td></td>
<td>y</td>
<td>0.110968</td>
</tr>
</tbody>
</table>

In [4]: dfm.loc[[1, 'z']]  
PerformanceWarning: indexing past lexsort depth may impact performance.

Out[4]:
<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>jolie</td>
</tr>
<tr>
<td>jim</td>
<td>joe</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>z</td>
<td>0.64094</td>
</tr>
</tbody>
</table>

Furthermore, if you try to index something that is not fully lexsorted, this can raise:

In [5]: dfm.loc[(0, 'y'):(1, 'z')]
UnsortedIndexError: 'Key length (2) was greater than MultiIndex lexsort depth (1)'

The `is_lexsorted()` method on a MultiIndex shows if the index is sorted, and the `lexsort_depth` property returns the sort depth:

In [115]: dfm.index.is_lexsorted()
Out[115]: False

In [116]: dfm.index.lexsort_depth
Out[116]: 1

In [117]: dfm = dfm.sort_index()

In [118]: dfm
Out[118]:
<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>jolie</td>
</tr>
<tr>
<td>jim</td>
<td>joe</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>x</td>
<td>0.490671</td>
</tr>
<tr>
<td></td>
<td>x</td>
<td>0.120248</td>
</tr>
<tr>
<td>1</td>
<td>y</td>
<td>0.110968</td>
</tr>
<tr>
<td></td>
<td>z</td>
<td>0.537020</td>
</tr>
</tbody>
</table>

In [119]: dfm.index.is_lexsorted()
Out[119]: True

In [120]: dfm.index.lexsort_depth
Out[120]: 2

And now selection works as expected.
2.6.4 Take methods

Similar to NumPy ndarrays, pandas Index, Series, and DataFrame also provides the `take()` method that retrieves elements along a given axis at the given indices. The given indices must be either a list or an ndarray of integer index positions. `take` will also accept negative integers as relative positions to the end of the object.

```
In [122]: index = pd.Index(np.random.randint(0, 1000, 10))
In [123]: index
Out[123]: Int64Index([214, 502, 712, 567, 786, 175, 993, 133, 758, 329], dtype='int64')
In [124]: positions = [0, 9, 3]
In [125]: index[positions]
Out[125]: Int64Index([214, 329, 567], dtype='int64')
In [126]: index.take(positions)
Out[126]: Int64Index([214, 329, 567], dtype='int64')
In [127]: ser = pd.Series(np.random.randn(10))
In [128]: ser.iloc[positions]
Out[128]:
   0  -0.179666
   9   1.824375
   3   0.392149
   dtype: float64
In [129]: ser.take(positions)
Out[129]:
   0  -0.179666
   9   1.824375
   3   0.392149
   dtype: float64
```

For DataFrames, the given indices should be a 1d list or ndarray that specifies row or column positions.

```
In [130]: frm = pd.DataFrame(np.random.randn(5, 3))
In [131]: frm.take([1, 4, 3])
Out[131]:
     0       1       2
   0 -1.237881  0.106854 -1.276829
   4  0.629675 -1.425966  1.857704
   3  0.979542 -1.633678  0.615855
In [132]: frm.take([0, 2], axis=1)
```

(continues on next page)
It is important to note that the `take` method on pandas objects are not intended to work on boolean indices and may return unexpected results.

```python
In [133]: arr = np.random.randn(10)
In [134]: arr.take([False, False, True, True])
Out[134]: array([-1.1935, -1.1935, 0.6775, 0.6775])
In [135]: arr[[0, 1]]
Out[135]: array([-1.1935, 0.6775])
In [136]: ser = pd.Series(np.random.randn(10))
In [137]: ser.take([False, False, True, True])
Out[137]:
   0   0.233141
   0   0.233141
   1  -0.223540
   1  -0.223540
dtype: float64
In [138]: ser.iloc[[0, 1]]
Out[138]:
   0   0.233141
   1  -0.223540
dtype: float64
```

Finally, as a small note on performance, because the `take` method handles a narrower range of inputs, it can offer performance that is a good deal faster than fancy indexing.

```python
In [139]: arr = np.random.randn(10000, 5)
In [140]: indexer = np.arange(10000)
In [141]: random.shuffle(indexer)
In [142]: %timeit arr[indexer]
   ....: %timeit arr.take(indexer, axis=0)
   ....:
217 us +- 6.24 us per loop (mean +- std. dev. of 7 runs, 1000 loops each)
66.6 us +- 855 ns per loop (mean +- std. dev. of 7 runs, 10000 loops each)
In [143]: ser = pd.Series(arr[:, 0])
In [144]: %timeit ser.iloc[indexer]
   ....: %timeit ser.take(indexer)
   ....:
140 us +- 2.6 us per loop (mean +- std. dev. of 7 runs, 10000 loops each)
```

2.6. MultiIndex / advanced indexing
2.6.5 Index types

We have discussed MultiIndex in the previous sections pretty extensively. Documentation about DatetimeIndex and PeriodIndex are shown here, and documentation about TimedeltaIndex is found here.

In the following sub-sections we will highlight some other index types.

**CategoricalIndex**

*CategoricalIndex* is a type of index that is useful for supporting indexing with duplicates. This is a container around a *Categorical* and allows efficient indexing and storage of an index with a large number of duplicated elements.

```
In [145]: from pandas.api.types import CategoricalDtype

In [146]: df = pd.DataFrame({'A': np.arange(6),
                     'B': list('aabbc')})

In [147]: df['B'] = df['B'].astype(CategoricalDtype(list('cab')))  

In [148]: df
Out[148]:  
   A B  
  0 0 a  
  1 1 a  
  2 2 b  
  3 3 b  
  4 4 c  
  5 5 a  

In [149]: df.dtypes
Out[149]:  
   A  int64
   B category
dtype: object

In [150]: df['B'].cat.categories  
Out[150]: Index(['c', 'a', 'b'], dtype='object')
```

Setting the index will create a *CategoricalIndex*.

```
In [151]: df2 = df.set_index('B')

In [152]: df2.index
Out[152]: CategoricalIndex(['a', 'a', 'b', 'b', 'c', 'a'], categories=['c', 'a', 'b'], ordered=False, name='B', dtype='category')
```

Indexing with *__getitem__/*.iloc/*.loc* works similarly to an Index with duplicates. The indexers must be in the category or the operation will raise a *KeyError*. 

In [153]: df2.loc['a']
Out[153]:
   A
   B
   c 4
   a 0
   a 1
   a 5
   b 2
   b 3

The CategoricalIndex is preserved after indexing:

In [154]: df2.loc['a'].index
Out[154]: CategoricalIndex(['a', 'a', 'a'], categories=['c', 'a', 'b'], ordered=False, name='B', dtype='category')

Sorting the index will sort by the order of the categories (recall that we created the index with CategoricalDtype(list('cab')), so the sorted order is cab).

In [155]: df2.sort_index()
Out[155]:
   A
   B
   c 4
   a 6
   b 5

Groupby operations on the index will preserve the index nature as well.

In [156]: df2.groupby(level=0).sum()
Out[156]:
   A
   B
   c 4
   a 6
   b 5

In [157]: df2.groupby(level=0).sum().index
Out[157]: CategoricalIndex(['c', 'a', 'b'], categories=['c', 'a', 'b'], ordered=False, name='B', dtype='category')

Reindexing operations will return a resulting index based on the type of the passed indexer. Passing a list will return a plain-old Index; indexing with a Categorical will return a CategoricalIndex, indexed according to the categories of the passed Categorical dtype. This allows one to arbitrarily index these even with values not in the categories, similarly to how you can reindex any pandas index.

In [158]: df3 = pd.DataFrame({'A': np.arange(3), 'B': pd.Series(list('abc')).astype('category')})
      .......
In [159]: df3 = df3.set_index('B')

In [160]: df3
Out[160]:
   A
   B
(continues on next page)
### pandas: powerful Python data analysis toolkit, Release 1.1.1

#### Warning:
Reshaping and Comparison operations on a `CategoricalIndex` must have the same categories or a `TypeError` will be raised.

In [165]: df4 = pd.DataFrame({'A': np.arange(2),
    'B': list('ab'))

In [166]: df4['B'] = df4['B'].astype(CategoricalDtype(list('ab')))

In [167]: df4 = df4.set_index('B')

In [168]: df4.index
Out[168]: CategoricalIndex(['b', 'a'], categories=['a', 'b'], ordered=False, name='B', dtype='category')

In [169]: df5 = pd.DataFrame({'A': np.arange(2),
    'B': list('bc'))

In [170]: df5['B'] = df5['B'].astype(CategoricalDtype(list('bc')))

In [171]: df5 = df5.set_index('B')

In [172]: df5.index
Out[172]: CategoricalIndex(['b', 'c'], categories=['b', 'c'], ordered=False, name='B', dtype='category')

In [1]: pd.concat([df4, df5])
Type Error: categories must match existing categories when appending
**Int64Index and RangelIndex**

*Int64Index* is a fundamental basic index in pandas. This is an immutable array implementing an ordered, sliceable set.

*RangeIndex* is a sub-class of *Int64Index* that provides the default index for all NDFrame objects. *RangeIndex* is an optimized version of *Int64Index* that can represent a monotonic ordered set. These are analogous to Python *range* types.

**Float64Index**

By default a *Float64Index* will be automatically created when passing floating, or mixed-integer-floating values in index creation. This enables a pure label-based slicing paradigm that makes [], *ix*, *loc* for scalar indexing and slicing work exactly the same.

```python
In [173]: indexf = pd.Index([1.5, 2, 3, 4.5, 5])
In [174]: indexf
Out[174]: Float64Index([1.5, 2.0, 3.0, 4.5, 5.0], dtype='float64')
In [175]: sf = pd.Series(range(5), index=indexf)
In [176]: sf
Out[176]:
1.5 0
2.0 1
3.0 2
4.5 3
5.0 4
dtype: int64
```

Scalar selection for [], *loc* will always be label based. An integer will match an equal float index (e.g. 3 is equivalent to 3.0).

```python
In [177]: sf[3]
Out[177]: 2
In [178]: sf[3.0]
Out[178]: 2
In [179]: sf.loc[3]
Out[179]: 2
In [180]: sf.loc[3.0]
Out[180]: 2
```

The only positional indexing is via *iloc*.

```python
In [181]: sf.iloc[3]
Out[181]: 3
```

A scalar index that is not found will raise a *KeyError*. Slicing is primarily on the values of the index when using [], *ix*, *loc*, and always positional when using *iloc*. The exception is when the slice is boolean, in which case it will always be positional.

---

**2.6. MultiIndex / advanced indexing**

425
In [182]: sf[2:4]
Out[182]:
2.0  1
3.0  2
dtype: int64

In [183]: sf.loc[2:4]
Out[183]:
2.0  1
3.0  2
dtype: int64

In [184]: sf.iloc[2:4]
Out[184]:
3.0  2
4.5  3
dtype: int64

In float indexes, slicing using floats is allowed.

In [185]: sf[2.1:4.6]
Out[185]:
3.0  2
4.5  3
dtype: int64

In [186]: sf.loc[2.1:4.6]
Out[186]:
3.0  2
4.5  3
dtype: int64

In non-float indexes, slicing using floats will raise a TypeError.

In [1]: pd.Series(range(5))[3.5]
TypeError: the label [3.5] is not a proper indexer for this index type (Int64Index)

In [1]: pd.Series(range(5))[3.5:4.5]
TypeError: the slice start [3.5] is not a proper indexer for this index type (Int64Index)

Here is a typical use-case for using this type of indexing. Imagine that you have a somewhat irregular timedelta-like indexing scheme, but the data is recorded as floats. This could, for example, be millisecond offsets.

In [187]: dfir = pd.concat([pd.DataFrame(np.random.randn(5, 2),
                   index=np.arange(5) * 250.0,
                   columns=list('AB')),
                   pd.DataFrame(np.random.randn(6, 2),
                   index=np.arange(4, 10) * 250.1,
                   columns=list('AB'))])

In [188]: dfir
Out[188]:
    A         B
0  0.0  -0.435772 -1.188928
250.0 -0.435772 -1.188928
Selection operations then will always work on a value basis, for all selection operators.

In [189]: dfir[0:1000.4]
Out [189]:
         A       B
0.0  -0.435772 -1.188928
250.0 -0.808286 -0.284634
500.0 -1.815703  1.347213
750.0 -0.243487  0.514704
1000.0  1.162969 -0.287725
1000.4 -0.179734  0.993962

In [190]: dfir.loc[0:1001, 'A']
Out [190]:
         A
0.0  -0.435772
250.0 -0.808286
500.0 -1.815703
750.0 -0.243487
1000.0  1.162969
1000.4 -0.179734

Name: A, dtype: float64

In [191]: dfir.loc[1000.4]
Out [191]:
         A
0.0  -0.435772
250.0 -0.808286
500.0 -1.815703
750.0 -0.243487
1000.0  1.162969
1000.4 -0.179734

Name: 1000.4, dtype: float64

You could retrieve the first 1 second (1000 ms) of data as such:

In [192]: dfir[0:1000]
Out [192]:
         A       B
0.0  -0.435772 -1.188928
250.0 -0.808286 -0.284634
500.0 -1.815703  1.347213
750.0 -0.243487  0.514704
1000.0  1.162969 -0.287725

If you need integer based selection, you should use iloc:

In [193]: dfir.iloc[0:5]
Out [193]:
         A       B
0.0  -0.435772 -1.188928
250.0 -0.808286 -0.284634
500.0 -1.815703  1.347213
750.0 -0.243487  0.514704
1000.0  1.162969 -0.287725

(continues on next page)
IntervalIndex

IntervalIndex together with its own dtype, IntervalDtype as well as the Interval scalar type, allow first-class support in pandas for interval notation.

The IntervalIndex allows some unique indexing and is also used as a return type for the categories in cut() and qcut().

Indexing with an IntervalIndex

An IntervalIndex can be used in Series and in DataFrame as the index.

```
In [194]: df = pd.DataFrame({'A': [1, 2, 3, 4]},
    index=pd.IntervalIndex.from_breaks([0, 1, 2, 3, 4]))
```
```
In [195]: df
Out[195]:
      A
(0, 1]  1
(1, 2]  2
(2, 3]  3
(3, 4]  4
```

Label based indexing via .loc along the edges of an interval works as you would expect, selecting that particular interval.

```
In [196]: df.loc[2]
Out[196]:
      A
0  2
Name: (1, 2], dtype: int64
```
```
In [197]: df.loc[[2, 3]]
Out[197]:
      A
(1, 2]  2
(2, 3]  3
```

If you select a label contained within an interval, this will also select the interval.

```
In [198]: df.loc[2.5]
Out[198]:
      A
0  3
Name: (2, 3], dtype: int64
```
```
In [199]: df.loc[[2.5, 3.5]]
Out[199]:
      A
(2, 3]  3
(3, 4]  4
```
Selecting using an `Interval` will only return exact matches (starting from pandas 0.25.0).

```python
In [200]: df.loc[pd.Interval(1, 2)]
Out[200]:
A  2
Name: (1, 2], dtype: int64
```

Trying to select an `Interval` that is not exactly contained in the `IntervalIndex` will raise a `KeyError`.

```python
In [7]: df.loc[pd.Interval(0.5, 2.5)]
---------------------------------------------------------------------------
KeyError: Interval(0.5, 2.5, closed='right')
```

Selecting all `Intervals` that overlap a given `Interval` can be performed using the `overlaps()` method to create a boolean indexer.

```python
In [201]: idxr = df.index.overlaps(pd.Interval(0.5, 2.5))
In [202]: idxr
Out[202]:
array([ True, True, True, False])
In [203]: df[idxr]
Out[203]:
A
(0, 1] 1
(1, 2] 2
(2, 3] 3
```

**Binning data with `cut` and `qcut`**

`cut()` and `qcut()` both return a `Categorical` object, and the bins they create are stored as an `IntervalIndex` in its `.categories` attribute.

```python
In [204]: c = pd.cut(range(4), bins=2)
In [205]: c
Out[205]:
[(-0.003, 1.5], (-0.003, 1.5], (1.5, 3.0], (1.5, 3.0]]
Categories (2, interval[float64]): [(-0.003, 1.5] < (1.5, 3.0]]
In [206]: c.categories
Out[206]:
IntervalIndex([(-0.003, 1.5], (1.5, 3.0] ],
closed='right',
dtype='interval[float64]' )
```

`cut()` also accepts an `IntervalIndex` for its `bins` argument, which enables a useful pandas idiom. First, we call `cut()` with some data and `bins` set to a fixed number, to generate the bins. Then, we pass the values of `.categories` as the `bins` argument in subsequent calls to `cut()`, supplying new data which will be binned into the same bins.

```python
In [207]: pd.cut([0, 3, 5, 1], bins=c.categories)
Out[207]:
[(-0.003, 1.5], (1.5, 3.0], NaN, (-0.003, 1.5]]
Categories (2, interval[float64]): [(-0.003, 1.5] < (1.5, 3.0]]
```

Any value which falls outside all bins will be assigned a `NaN` value.
Generating ranges of intervals

If we need intervals on a regular frequency, we can use the `interval_range()` function to create an `IntervalIndex` using various combinations of `start`, `end`, and `periods`. The default frequency for `interval_range` is 1 for numeric intervals, and calendar day for datetime-like intervals:

```python
In [208]: pd.interval_range(start=0, end=5)
Out[208]:
IntervalIndex([(0, 1], (1, 2], (2, 3], (3, 4], (4, 5]],
closed='right',
dtype='interval[int64]')

In [209]: pd.interval_range(start=pd.Timestamp('2017-01-01'), periods=4)
Out[209]:
IntervalIndex([(2017-01-01, 2017-01-02], (2017-01-02, 2017-01-03], (2017-01-03, 2017-
-->01-04], (2017-01-04, 2017-01-05]],
closed='right',
dtype='interval[datetime64[ns]]')

In [210]: pd.interval_range(end=pd.Timedelta('3 days'), periods=3)
Out[210]:
IntervalIndex([(0 days 00:00:00, 1 days 00:00:00], (1 days 00:00:00, 2 days 00:00:00],
--> (2 days 00:00:00, 3 days 00:00:00]],
closed='right',
dtype='interval[timedelta64[ns]]')
```

The `freq` parameter can be used to specify non-default frequencies, and can utilize a variety of `frequency aliases` with datetime-like intervals:

```python
In [211]: pd.interval_range(start=0, periods=5, freq=1.5)
Out[211]:
IntervalIndex([(0.0, 1.5], (1.5, 3.0], (3.0, 4.5], (4.5, 6.0], (6.0, 7.5]],
closed='right',
dtype='interval[float64]')

In [212]: pd.interval_range(start=pd.Timestamp('2017-01-01'), periods=4, freq='W')
Out[212]:
IntervalIndex([(2017-01-01, 2017-01-08], (2017-01-08, 2017-01-15], (2017-01-15, 2017-
-->01-22], (2017-01-22, 2017-01-29]],
closed='right',
dtype='interval[datetime64[ns]]')

In [213]: pd.interval_range(start=pd.Timedelta('0 days'), periods=3, freq='9H')
Out[213]:
IntervalIndex([(0 days 00:00:00, 0 days 09:00:00], (0 days 09:00:00, 0 days 18:00:00],
--> (0 days 18:00:00, 1 days 03:00:00]],
closed='right',
dtype='interval[timedelta64[ns]]')
```

Additionally, the `closed` parameter can be used to specify which side(s) the intervals are closed on. Intervals are closed on the right side by default.

```python
In [214]: pd.interval_range(start=0, end=4, closed='both')
Out[214]:
IntervalIndex([(0, 1], [1, 2], [2, 3], [3, 4]],
closed='both',
dtype='interval[int64]')
```

(continues on next page)
New in version 0.23.0.

Specifying \texttt{start}, \texttt{end}, and \texttt{periods} will generate a range of evenly spaced intervals from \texttt{start} to \texttt{end} inclusively, with \texttt{periods} number of elements in the resulting \texttt{IntervalIndex}:

\begin{verbatim}
In [216]: pd.interval_range(start=0, end=6, periods=4)
Out[216]: IntervalIndex([(0.0, 1.5], [1.5, 3.0], [3.0, 4.5], [4.5, 6.0]],
                           closed='right',
                           dtype='interval[float64]')

In [217]: pd.interval_range(pd.Timestamp('2018-01-01'),
                           pd.Timestamp('2018-02-28'), periods=3)
Out[217]: IntervalIndex([(2018-01-01, 2018-01-20 08:00:00],
                          (2018-01-20 08:00:00, 2018-02-08 16:00:00],
                          (2018-02-08 16:00:00, 2018-02-28]],
                          closed='right',
                          dtype='interval[datetime64[ns]]')
\end{verbatim}

2.6.6 Miscellaneous indexing FAQ

\textbf{Integer indexing}

Label-based indexing with integer axis labels is a thorny topic. It has been discussed heavily on mailing lists and among various members of the scientific Python community. In pandas, our general viewpoint is that labels matter more than integer locations. Therefore, with an integer axis index \textit{only} label-based indexing is possible with the standard tools like \texttt{.loc}. The following code will generate exceptions:

\begin{verbatim}
In [218]: s = pd.Series(range(5))
In [219]: s[-1] # will generate exceptions
\end{verbatim}

The above exception was the direct cause of the following exception:

\begin{verbatim}
KeyError Traceback (most recent call last)
<ipython-input-219-76c3dce40054> in <module>
----> 1 s[-1]

KeyError: -1 is not in range
\end{verbatim}
This deliberate decision was made to prevent ambiguities and subtle bugs (many users reported finding bugs when the API change was made to stop “falling back” on position-based indexing).
Non-monotonic indexes require exact matches

If the index of a Series or DataFrame is monotonically increasing or decreasing, then the bounds of a label-based slice can be outside the range of the index, much like slice indexing a normal Python list. Monotonicity of an index can be tested with the `is_monotonic_increasing()` and `is_monotonic_decreasing()` attributes.

```python
In [223]: df = pd.DataFrame(index=[2, 3, 3, 4, 5], columns=['data'],
    ....:       data=list(range(5)))

In [224]: df.index.is_monotonic_increasing
Out[224]: True

# no rows 0 or 1, but still returns rows 2, 3 (both of them), and 4:
In [225]: df.loc[0:4, :]
Out[225]:
    data
   2   0
   3   1
   3   2
   4   3

# slice is are outside the index, so empty DataFrame is returned
In [226]: df.loc[13:15, :]
Out[226]:
Empty DataFrame
Columns: [data]
Index: []
```

On the other hand, if the index is not monotonic, then both slice bounds must be *unique* members of the index.

```python
In [227]: df = pd.DataFrame(index=[2, 3, 1, 4, 3, 5], columns=['data'], data=list(range(6)))

In [228]: df.index.is_monotonic_increasing
Out[228]: False

# OK because 2 and 4 are in the index
In [229]: df.loc[2:4, :]
Out[229]:
    data
   2   0
   3   1
   1   2
   4   3

# 0 is not in the index
In [9]: df.loc[0:4, :]
KeyError: 0

# 3 is not a unique label
In [11]: df.loc[2:3, :]
KeyError: 'Cannot get right slice bound for non-unique label: 3'
```

Index.is_monotonic_increasing and Index.is_monotonic_decreasing only check that an index is weakly monotonic. To check for strict monotonicity, you can combine one of those with the `is_unique()` attribute.
Endpoints are inclusive

Compared with standard Python sequence slicing in which the slice endpoint is not inclusive, label-based slicing in pandas is inclusive. The primary reason for this is that it is often not possible to easily determine the “successor” or next element after a particular label in an index. For example, consider the following Series:

```python
In [234]: s = pd.Series(np.random.randn(6), index=list('abcdef'))
```

```plaintext
a  0.301379
b  1.240445
c  0.846068
d  0.043312
e  1.658747
f  0.819549
dtype: float64
```

Suppose we wished to slice from c to e, using integers this would be accomplished as such:

```python
In [236]: s[2:5]
```

```plaintext
c  0.846068
d  0.043312
e  1.658747
dtype: float64
```

However, if you only had c and e, determining the next element in the index can be somewhat complicated. For example, the following does not work:

```python
s.loc['c':'e' + 1]
```

A very common use case is to limit a time series to start and end at two specific dates. To enable this, we made the design choice to make label-based slicing include both endpoints:

```python
In [237]: s.loc['c':'e']
```

```plaintext
c  0.846068
d  0.043312
e  1.658747
dtype: float64
```

This is most definitely a “practicality beats purity” sort of thing, but it is something to watch out for if you expect label-based slicing to behave exactly in the way that standard Python integer slicing works.
Indexing potentially changes underlying Series dtype

The different indexing operation can potentially change the dtype of a Series.

```python
In [238]: series1 = pd.Series([1, 2, 3])

In [239]: series1.dtype
Out[239]: dtype('int64')

In [240]: res = series1.reindex([0, 4])

In [241]: res.dtype
Out[241]: dtype('float64')

In [242]: res
Out[242]:
0  1.0
4  NaN
dtype: float64

In [243]: series2 = pd.Series([True])

In [244]: series2.dtype
Out[244]: dtype('bool')

In [245]: res = series2.reindex_like(series1)

In [246]: res.dtype
Out[246]: dtype('O')

In [247]: res
Out[247]:
0  True
1  NaN
2  NaN
dtype: object
```

This is because the (re)indexing operations above silently inserts NaNs and the dtype changes accordingly. This can cause some issues when using numpy ufuncs such as numpy.logical_and.

See the this old issue for a more detailed discussion.
2.7 Merge, join, concatenate and compare

pandas provides various facilities for easily combining together Series or DataFrame with various kinds of set logic for the indexes and relational algebra functionality in the case of join / merge-type operations.

In addition, pandas also provides utilities to compare two Series or DataFrame and summarize their differences.

2.7.1 Concatenating objects

The `concat()` function (in the main pandas namespace) does all of the heavy lifting of performing concatenation operations along an axis while performing optional set logic (union or intersection) of the indexes (if any) on the other axes. Note that I say “if any” because there is only a single possible axis of concatenation for Series.

Before diving into all of the details of `concat` and what it can do, here is a simple example:

```python
In [1]: df1 = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
                      'B': ['B0', 'B1', 'B2', 'B3'],
                      'C': ['C0', 'C1', 'C2', 'C3'],
                      'D': ['D0', 'D1', 'D2', 'D3']},
                     index=[0, 1, 2, 3])

In [2]: df2 = pd.DataFrame({'A': ['A4', 'A5', 'A6', 'A7'],
                      'B': ['B4', 'B5', 'B6', 'B7'],
                      'C': ['C4', 'C5', 'C6', 'C7'],
                      'D': ['D4', 'D5', 'D6', 'D7']},
                     index=[4, 5, 6, 7])

In [3]: df3 = pd.DataFrame({'A': ['A8', 'A9', 'A10', 'A11'],
                      'B': ['B8', 'B9', 'B10', 'B11'],
                      'C': ['C8', 'C9', 'C10', 'C11'],
                      'D': ['D8', 'D9', 'D10', 'D11']},
                     index=[8, 9, 10, 11])

In [4]: frames = [df1, df2, df3]

In [5]: result = pd.concat(frames)
```
Like its sibling function on ndarrays, `numpy.concatenate`, `pandas.concat` takes a list or dict of homogeneously-typed objects and concatenates them with some configurable handling of “what to do with the other axes”:

```
pd.concat(objs, axis=0, join='outer', ignore_index=False, keys=None, levels=None, names=None, verify_integrity=False, copy=True)
```

- **objs**: a sequence or mapping of Series or DataFrame objects. If a dict is passed, the sorted keys will be used as the `keys` argument, unless it is passed, in which case the values will be selected (see below). Any None objects will be dropped silently unless they are all None in which case a ValueError will be raised.

- **axis**: {0, 1, ...}, default 0. The axis to concatenate along.

- **join**: {'inner', 'outer'}, default ‘outer’. How to handle indexes on other axis(es). Outer for union and inner for intersection.

- **ignore_index**: boolean, default False. If True, do not use the index values on the concatenation axis. The resulting axis will be labeled 0, ..., n - 1. This is useful if you are concatenating objects where the concatenation axis does not have meaningful indexing information. Note the index values on the other axes are still respected in the join.

- **keys**: sequence, default None. Construct hierarchical index using the passed keys as the outermost level. If multiple levels passed, should contain tuples.

- **levels**: list of sequences, default None. Specific levels (unique values) to use for constructing a MultiIndex. Otherwise they will be inferred from the keys.

- **names**: list, default None. Names for the levels in the resulting hierarchical index.

- **verify_integrity**: boolean, default False. Check whether the new concatenated axis contains duplicates. This can be very expensive relative to the actual data concatenation.

- **copy**: boolean, default True. If False, do not copy data unnecessarily.
Without a little bit of context many of these arguments don’t make much sense. Let’s revisit the above example. Suppose we wanted to associate specific keys with each of the pieces of the chopped up DataFrame. We can do this using the `keys` argument:

```python
In [6]: result = pd.concat(frames, keys=['x', 'y', 'z'])
```

As you can see (if you’ve read the rest of the documentation), the resulting object’s index has a hierarchical index. This means that we can now select out each chunk by key:

```python
In [7]: result.loc['y']
Out[7]:
   A  B  C  D
0 A4 B4 C4 D4
1 A5 B5 C5 D5
2 A6 B6 C6 D6
3 A7 B7 C7 D7
```

It’s not a stretch to see how this can be very useful. More detail on this functionality below.

**Note:** It is worth noting that `concat()` (and therefore `append()`) makes a full copy of the data, and that constantly reusing this function can create a significant performance hit. If you need to use the operation over several datasets, use a list comprehension.

```python
frames = [ process_your_file(f) for f in files ]
result = pd.concat(frames)
```
Set logic on the other axes

When gluing together multiple DataFrames, you have a choice of how to handle the other axes (other than the one being concatenated). This can be done in the following two ways:

- Take the union of them all, join='outer'. This is the default option as it results in zero information loss.
- Take the intersection, join='inner'.

Here is an example of each of these methods. First, the default join='outer' behavior:

```python
In [8]: df4 = pd.DataFrame({'B': ['B2', 'B3', 'B6', 'B7'],
                        'D': ['D2', 'D3', 'D6', 'D7'],
                        'F': ['F2', 'F3', 'F6', 'F7']},
                      index=[2, 3, 6, 7])

In [9]: result = pd.concat([df1, df4], axis=1, sort=False)
```

Here is the same thing with join='inner':

```python
In [10]: result = pd.concat([df1, df4], axis=1, join='inner')
```

Lastly, suppose we just wanted to reuse the exact index from the original DataFrame:
In [11]: result = pd.concat([df1, df4], axis=1).reindex(df1.index)

Similarly, we could index before the concatenation:

In [12]: pd.concat([df1, df4.reindex(df1.index)], axis=1)
Out[12]:
    A  B  C  D  B  D  F
0  A0  B0  C0  D0  NaN  NaN  NaN
1  A1  B1  C1  D1  NaN  NaN  NaN
2  A2  B2  C2  D2  B2  D2  F2
3  A3  B3  C3  D3  B3  D3  F3

Concatenating using `append`

A useful shortcut to `concat()` are the `append()` instance methods on `Series` and `DataFrame`. These methods actually predated `concat`. They concatenate along `axis=0`, namely the index:

In [13]: result = df1.append(df2)

In the case of `DataFrame`, the indexes must be disjoint but the columns do not need to be:

In [14]: result = df1.append(df4, sort=False)
append may take multiple objects to concatenate:

In [15]: result = df1.append([df2, df3])

Note: Unlike the `append()` method, which appends to the original list and returns `None`, `append()` here does not modify `df1` and returns its copy with `df2` appended.
Ignoring indexes on the concatenation axis

For DataFrame objects which don’t have a meaningful index, you may wish to append them and ignore the fact that they may have overlapping indexes. To do this, use the **ignore_index** argument:

```python
In [16]: result = pd.concat([df1, df4], ignore_index=True, sort=False)
```

This is also a valid argument to `DataFrame.append()`:

```python
In [17]: result = df1.append(df4, ignore_index=True, sort=False)
```
**Concatenating with mixed ndims**

You can concatenate a mix of `Series` and `DataFrame` objects. The `Series` will be transformed to `DataFrame` with the column name as the name of the `Series`.

```
In [18]: sl = pd.Series(['X0', 'X1', 'X2', 'X3'], name='X')
In [19]: result = pd.concat([df1, sl], axis=1)
```

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>X</th>
</tr>
</thead>
<tbody>
<tr>
<td>A0</td>
<td>B0</td>
<td>C0</td>
<td>D0</td>
<td>X0</td>
</tr>
<tr>
<td>A1</td>
<td>B1</td>
<td>C1</td>
<td>D1</td>
<td>X1</td>
</tr>
<tr>
<td>A2</td>
<td>B2</td>
<td>C2</td>
<td>D2</td>
<td>X2</td>
</tr>
<tr>
<td>A3</td>
<td>B3</td>
<td>C3</td>
<td>D3</td>
<td>X3</td>
</tr>
<tr>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
<td></td>
</tr>
</tbody>
</table>

Note: Since we're concatenating a `Series` to a `DataFrame`, we could have achieved the same result with `DataFrame.assign()`. To concatenate an arbitrary number of pandas objects (`DataFrame` or `Series`), use `concat`.

If unnamed `Series` are passed they will be numbered consecutively.

```
In [20]: s2 = pd.Series(['_0', '_1', '_2', '_3'])
In [21]: result = pd.concat([df1, s2, s2, s2], axis=1)
```

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>A0</td>
<td>B0</td>
<td>C0</td>
<td>D0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A1</td>
<td>B1</td>
<td>C1</td>
<td>D1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A2</td>
<td>B2</td>
<td>C2</td>
<td>D2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A3</td>
<td>B3</td>
<td>C3</td>
<td>D3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>3</td>
</tr>
</tbody>
</table>

Passing `ignore_index=True` will drop all name references.

```
In [22]: result = pd.concat([df1, sl], axis=1, ignore_index=True)
```

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>A0</td>
<td>B0</td>
<td>C0</td>
<td>D0</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A1</td>
<td>B1</td>
<td>C1</td>
<td>D1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A2</td>
<td>B2</td>
<td>C2</td>
<td>D2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A3</td>
<td>B3</td>
<td>C3</td>
<td>D3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>3</td>
</tr>
</tbody>
</table>
More concatenating with group keys

A fairly common use of the `keys` argument is to override the column names when creating a new `DataFrame` based on existing `Series`. Notice how the default behaviour consists on letting the resulting `DataFrame` inherit the parent `Series`' name, when these existed.

Through the `keys` argument we can override the existing column names.

Let's consider a variation of the very first example presented:

```python
In [28]: result = pd.concat(frames, keys=['x', 'y', 'z'])
```
You can also pass a dict to `concat` in which case the dict keys will be used for the `keys` argument (unless other keys are specified):

```python
In [29]: pieces = {'x': df1, 'y': df2, 'z': df3)

In [30]: result = pd.concat(pieces)
```
The MultiIndex created has levels that are constructed from the passed keys and the index of the DataFrame pieces:

```
In [31]: result = pd.concat(pieces, keys=['z', 'y'])
```
If you wish to specify other levels (as will occasionally be the case), you can do so using the `levels` argument:

```python
In [33]: result = pd.concat(pieces, keys=['x', 'y', 'z'],
            levels=[['z', 'y', 'x', 'w']],
            names=['group_key'])
```

This is fairly esoteric, but it is actually necessary for implementing things like GroupBy where the order of a categorical variable is meaningful.

### Appending rows to a DataFrame

While not especially efficient (since a new object must be created), you can append a single row to a DataFrame by passing a `Series` or dict to `append`, which returns a new DataFrame as above.

```python
In [35]: s2 = pd.Series(['X0', 'X1', 'X2', 'X3'], index=['A', 'B', 'C', 'D'])

In [36]: result = df1.append(s2, ignore_index=True)
```
You should use `ignore_index` with this method to instruct DataFrame to discard its index. If you wish to preserve the index, you should construct an appropriately-indexed DataFrame and append or concatenate those objects.

You can also pass a list of dicts or Series:

```python
In [37]: dicts = [{'A': 1, 'B': 2, 'C': 3, 'X': 4},
            {'A': 5, 'B': 6, 'C': 7, 'Y': 8}]
In [38]: result = df1.append(dicts, ignore_index=True, sort=False)
```

### 2.7.2 Database-style DataFrame or named Series joining/merging

pandas has full-featured, **high performance** in-memory join operations idiomatically very similar to relational databases like SQL. These methods perform significantly better (in some cases well over an order of magnitude better) than other open source implementations (like `base::merge.data.frame` in R). The reason for this is careful algorithmic design and the internal layout of the data in DataFrame.

See the cookbook for some advanced strategies.

Users who are familiar with SQL but new to pandas might be interested in a **comparison with SQL**.

pandas provides a single function, `merge()`, as the entry point for all standard database join operations between DataFrame or named Series objects:
pd.merge(left, right, how='inner', on=None, left_on=None, right_on=None,
left_index=False, right_index=False, sort=True,
suffixes=('_x', '_y'), copy=True, indicator=False,
validate=None)

- left: A DataFrame or named Series object.
- right: Another DataFrame or named Series object.
- on: Column or index level names to join on. Must be found in both the left and right DataFrame and/or Series objects. If not passed and left_index and right_index are False, the intersection of the columns in the DataFrames and/or Series will be inferred to be the join keys.
- left_on: Columns or index levels from the left DataFrame or Series to use as keys. Can either be column names, index level names, or arrays with length equal to the length of the DataFrame or Series.
- right_on: Columns or index levels from the right DataFrame or Series to use as keys. Can either be column names, index level names, or arrays with length equal to the length of the DataFrame or Series.
- left_index: If True, use the index (row labels) from the left DataFrame or Series as its join key(s). In the case of a DataFrame or Series with a MultiIndex (hierarchical), the number of levels must match the number of join keys from the right DataFrame or Series.
- right_index: Same usage as left_index for the right DataFrame or Series.
- how: One of 'left', 'right', 'outer', 'inner'. Defaults to inner. See below for more detailed description of each method.
- sort: Sort the result DataFrame by the join keys in lexicographical order. Defaults to True, setting to False will improve performance substantially in many cases.
- suffixes: A tuple of string suffixes to apply to overlapping columns. Defaults to ('_x', '_y').
- copy: Always copy data (default True) from the passed DataFrame or named Series objects, even when reindexing is not necessary. Cannot be avoided in many cases but may improve performance / memory usage. The cases where copying can be avoided are somewhat pathological but this option is provided nonetheless.
- indicator: Add a column to the output DataFrame called _merge with information on the source of each row. _merge is Categorical-type and takes on a value of left_only for observations whose merge key only appears in 'left' DataFrame or Series, right_only for observations whose merge key only appears in 'right' DataFrame or Series, and both if the observation’s merge key is found in both.
- validate: string, default None. If specified, checks if merge is of specified type.
  - “one_to_one” or “1:1”: checks if merge keys are unique in both left and right datasets.
  - “one_to_many” or “1:m”: checks if merge keys are unique in left dataset.
  - “many_to_one” or “m:1”: checks if merge keys are unique in right dataset.
  - “many_to_many” or “m:m”: allowed, but does not result in checks.

Note: Support for specifying index levels as the on, left_on, and right_on parameters was added in version 0.23.0. Support for merging named Series objects was added in version 0.24.0.

The return type will be the same as left. If left is a DataFrame or named Series and right is a subclass of DataFrame, the return type will still be DataFrame.

merge is a function in the pandas namespace, and it is also available as a DataFrame instance method merge(), with the calling DataFrame being implicitly considered the left object in the join.

2.7. Merge, join, concatenate and compare
The related `join()` method, uses `merge` internally for the index-on-index (by default) and column(s)-on-index join. If you are joining on index only, you may wish to use `DataFrame.join` to save yourself some typing.

**Brief primer on merge methods (relational algebra)**

Experienced users of relational databases like SQL will be familiar with the terminology used to describe join operations between two SQL-table like structures (`DataFrame` objects). There are several cases to consider which are very important to understand:

- **one-to-one** joins: for example when joining two `DataFrame` objects on their indexes (which must contain unique values).
- **many-to-one** joins: for example when joining an index (unique) to one or more columns in a different `DataFrame`.
- **many-to-many** joins: joining columns on columns.

**Note:** When joining columns on columns (potentially a many-to-many join), any indexes on the passed `DataFrame` objects will be discarded.

It is worth spending some time understanding the result of the **many-to-many** join case. In SQL / standard relational algebra, if a key combination appears more than once in both tables, the resulting table will have the **Cartesian product** of the associated data. Here is a very basic example with one unique key combination:

```python
In [39]: left = pd.DataFrame({'key': ['K0', 'K1', 'K2', 'K3'],
                         'A': ['A0', 'A1', 'A2', 'A3'],
                         'B': ['B0', 'B1', 'B2', 'B3']})

In [40]: right = pd.DataFrame({'key': ['K0', 'K1', 'K2', 'K3'],
                            'C': ['C0', 'C1', 'C2', 'C3'],
                            'D': ['D0', 'D1', 'D2', 'D3']})

In [41]: result = pd.merge(left, right, on='key')
```

Here is a more complicated example with multiple join keys. Only the keys appearing in `left` and `right` are present (the intersection), since `how='inner'` by default.

```python
In [42]: left = pd.DataFrame({'key1': ['K0', 'K0', 'K1', 'K2'],
                         'key2': ['K0', 'K1', 'K0', 'K1'],
                         'A': ['A0', 'A1', 'A2', 'A3'],
                         'B': ['B0', 'B1', 'B2', 'B3']})
```

(continues on next page)
In [43]: right = pd.DataFrame({'key1': ['K0', 'K1', 'K1', 'K2'],
....:                        'key2': ['K0', 'K0', 'K0', 'K0'],
....:                        'C': ['C0', 'C1', 'C2', 'C3'],
....:                        'D': ['D0', 'D1', 'D2', 'D3']})

In [44]: result = pd.merge(left, right, on=['key1', 'key2'])

The `how` argument to `merge` specifies how to determine which keys are to be included in the resulting table. If a key combination does not appear in either the left or right tables, the values in the joined table will be `NA`. Here is a summary of the `how` options and their SQL equivalent names:

<table>
<thead>
<tr>
<th>Merge method</th>
<th>SQL Join Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>left</td>
<td>LEFT OUTER JOIN</td>
<td>Use keys from left frame only</td>
</tr>
<tr>
<td>right</td>
<td>RIGHT OUTER JOIN</td>
<td>Use keys from right frame only</td>
</tr>
<tr>
<td>outer</td>
<td>FULL OUTER JOIN</td>
<td>Use union of keys from both frames</td>
</tr>
<tr>
<td>inner</td>
<td>INNER JOIN</td>
<td>Use intersection of keys from both frames</td>
</tr>
</tbody>
</table>

In [45]: result = pd.merge(left, right, how='left', on=['key1', 'key2'])

In [46]: result = pd.merge(left, right, how='right', on=['key1', 'key2'])
You can merge a mult-indexed Series and a DataFrame, if the names of the MultiIndex correspond to the columns from the DataFrame. Transform the Series to a DataFrame using `Series.reset_index()` before merging, as shown in the following example.

```
In [50]: df
Out[50]:
   Let  Num
0    A   1
1    B   2
2    C   3
```

```
In [51]: ser = Series(
       ....:     ["a", "b", "c", "d", "e", "f"],
       ....:     index=pd.MultiIndex.from_arrays(
       ....:         ["A", "B", "C"] * 2, [1, 2, 3, 4, 5, 6]), names=["Let", "Num"]
       )
```
In [52]: ser
Out[52]:
   Let  Num
  A   1   a
  B   2   b
  C   3   c
  A   4   d
  B   5   e
  C   6   f
dtype: object

In [53]: pd.merge(df, ser.reset_index(), on=['Let', 'Num'])
Out[53]:
   Let  Num  
  0     A     1   a
  1     B     2   b
  2     C     3   c

Here is another example with duplicate join keys in DataFrames:

In [54]: left = pd.DataFrame({'A': [1, 2], 'B': [2, 2]})
In [55]: right = pd.DataFrame({'A': [4, 5, 6], 'B': [2, 2, 2]})
In [56]: result = pd.merge(left, right, on='B', how='outer')

Warning: Joining / merging on duplicate keys can cause a returned frame that is the multiplication of the row dimensions, which may result in memory overflow. It is the user’s responsibility to manage duplicate values in keys before joining large DataFrames.
Checking for duplicate keys

Users can use the `validate` argument to automatically check whether there are unexpected duplicates in their merge keys. Key uniqueness is checked before merge operations and so should protect against memory overflows. Checking key uniqueness is also a good way to ensure user data structures are as expected.

In the following example, there are duplicate values of B in the right DataFrame. As this is not a one-to-one merge – as specified in the `validate` argument – an exception will be raised.

```
In [57]: left = pd.DataFrame({'A': [1, 2], 'B': [1, 2]})
In [58]: right = pd.DataFrame({'A': [4, 5, 6], 'B': [2, 2, 2]})
In [53]: result = pd.merge(left, right, on='B', how='outer', validate="one_to_one")
...: MergeError: Merge keys are not unique in right dataset; not a one-to-one merge
```

If the user is aware of the duplicates in the right DataFrame but wants to ensure there are no duplicates in the left DataFrame, one can use the `validate='one_to_many'` argument instead, which will not raise an exception.

```
In [59]: pd.merge(left, right, on='B', how='outer', validate="one_to_many")
Out[59]:
   A_x  B  A_y
0   1  1  NaN
1   2  2  4.0
2   2  2  5.0
3   2  2  6.0
```

The merge indicator

`merge()` accepts the argument `indicator`. If `True`, a Categorical-type column called `_merge` will be added to the output object that takes on values:

```
Observation Origin   _merge value
Merge key only in 'left' frame    left_only
Merge key only in 'right' frame   right_only
Merge key in both frames         both
```

```
In [60]: df1 = pd.DataFrame({'col1': [0, 1], 'col_left': ['a', 'b']})
In [61]: df2 = pd.DataFrame({'col1': [1, 2, 2], 'col_right': [2, 2, 2]})
In [62]: pd.merge(df1, df2, on='col1', how='outer', indicator=True)
Out[62]:
   col1  col_left  col_right  _merge
0     0        a          NaN  left_only
1     1        b          2.0  both
2     2        NaN        2.0  right_only
3     2        NaN        2.0  right_only
```

The `indicator` argument will also accept string arguments, in which case the indicator function will use the value of the passed string as the name for the indicator column.
In [63]: pd.merge(df1, df2, on='col1', how='outer', indicator='indicator_column')
Out[63]:
   col1  col_left  col_right  indicator_column
0    0        a     NaN   left_only
1    1        b     2.0     both
2    2       NaN     2.0  right_only
3    2       NaN     2.0  right_only

Merge dtypes

Merging will preserve the dtype of the join keys.

In [64]: left = pd.DataFrame({'key': [1], 'v1': [10]})
In [65]: left
Out[65]:
   key  v1
0   1  10
In [66]: right = pd.DataFrame({'key': [1, 2], 'v1': [20, 30]})
In [67]: right
Out[67]:
   key  v1
0   1  20
1   2  30

We are able to preserve the join keys:

In [68]: pd.merge(left, right, how='outer')
Out[68]:
   key  v1_x  v1_y
0   1    10.0   20
1   2     NaN   30

In [69]: pd.merge(left, right, how='outer').dtypes
Out[69]:
   key  int64
  v1_x float64
  v1_y  int64
dtype: object

Of course if you have missing values that are introduced, then the resulting dtype will be upcast.

In [70]: pd.merge(left, right, how='outer', on='key')
Out[70]:
   key  v1_x  v1_y
0   1    10.0   20
1   2     NaN   30

In [71]: pd.merge(left, right, how='outer', on='key').dtypes
Out[71]:
   key  int64
  v1_x float64
  v1_y  int64
dtype: object

2.7. Merge, join, concatenate and compare
Merging will preserve category dtypes of the mergands. See also the section on `categoricals`.

The left frame.

```
In [72]: from pandas.api.types import CategoricalDtype

In [73]: X = pd.Series(np.random.choice(['foo', 'bar'], size=(10,)))

In [74]: X = X.astype(CategoricalDtype(categories=['foo', 'bar']))

In [75]: left = pd.DataFrame({'X': X,
                         'Y': np.random.choice(['one', 'two', 'three'],
                         size=(10,))})

In [76]: left
Out[76]:
   X  Y
0  bar  one
1  foo  one
2  foo  three
3  bar  three
4  foo  one
5  bar  one
6  bar  three
7  bar  three
8  bar  three
9  bar  three

In [77]: left.dtypes
Out[77]:
   X   category
  Y   object
```

The right frame.

```
In [78]: right = pd.DataFrame({'X': pd.Series(['foo', 'bar'],
                         dtype=CategoricalDtype(['foo', 'bar'])),
                         'Z': [1, 2]})

In [79]: right
Out[79]:
   X  Z
0  foo  1
1  bar  2

In [80]: right.dtypes
Out[80]:
   X   category
  Z   int64
```

The merged result:

```
In [81]: result = pd.merge(left, right, how='outer')

(continues on next page)
In [82]: result
Out[82]:
   X    Y    Z
0  bar  one  2
1  bar  three  2
2  bar  one  2
3  bar  three  2
4  bar  three  2
5  bar  three  2
6  foo  one  1
7  foo  three  1
8  foo  one  1
9  foo  three  1

In [83]: result.dtypes
Out[83]:
   X  Y  Z
name: dtypes
  X category
  Y object
  Z int64
dtype: object

Note: The category dtypes must be exactly the same, meaning the same categories and the ordered attribute. Otherwise the result will coerce to the categories’ dtype.

Note: Merging on category dtypes that are the same can be quite performant compared to object dtype merging.

Joining on index

DataFrame.join() is a convenient method for combining the columns of two potentially differently-indexed DataFrames into a single result DataFrame. Here is a very basic example:

In [84]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2'],
......:   'B': ['B0', 'B1', 'B2'],
......:   index=['K0', 'K1', 'K2'])
......:

In [85]: right = pd.DataFrame({'C': ['C0', 'C2', 'C3'],
......:   'D': ['D0', 'D2', 'D3'],
......:   index=['K0', 'K2', 'K3'])
......:

In [86]: result = left.join(right)
In [87]: result = left.join(right, how='outer')

<table>
<thead>
<tr>
<th>left</th>
<th>right</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>B</td>
<td>A</td>
</tr>
<tr>
<td>K0</td>
<td>A0</td>
<td>K0</td>
</tr>
<tr>
<td>K1</td>
<td>A1</td>
<td>K2</td>
</tr>
<tr>
<td>K2</td>
<td>A2</td>
<td>K3</td>
</tr>
</tbody>
</table>

The same as above, but with how='inner'.

In [88]: result = left.join(right, how='inner')

<table>
<thead>
<tr>
<th>left</th>
<th>right</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>B</td>
<td>A</td>
</tr>
<tr>
<td>K0</td>
<td>A0</td>
<td>K0</td>
</tr>
<tr>
<td>K1</td>
<td>A1</td>
<td>K2</td>
</tr>
<tr>
<td>K2</td>
<td>A2</td>
<td>K3</td>
</tr>
</tbody>
</table>

The data alignment here is on the indexes (row labels). This same behavior can be achieved using merge plus additional arguments instructing it to use the indexes:

In [89]: result = pd.merge(left, right, left_index=True, right_index=True, how='outer')

<table>
<thead>
<tr>
<th>left</th>
<th>right</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>B</td>
<td>A</td>
</tr>
<tr>
<td>K0</td>
<td>A0</td>
<td>K0</td>
</tr>
<tr>
<td>K1</td>
<td>A1</td>
<td>K2</td>
</tr>
<tr>
<td>K2</td>
<td>A2</td>
<td>K3</td>
</tr>
</tbody>
</table>

In [90]: result = pd.merge(left, right, left_index=True, right_index=True, how='inner');
Joining key columns on an index

`join()` takes an optional `on` argument which may be a column or multiple column names, which specifies that the passed DataFrame is to be aligned on that column in the DataFrame. These two function calls are completely equivalent:

```python
left.join(right, on=key_or_keys)
pd.merge(left, right, left_on=key_or_keys, right_index=True,
         how='left', sort=False)
```

Obviously you can choose whichever form you find more convenient. For many-to-one joins (where one of the DataFrame's is already indexed by the join key), using `join` may be more convenient. Here is a simple example:

```python
In [91]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
                         'B': ['B0', 'B1', 'B2', 'B3'],
                         'key': ['K0', 'K1', 'K0', 'K1']})
In [92]: right = pd.DataFrame({'C': ['C0', 'C1'],
                          'D': ['D0', 'D1']},
                         index=['K0', 'K1'])
In [93]: result = left.join(right, on='key')
In [94]: result = pd.merge(left, right, left_on='key', right_index=True,
                        how='left', sort=False);
```

To join on multiple keys, the passed DataFrame must have a MultiIndex:

```python
In [95]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
                         'B': ['B0', 'B1', 'B2', 'B3'],
                         'key1': ['K0', 'K0', 'K1', 'K2']},
                         columns=['A', 'B', 'key1'])
```

(continues on next page)
.....: 'key2': ['K0', 'K1', 'K0', 'K1']}
.....:

In [96]: index = pd.MultiIndex.from_tuples([(K0, K0), (K1, K0),
.....:          (K2, K0), (K2, K1)])
.....:

In [97]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
.....:          'D': ['D0', 'D1', 'D2', 'D3']},
.....:          index=index)
.....:

Now this can be joined by passing the two key column names:

In [98]: result = left.join(right, on=['key1', 'key2'])

<table>
<thead>
<tr>
<th>left</th>
<th>right</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>B</td>
<td>key1</td>
</tr>
<tr>
<td>0 A0</td>
<td>B0</td>
<td>K0</td>
</tr>
<tr>
<td>1 A1</td>
<td>B1</td>
<td>K0</td>
</tr>
<tr>
<td>2 A2</td>
<td>B2</td>
<td>K1</td>
</tr>
<tr>
<td>3 A3</td>
<td>B3</td>
<td>K2</td>
</tr>
</tbody>
</table>

The default for DataFrame.join is to perform a left join (essentially a “VLOOKUP” operation, for Excel users), which uses only the keys found in the calling DataFrame. Other join types, for example inner join, can be just as easily performed:

In [99]: result = left.join(right, on=['key1', 'key2'], how='inner')

<table>
<thead>
<tr>
<th>left</th>
<th>right</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>B</td>
<td>key1</td>
</tr>
<tr>
<td>0 A0</td>
<td>B0</td>
<td>K0</td>
</tr>
<tr>
<td>1 A1</td>
<td>B1</td>
<td>K0</td>
</tr>
<tr>
<td>2 A2</td>
<td>B2</td>
<td>K1</td>
</tr>
<tr>
<td>3 A3</td>
<td>B3</td>
<td>K2</td>
</tr>
</tbody>
</table>

As you can see, this drops any rows where there was no match.
### Joining a single Index to a MultiIndex

You can join a singly-indexed DataFrame with a level of a MultiIndexed DataFrame. The level will match on the name of the index of the singly-indexed frame against a level name of the MultiIndexed frame.

```python
In [100]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2'],
                         'B': ['B0', 'B1', 'B2'],
                         index=pd.Index(['K0', 'K1', 'K2'], name='key'))
       ....:

In [101]: index = pd.MultiIndex.from_tuples([('K0', 'Y0'), ('K1', 'Y1'),
                                          ('K2', 'Y2'), ('K2', 'Y3')],
                                          names=['key', 'Y'])
       ....:

In [102]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
                           'D': ['D0', 'D1', 'D2', 'D3'],
                           index=index)
       ....:

In [103]: result = left.join(right, how='inner')
```

<table>
<thead>
<tr>
<th>left</th>
<th>right</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td></td>
<td>A</td>
</tr>
<tr>
<td>B</td>
<td></td>
<td>B</td>
</tr>
<tr>
<td>A0</td>
<td>C0</td>
<td>B0</td>
</tr>
<tr>
<td>B0</td>
<td>D0</td>
<td>D0</td>
</tr>
<tr>
<td>A1</td>
<td>C1</td>
<td>B1</td>
</tr>
<tr>
<td>C1</td>
<td>D1</td>
<td>D1</td>
</tr>
<tr>
<td>A2</td>
<td>C2</td>
<td>B2</td>
</tr>
<tr>
<td>C2</td>
<td>D2</td>
<td>D2</td>
</tr>
<tr>
<td>A3</td>
<td>C3</td>
<td>B3</td>
</tr>
<tr>
<td>C3</td>
<td>D3</td>
<td>D3</td>
</tr>
</tbody>
</table>

This is equivalent but less verbose and more memory efficient / faster than this.

```python
In [104]: result = pd.merge(left.reset_index(), right.reset_index(),
                        on=['key'], how='inner').set_index(['key', 'Y'])
```
Joining with two MultiIndexes

This is supported in a limited way, provided that the index for the right argument is completely used in the join, and is a subset of the indices in the left argument, as in this example:

```python
In [105]: leftindex = pd.MultiIndex.from_product([list('abc'), list('xy'), [1, 2]], names=['abc', 'xy', 'num'])

In [106]: left = pd.DataFrame({'v1': range(12)}, index=leftindex)

In [107]: left
Out[107]:
   abc  xy  num
a x  1  0
    2  1  
    3
y x  4
    5  2
    3
b x  8
    9  2
    3
y x  10
    11

In [108]: rightindex = pd.MultiIndex.from_product([list('abc'), list('xy')], names=['abc', 'xy'])

In [109]: right = pd.DataFrame({'v2': [100 * i for i in range(1, 7)]}, index=rightindex)

In [110]: right
Out[110]:
   abc  xy
a x  100
    200
y x  300
    400
b x  500
    600

c x  1
    2
x y  1
    2
b x  4
    5
y x  6
    7

In [111]: left.join(right, on=['abc', 'xy'], how='inner')
Out[111]:
   v1  v2
a x  1  100
    1  100
    2  200
    3  200
y x  4  300
    5  300
    6  400
    7  400
```
If that condition is not satisfied, a join with two multi-indexes can be done using the following code.

```python
In [112]: leftindex = pd.MultiIndex.from_tuples([
                   ('K0', 'X0'), ('K0', 'X1'),
                   ('K1', 'X2')],
                   names=['key', 'X'])

In [113]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2'],
                            'B': ['B0', 'B1', 'B2']},
                            index=leftindex)

In [114]: rightindex = pd.MultiIndex.from_tuples([
                   ('K0', 'Y0'), ('K1', 'Y1'),
                   ('K2', 'Y2'), ('K2', 'Y3')],
                   names=['key', 'Y'])

In [115]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
                            'D': ['D0', 'D1', 'D2', 'D3']},
                            index=rightindex)

In [116]: result = pd.merge(left.reset_index(), right.reset_index(),
                        on=['key'], how='inner').set_index(['key', 'X', 'Y'])
```

Merging on a combination of columns and index levels

New in version 0.23.

Strings passed as the `on`, `left_on`, and `right_on` parameters may refer to either column names or index level names. This enables merging `DataFrame` instances on a combination of index levels and columns without resetting indexes.

```python
In [117]: left_index = pd.Index(['K0', 'K0', 'K1', 'K2'], name='key1')

In [118]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
                            'B': ['B0', 'B1', 'B2', 'B3'],
                            'key2': ['K0', 'K1', 'K0', 'K1']})
```

(continues on next page)
In [119]: right_index = pd.Index(['K0', 'K1', 'K2', 'K2'], name='key1')

In [120]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
                           'D': ['D0', 'D1', 'D2', 'D3'],
                           'key2': ['K0', 'K0', 'K0', 'K1']},
                           index=right_index)

In [121]: result = left.merge(right, on=['key1', 'key2'])

Note: When DataFrames are merged on a string that matches an index level in both frames, the index level is preserved as an index level in the resulting DataFrame.

Note: When DataFrames are merged using only some of the levels of a MultiIndex, the extra levels will be dropped from the resulting merge. In order to preserve those levels, use reset_index on those level names to move those levels to columns prior to doing the merge.

Note: If a string matches both a column name and an index level name, then a warning is issued and the column takes precedence. This will result in an ambiguity error in a future version.

Overlapping value columns

The merge suffixes argument takes a tuple of list of strings to append to overlapping column names in the input DataFrames to disambiguate the result columns:

In [122]: left = pd.DataFrame({'k': ['K0', 'K1', 'K2'], 'v': [1, 2, 3]})

In [123]: right = pd.DataFrame({'k': ['K0', 'K0', 'K3'], 'v': [4, 5, 6]})

In [124]: result = pd.merge(left, right, on='k')
Joining multiple DataFrames

A list or tuple of DataFrames can also be passed to `join()` to join them together on their indexes.

```
In [129]: right2 = pd.DataFrame({'v': [7, 8, 9]}, index=['K1', 'K1', 'K2'])
In [130]: result = left.join([right, right2])
```
Merging together values within Series or DataFrame columns

Another fairly common situation is to have two like-indexed (or similarly indexed) Series or DataFrame objects and wanting to “patch” values in one object from values for matching indices in the other. Here is an example:

In [131]: df1 = pd.DataFrame([[np.nan, 3., 5.], [-4.6, np.nan, np.nan], [np.nan, 7., np.nan]])
   ....:

In [132]: df2 = pd.DataFrame([[-42.6, np.nan, -8.2], [-5., 1.6, 4.]], index=[1, 2])
   ....:

For this, use the `combine_first()` method:

In [133]: result = df1.combine_first(df2)

Note that this method only takes values from the right DataFrame if they are missing in the left DataFrame. A related method, `update()`, alters non-NA values in place:

In [134]: df1.update(df2)
2.7.3 Timeseries friendly merging

Merging ordered data

A `merge_ordered()` function allows combining time series and other ordered data. In particular it has an optional `fill_method` keyword to fill/interpolate missing data:

```python
In [135]: left = pd.DataFrame({
     ...:     'k': ['K0', 'K1', 'K1', 'K2'],
     ...:     'lv': [1, 2, 3, 4],
     ...:     's': ['a', 'b', 'c', 'd']})

In [136]: right = pd.DataFrame({
     ...:     'k': ['K1', 'K2', 'K4'],
     ...:     'rv': [1, 2, 3]})

In [137]: pd.merge_ordered(left, right, fill_method='ffill', left_by='s')
Out[137]:
   k  lv  s  rv
0  K0  1.0  a  NaN
1  K1  1.0  a  1.0
2  K2  1.0  a  2.0
3  K4  1.0  a  3.0
4  K1  2.0  b  1.0
5  K2  2.0  b  2.0
6  K4  2.0  b  3.0
7  K1  3.0  c  1.0
8  K2  3.0  c  2.0
9  K4  3.0  c  3.0
10 K1  NaN  d  1.0
11 K2  4.0  d  2.0
12 K4  4.0  d  3.0
```

Merging asof

A `merge_asof()` is similar to an ordered left-join except that we match on nearest key rather than equal keys. For each row in the left DataFrame, we select the last row in the right DataFrame whose on key is less than the left’s key. Both DataFrames must be sorted by the key.

Optionally an asof merge can perform a group-wise merge. This matches the by key equally, in addition to the nearest match on the on key.

For example; we might have trades and quotes and we want to asof merge them.

```python
In [138]: trades = pd.DataFrame({
     ...:     'time': pd.to_datetime(['20160525 13:30:00.023',
     ...:                               '20160525 13:30:00.038',
     ...:                               '20160525 13:30:00.048',
     ...:                               '20160525 13:30:00.048'])),
     ...:     'ticker': ['MSFT', 'MSFT', 'GOOG', 'GOOG', 'AAPL'],
     ...:     'price': [51.95, 51.95, 720.77, 720.92, 98.00],
     ...:     'quantity': [75, 155, 100, 100, 100]})
```

(continues on next page)
.....: columns=['time', 'ticker', 'price', 'quantity'])

In [139]: quotes = pd.DataFrame(
.....:    {'time': pd.to_datetime(['20160525 13:30:00.023',
.....:                        '20160525 13:30:00.041',
.....:                        '20160525 13:30:00.048',
.....:                        '20160525 13:30:00.049',
.....:                        '20160525 13:30:00.072',
.....:                        '20160525 13:30:00.075']),
.....:    'ticker': ['GOOG', 'MSFT', 'MSFT',
.....:              'MSFT', 'GOOG', 'AAPL', 'GOOG',
.....:              'MSFT'],
.....:    'bid': [720.50, 51.95, 51.97, 51.99,
.....:             720.50, 97.99, 720.50, 52.01],
.....:    'ask': [720.93, 51.96, 51.98, 52.00,
.....:             720.93, 98.01, 720.88, 52.03]),
.....: columns=['time', 'ticker', 'bid', 'ask'])

In [141]: quotes                                                                 
Out[141]:
  time  ticker  bid   ask  
0 2016-05-25 13:30:00.023  GOOG  720.50  720.93 
1 2016-05-25 13:30:00.023  MSFT  51.95  51.96 
2 2016-05-25 13:30:00.041  MSFT  51.97  51.98 
3 2016-05-25 13:30:00.048  GOOG  720.50  720.93 
4 2016-05-25 13:30:00.049  AAPL  97.99  98.01 
5 2016-05-25 13:30:00.072  GOOG  720.92  720.88 
6 2016-05-25 13:30:00.075  MSFT  52.01  52.03

By default we are taking the asof of the quotes.

In [142]: pd.merge_asof(trades, quotes,                                             
.....:    on='time',                                               
.....:    by='ticker')                                             
Out[142]:
  time  ticker  price  quantity  bid   ask  
0 2016-05-25 13:30:00.023  MSFT  51.95  75  51.95  51.96 
1 2016-05-25 13:30:00.038  MSFT  51.95 155  51.97  51.98 
2 2016-05-25 13:30:00.048  GOOG  720.77 100  720.50  720.93 
3 2016-05-25 13:30:00.049  GOOG  720.92 100  720.50  720.93 
4 2016-05-25 13:30:00.049  AAPL  98.00  100  NaN   NaN

468 Chapter 2. User Guide
We only asof within 2ms between the quote time and the trade time.

```
In [143]: pd.merge_asof(trades, quotes,
....:     on='time',
....:     by='ticker',
....:     tolerance=pd.Timedelta('2ms'))
Out[143]:
   time  ticker  price  quantity  bid  ask
0 2016-05-25 13:30:00.023  MSFT   51.95       75  51.95  51.96
1 2016-05-25 13:30:00.038  MSFT   51.95      155  NaN     NaN
2 2016-05-25 13:30:00.048  GOOG   720.77      100 720.50  720.93
3 2016-05-25 13:30:00.048  GOOG   720.92      100 720.50  720.93
4 2016-05-25 13:30:00.048  AAPL   98.00      100   NaN     NaN
```

We only asof within 10ms between the quote time and the trade time and we exclude exact matches on time. Note that though we exclude the exact matches (of the quotes), prior quotes do propagate to that point in time.

```
In [144]: pd.merge_asof(trades, quotes,
....:     on='time',
....:     by='ticker',
....:     tolerance=pd.Timedelta('10ms'),
....:     allow_exact_matches=False)
Out[144]:
   time  ticker  price  quantity  bid  ask
0 2016-05-25 13:30:00.023  MSFT   51.95       75   NaN     NaN
1 2016-05-25 13:30:00.038  MSFT   51.95      155  51.97  51.98
2 2016-05-25 13:30:00.048  GOOG   720.77      100 720.50  720.93
3 2016-05-25 13:30:00.048  GOOG   720.92      100 720.50  720.93
4 2016-05-25 13:30:00.048  AAPL   98.00      100   NaN     NaN
```

### 2.7.4 Comparing objects

The `compare()` and `compare()` methods allow you to compare two DataFrame or Series, respectively, and summarize their differences.

This feature was added in V1.1.0.

For example, you might want to compare two `DataFrame` and stack their differences side by side.

```
In [145]: df = pd.DataFrame(
....:     {
....:         "col1": ["a", "a", "b", "b", "a"],
....:         "col2": [1.0, 2.0, 3.0, np.nan, 5.0],
....:         "col3": [1.0, 2.0, 3.0, 4.0, 5.0]
....:     },
....:     columns=["col1", "col2", "col3"],
....:     )
.....:

In [146]: df
Out[146]:
   col1  col2  col3
0    a    1.0    1.0
1    a    2.0    2.0
2    b    3.0    3.0
```

(continues on next page)
3  b  NaN  4.0
4  a  5.0  5.0

In [147]: df2 = df.copy()

In [148]: df2.loc[0, 'col1'] = 'c'

In [149]: df2.loc[2, 'col3'] = 4.0

In [150]: df2
Out[150]:
   col1 col2 col3
0    c  1.0  1.0
1    a  2.0  2.0
2    b  3.0  4.0
3    b  NaN  4.0
4    a  5.0  5.0

In [151]: df.compare(df2)
Out[151]:
   col1 col3
self other self other
0    a    c  NaN  NaN
2    NaN  NaN  3.0  4.0

By default, if two corresponding values are equal, they will be shown as NaN. Furthermore, if all values in an entire row / column, the row / column will be omitted from the result. The remaining differences will be aligned on columns.

If you wish, you may choose to stack the differences on rows.

In [152]: df.compare(df2, align_axis=0)
Out[152]:
   col1 col3
self other self other
0    a    NaN
other c    NaN
2    NaN  3.0
other NaN  4.0

If you wish to keep all original rows and columns, set keep_shape argument to True.

In [153]: df.compare(df2, keep_shape=True)
Out[153]:
   col1 col2 col3
self other self other self other
0    a    c  NaN  NaN  NaN  NaN
1    NaN  NaN  NaN  NaN  NaN  NaN
2    NaN  NaN  NaN  NaN  3.0  4.0
3    NaN  NaN  NaN  NaN  NaN  NaN
4    NaN  NaN  NaN  NaN  NaN  NaN

You may also keep all the original values even if they are equal.
2.8 Reshaping and pivot tables

2.8.1 Reshaping by pivoting DataFrame objects

Data is often stored in so-called “stacked” or “record” format:

```
In [1]: df
Out[1]:
   date  variable value
0 2000-01-03      A  0.469112
1 2000-01-04      A -0.282863
2 2000-01-05      A -1.509059
3 2000-01-03      B -1.135632
4 2000-01-04      B  1.212112
5 2000-01-05      B -0.173215
6 2000-01-03      C  0.119209
7 2000-01-04      C -1.044236
8 2000-01-05      C -0.861849
9 2000-01-03      D -2.104569
10 2000-01-04     D -0.494929
11 2000-01-05     D  1.071804
```

For the curious here is how the above DataFrame was created:

```python
import pandas._testing as tm
def unpivot(frame):
    N, K = frame.shape
    data = {'value': frame.to_numpy().ravel('F'),
            'variable': np.asarray(frame.columns).repeat(N),
            'date': np.tile(np.asarray(frame.index), K)}
    return pd.DataFrame(data, columns=['date', 'variable', 'value'])
```

(continues on next page)
df = unpivot(tm.makeTimeDataFrame(3))

To select out everything for variable A we could do:

```python
In [2]: df[df['variable'] == 'A']
Out[2]:

<table>
<thead>
<tr>
<th>date</th>
<th>variable</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 2000-01-03</td>
<td>A</td>
<td>0.469112</td>
</tr>
<tr>
<td>1 2000-01-04</td>
<td>A</td>
<td>-0.282863</td>
</tr>
<tr>
<td>2 2000-01-05</td>
<td>A</td>
<td>-1.509059</td>
</tr>
</tbody>
</table>
```

But suppose we wish to do time series operations with the variables. A better representation would be where the columns are the unique variables and an index of dates identifies individual observations. To reshape the data into this form, we use the `DataFrame.pivot()` method (also implemented as a top level function `pivot()`):

```python
In [3]: df.pivot(index='date', columns='variable', values='value')
Out[3]:

<table>
<thead>
<tr>
<th>variable</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>date</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2000-01-03</td>
<td>0.469112</td>
<td>-1.135632</td>
<td>0.119209</td>
<td>-2.104569</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>-0.282863</td>
<td>1.212112</td>
<td>-1.044236</td>
<td>-0.494929</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>-1.509059</td>
<td>-0.173215</td>
<td>-0.861849</td>
<td>1.071804</td>
</tr>
</tbody>
</table>
```

If the `values` argument is omitted, and the input DataFrame has more than one column of values which are not used as column or index inputs to `pivot`, then the resulting “pivoted” DataFrame will have hierarchical columns whose topmost level indicates the respective value column:

```python
In [4]: df['value2'] = df['value'] * 2
In [5]: pivoted = df.pivot(index='date', columns='variable')
In [6]: pivoted
Out[6]:

<table>
<thead>
<tr>
<th>variable</th>
<th>value</th>
<th>value2</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>value</td>
<td>value2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>variable</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
<td>A</td>
</tr>
<tr>
<td>date</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2000-01-03</td>
<td>0.469112</td>
<td>-1.135632</td>
<td>0.119209</td>
<td>-2.104569</td>
<td>0.938225</td>
<td>-2.271265</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>-0.282863</td>
<td>1.212112</td>
<td>-1.044236</td>
<td>-0.494929</td>
<td>-0.565727</td>
<td>2.424224</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>-1.509059</td>
<td>-0.173215</td>
<td>-0.861849</td>
<td>1.071804</td>
<td>-3.018117</td>
<td>-0.346429</td>
</tr>
</tbody>
</table>
```

You can then select subsets from the pivoted DataFrame:

```python
In [7]: pivoted['value2']
Out[7]:

<table>
<thead>
<tr>
<th>variable</th>
<th>value</th>
<th>value2</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>value</td>
<td>value2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>variable</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
<td>A</td>
</tr>
<tr>
<td>date</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2000-01-03</td>
<td>0.469112</td>
<td>-1.135632</td>
<td>0.119209</td>
<td>-2.104569</td>
<td>0.938225</td>
<td>-2.271265</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>-0.282863</td>
<td>1.212112</td>
<td>-1.044236</td>
<td>-0.494929</td>
<td>-0.565727</td>
<td>2.424224</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>-1.509059</td>
<td>-0.173215</td>
<td>-0.861849</td>
<td>1.071804</td>
<td>-3.018117</td>
<td>-0.346429</td>
</tr>
</tbody>
</table>
```
Note that this returns a view on the underlying data in the case where the data are homogeneously-typed.

**Note:** `pivot()` will error with a `ValueError: Index contains duplicate entries, cannot reshape` if the index/column pair is not unique. In this case, consider using `pivot_table()` which is a generalization of pivot that can handle duplicate values for one index/column pair.

### 2.8.2 Reshaping by stacking and unstacking

#### Stack

Closely related to the `pivot()` method are the related `stack()` and `unstack()` methods available on Series and DataFrame. These methods are designed to work together with MultiIndex objects (see the section on hierarchical indexing). Here are essentially what these methods do:

- **stack:** “pivot” a level of the (possibly hierarchical) column labels, returning a DataFrame with an index with a new inner-most level of row labels.

- **unstack:** (inverse operation of `stack`) “pivot” a level of the (possibly hierarchical) row index to the column axis, producing a reshaped DataFrame with a new inner-most level of column labels.
Unstack

The clearest way to explain is by example. Let's take a prior example data set from the hierarchical indexing section:

```
In [8]: tuples = list(zip(*[['bar', 'bar', 'baz', 'baz',
                      'foo', 'foo', 'qux', 'qux'],
                      ['one', 'two', 'one', 'two',
                      'one', 'two', 'one', 'two']]))

In [9]: index = pd.MultiIndex.from_tuples(tuples, names=['first', 'second'])

In [10]: df = pd.DataFrame(np.random.randn(8, 2), index=index, columns=['A', 'B'])

In [11]: df2 = df[:4]

In [12]: df2
```

Output:
```
          A         B
first second
bar   one  0.721555 -0.706771
      two -1.039575  0.271860
baz   one -0.424972  0.567020
      two  0.276232 -1.087401
```

The `stack` function “compresses” a level in the DataFrame’s columns to produce either:

- A `Series`, in the case of a simple column Index.
- A `DataFrame`, in the case of a MultiIndex in the columns.

If the columns have a MultiIndex, you can choose which level to stack. The stacked level becomes the new lowest level in a MultiIndex on the columns:
In [13]: stacked = df2.stack()

In [14]: stacked
Out[14]:
first     second
bar one    A    0.721555
           B    -0.706771
    two  A   -1.039575
           B     0.271860
baz one    A   -0.424972
           B     0.567020
    two  A     0.276232
           B   -1.087401
dtype: float64

With a “stacked” DataFrame or Series (having a MultiIndex as the index), the inverse operation of stack is unstack, which by default unstacks the last level:

In [15]: stacked.unstack()
Out[15]:

In [16]: stacked.unstack(1)
Out[16]:

In [17]: stacked.unstack(0)
Out[17]:

2.8. Reshaping and pivot tables
Unstack(1)

If the indexes have names, you can use the level names instead of specifying the level numbers:

```python
In [18]: stacked.unstack('second')
Out[18]:
    second  one  two
  first
bar  A  0.721555 -1.039575
     B -0.706771  0.271860
baz  A -0.424972  0.276232
     B  0.567020 -1.087401
```

If the indexes have names, you can use the level names instead of specifying the level numbers:
Notice that the `stack` and `unstack` methods implicitly sort the index levels involved. Hence a call to `stack` and then `unstack`, or vice versa, will result in a sorted copy of the original DataFrame or Series:

```
In [19]: index = pd.MultiIndex.from_product([[2, 1], ['a', 'b']])
In [20]: df = pd.DataFrame(np.random.randn(4), index=index, columns=['A'])
In [21]: df
Out[21]:
   A
0  2 a -0.370647
  b -1.157892
1  1 a -1.344312
  b  0.844885
In [22]: all(df.unstack().stack() == df.sort_index())
Out[22]: True
```

The above code will raise a `TypeError` if the call to `sort_index` is removed.

Multiple levels

You may also stack or unstack more than one level at a time by passing a list of levels, in which case the end result is as if each level in the list were processed individually.
In 

```
In [24]: df = pd.DataFrame(np.random.randn(4, 4), columns=columns)
```

```
In [25]: df
Out[25]:

<table>
<thead>
<tr>
<th>exp</th>
<th>A</th>
<th>B</th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>cat</td>
<td>cat</td>
<td>dog</td>
<td>dog</td>
</tr>
<tr>
<td>animal</td>
<td>long</td>
<td>long</td>
<td>short</td>
<td>short</td>
</tr>
<tr>
<td>0</td>
<td>1.075770</td>
<td>-0.109050</td>
<td>1.643563</td>
<td>-1.469388</td>
</tr>
<tr>
<td>1</td>
<td>0.357021</td>
<td>-0.674600</td>
<td>-1.776904</td>
<td>-0.968914</td>
</tr>
<tr>
<td>2</td>
<td>-1.294524</td>
<td>0.413738</td>
<td>0.276662</td>
<td>-0.472035</td>
</tr>
<tr>
<td>3</td>
<td>-0.013960</td>
<td>-0.362543</td>
<td>-0.006154</td>
<td>-0.923061</td>
</tr>
</tbody>
</table>
```

In 

```
In [26]: df.stack(level=['animal', 'hair_length'])
```

```
Out[26]:

<table>
<thead>
<tr>
<th>exp</th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>animal</td>
<td>hair_length</td>
</tr>
<tr>
<td>0</td>
<td>cat</td>
<td>long</td>
</tr>
<tr>
<td></td>
<td>dog</td>
<td>short</td>
</tr>
<tr>
<td>1</td>
<td>cat</td>
<td>long</td>
</tr>
<tr>
<td></td>
<td>dog</td>
<td>short</td>
</tr>
<tr>
<td>2</td>
<td>cat</td>
<td>long</td>
</tr>
<tr>
<td></td>
<td>dog</td>
<td>short</td>
</tr>
<tr>
<td>3</td>
<td>cat</td>
<td>long</td>
</tr>
<tr>
<td></td>
<td>dog</td>
<td>short</td>
</tr>
</tbody>
</table>
```

The list of levels can contain either level names or level numbers (but not a mixture of the two).

```
# df.stack(level=['animal', 'hair_length'])
# from above is equivalent to:
In [27]: df.stack(level=[1, 2])
```

```
Out[27]:

<table>
<thead>
<tr>
<th>exp</th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>animal</td>
<td>hair_length</td>
</tr>
<tr>
<td>0</td>
<td>cat</td>
<td>long</td>
</tr>
<tr>
<td></td>
<td>dog</td>
<td>short</td>
</tr>
<tr>
<td>1</td>
<td>cat</td>
<td>long</td>
</tr>
<tr>
<td></td>
<td>dog</td>
<td>short</td>
</tr>
<tr>
<td>2</td>
<td>cat</td>
<td>long</td>
</tr>
<tr>
<td></td>
<td>dog</td>
<td>short</td>
</tr>
<tr>
<td>3</td>
<td>cat</td>
<td>long</td>
</tr>
<tr>
<td></td>
<td>dog</td>
<td>short</td>
</tr>
</tbody>
</table>
```

### Missing data

These functions are intelligent about handling missing data and do not expect each subgroup within the hierarchical index to have the same set of labels. They also can handle the index being unsorted (but you can make it sorted by calling `sort_index`, of course). Here is a more complex example:

```
In [28]: columns = pd.MultiIndex.from_tuples([('A', 'cat'), ('B', 'dog'),
                                             ('B', 'cat'), ('A', 'dog')],
                                            names=['exp', 'animal'])

In [29]: index = pd.MultiIndex.from_product([('bar', 'baz', 'foo', 'qux'),
                                           ('one', 'two')],
                                          names=['exp', 'animal'])
```

(continues on next page)
As mentioned above, `stack` can be called with a `level` argument to select which level in the columns to stack:

```
In [33]: df2.stack('exp')
Out[33]:
animal     exp
  animal  exp
bar  one -0.895717  2.565646
      two -0.431256  1.340309
  baz  one -0.410835 -0.827317
      two -0.875906 -2.211372
  foo  one -1.413681  0.569605
      two  0.875906 -2.006747
  qux  one -0.858255  0.769804
      two -1.226825 -0.727707
```

Unstacking can result in missing values if subgroups do not have the same set of labels. By default, missing values will be replaced with the default fill value for that data type, `NaN` for float, `NaT` for datetimelike, etc. For integer types,
by default data will converted to float and missing values will be set to NaN.

```python
In [35]: df3 = df.iloc[[0, 1, 4, 7], [1, 2]]
```

```python
In [36]: df3
Out[36]:
exp B
animal dog cat
first second
bar one 0.805244 -1.206412
two 1.340309 -1.170299
foo one 1.607920 1.024180
two 0.769804 -1.281247
```

```python
In [37]: df3.unstack()
Out[37]:
exp B
animal dog cat
second one two one two
first
bar 0.805244 1.340309 -1.206412 -1.170299
foo 1.607920 NaN 1.024180 NaN
qux NaN 0.769804 NaN -1.281247
```

Alternatively, unstack takes an optional `fill_value` argument, for specifying the value of missing data.

```python
In [38]: df3.unstack(fill_value=-1e9)
Out[38]:
exp B
animal dog cat
second one two one two
first
bar 8.052440e-01 1.340309e+00 -1.206412e+00 -1.170299e+00
foo 1.607920e+00 -1.000000e+09 1.024180e+00 -1.000000e+09
qux -1.000000e+09 7.698036e-01 -1.000000e+09 -1.281247e+00
```

**With a MultiIndex**

Unstacking when the columns are a `MultiIndex` is also careful about doing the right thing:

```python
In [39]: df[:3].unstack(0)
Out[39]:
exp A B A
animal cat dog cat
dog cat
dog
first bar baz bar baz bar baz bar baz
second
one 0.895717 0.410835 0.805244 0.81385 -1.206412 0.132003 2.565646 -0.827317
two 1.431256 NaN 1.340309 NaN -1.170299 NaN -0.226169 NaN
```

```python
In [40]: df2.unstack(1)
Out[40]:
exp A B A
animal cat dog cat
dog cat
dog
dog
second one two one two one two one two
first
bar 0.895717 1.431256 0.805244 1.340309 -1.206412 -1.170299 2.565646 -0.226169
```

(continues on next page)
The top-level `melt()` function and the corresponding `DataFrame.melt()` are useful to massage a DataFrame into a format where one or more columns are **identifier variables**, while all other columns, considered **measured variables**, are “unpivoted” to the row axis, leaving just two non-identifier columns, “variable” and “value”. The names of those columns can be customized by supplying the `var_name` and `value_name` parameters.

For instance,

```python
In [41]: cheese = pd.DataFrame({'first': ['John', 'Mary'],
                           'last': ['Doe', 'Bo'],
                           'height': [5.5, 6.0],
                           'weight': [130, 150]})

In [42]: cheese
Out[42]:
       first  last  height  weight
0     John  Doe     5.5      130
1    Mary  Bo      6.0      150

In [43]: cheese.melt(id_vars=['first', 'last'])
Out[43]:
      first  last  variable  value
0     John  Doe     height   5.5
1    Mary  Bo     height   6.0
2     John  Doe     weight  130.0
3    Mary  Bo     weight  150.0
```
When transforming a DataFrame using `melt()`, the index will be ignored. The original index values can be kept around by setting the `ignore_index` parameter to `False` (default is `True`). This will however duplicate them.

New in version 1.1.0.

Another way to transform is to use the `wide_to_long()` panel data convenience function. It is less flexible than `melt()`, but more user-friendly.
In [52]: dft
Out[52]:
0     a      d     2.5   3.2 -0.121306  0
1     b      e     1.2   1.3  0.097883  1
2     c      f     0.7   0.1  0.695775  2

In [53]: pd.wide_to_long(dft, ["A", "B"], i="id", j="year")
Out[53]:
    X   A   B
id year
0  1970 -0.121306  a  2.5
1  1970 -0.097883  b  1.2
2  1970  0.695775  c  0.7
0  1980 -0.121306  d  3.2
1  1980 -0.097883  e  1.3
2  1980  0.695775  f  0.1

2.8.4 Combining with stats and GroupBy

It should be no shock that combining `pivot`/`stack`/`unstack` with `GroupBy` and the basic Series and DataFrame statistical functions can produce some very expressive and fast data manipulations.

In [54]: df
Out[54]:
          exp     A  B     A
animal     cat  dog  cat  dog
first second
bar  one  0.895717  0.805244 -1.206412  2.565646
     two  1.431256  1.340309 -1.170299 -0.226169
baz  one  0.410835  0.813850  0.132003 -0.827317
     two -0.076467 -1.187678  1.130127 -1.436737
foo  one -1.413681  1.607920  1.024180  0.569605
     two  0.875906 -2.211372  0.974466 -2.006747
qux  one -0.410001 -0.078638  0.545952 -1.219217
     two -1.226825  0.769804 -1.281247 -0.727707

In [55]: df.stack().mean(1).unstack()
Out[55]:
          animal  cat  dog
first second
bar  one -0.155347  1.685445
     two  0.130479  0.557070
baz  one  0.271419 -0.006733
     two  0.526830 -1.312207
foo  one -0.194750  1.088763
     two  0.925186 -2.109060
qux  one  0.067976 -0.648927
     two -1.254036  0.021048

# same result, another way
In [56]: df.groupby(level=1, axis=1).mean()
Out[56]:
          animal  cat  dog
first second
bar  one -0.155347  1.685445
     two  0.130479  0.557070
baz  one  0.271419 -0.006733
     two  0.526830 -1.312207
foo  one -0.194750  1.088763
     two  0.925186 -2.109060
qux  one  0.067976 -0.648927
     two -1.254036  0.021048

(continues on previous page)
2.8.5 Pivot tables

While `pivot()` provides general purpose pivoting with various data types (strings, numerics, etc.), pandas also provides `pivot_table()` for pivoting with aggregation of numeric data.

The function `pivot_table()` can be used to create spreadsheet-style pivot tables. See the `cookbook` for some advanced strategies.

It takes a number of arguments:

- `data`: a DataFrame object.
- `values`: a column or a list of columns to aggregate.
- `index`: a column, Grouper, array which has the same length as data, or list of them. Keys to group by on the pivot table index. If an array is passed, it is being used as the same manner as column values.
- `columns`: a column, Grouper, array which has the same length as data, or list of them. Keys to group by on the pivot table column. If an array is passed, it is being used as the same manner as column values.
- `aggfunc`: function to use for aggregation, defaulting to `numpy.mean`.

Consider a data set like this:

```python
In [59]: import datetime
In [60]: df = pd.DataFrame({'A': ['one', 'one', 'two', 'three'] * 6,
                        'B': ['A', 'B', 'C'] * 8,
                        'C': ['foo', 'foo', 'foo', 'bar', 'bar', 'bar'] * 4,
                        'D': np.random.randn(24),
                        'E': np.random.randn(24),
                        'F': [datetime.datetime(2013, i, 1) for i in range(1, 13)]
                        + [datetime.datetime(2013, i, 15) for i in range(1, 13)]})
```

```python
first second
--|---------|---------|
bar| one     | -0.155347 1.685445 |
two | 0.130479 0.557070 |
 baz| one     | 0.271419 -0.006733 |
two | 0.526830 -1.312207 |
 foo| one     | -0.194750 1.088763 |
two | 0.925186 -2.109060 |
 qux| one     | 0.067976 -0.648927 |
two | -1.254036 0.021048 |
In [57]: df.stack().groupby(level=1).mean()
Out[57]:
exp  A  B
--|---|---|
one | 0.071448 0.455513 |
two | -0.424186 -0.204486 |
In [58]: df.mean().unstack(0)
Out[58]:
exp  A  B
--|---|---|
animal| 0.060843 0.018596 |
dog  | -0.413580 0.232430 |
```
In [61]: df
Out[61]:
\[
\begin{array}{cccccc}
\text{A} & \text{B} & \text{C} & \text{D} & \text{E} & \text{F} \\
0 & \text{one} & \text{A} & \text{foo} & 0.341734 & -0.317441 & 2013-01-01 \\
1 & \text{one} & \text{B} & \text{foo} & 0.959726 & -1.236269 & 2013-02-01 \\
2 & \text{two} & \text{C} & \text{foo} & -1.110336 & 0.896171 & 2013-03-01 \\
3 & \text{three} & \text{A} & \text{bar} & -0.619976 & -0.487602 & 2013-04-01 \\
4 & \text{one} & \text{B} & \text{bar} & 0.149748 & -0.082240 & 2013-05-01 \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
19 & \text{three} & \text{B} & \text{foo} & 0.690579 & -2.213588 & 2013-08-15 \\
20 & \text{one} & \text{C} & \text{foo} & 0.995761 & 1.063327 & 2013-09-15 \\
21 & \text{one} & \text{A} & \text{bar} & 2.396780 & 1.266143 & 2013-10-15 \\
22 & \text{two} & \text{B} & \text{bar} & 0.014871 & 0.299368 & 2013-11-15 \\
23 & \text{three} & \text{C} & \text{bar} & 3.357427 & -0.863838 & 2013-12-15 \\
\end{array}
\]
[24 rows x 6 columns]

We can produce pivot tables from this data very easily:

In [62]: pd.pivot_table(df, values='D', index=['A', 'B'], columns=['C'])
Out[62]:
\[
\begin{array}{cccc}
\text{C} & \text{bar} & \text{foo} \\
\text{A} & \text{B} & \\
\text{one} & 1.120915 & -0.514058 \\
& -0.338421 & 0.002759 \\
& -0.538846 & 0.699535 \\
\text{three} & -1.181568 & \text{NaN} \\
& \text{NaN} & 0.433512 \\
& \text{0.588783} & \text{NaN} \\
\text{two} & \text{NaN} & 1.000985 \\
& 0.158248 & \text{NaN} \\
& \text{NaN} & 0.176180 \\
\end{array}
\]

In [63]: pd.pivot_table(df, values='D', index=['B'], columns=['A', 'C'], aggfunc=np.sum)
Out[63]:
\[
\begin{array}{cccc}
\text{A} & \text{one} & \text{three} & \text{two} \\
\text{C} & \text{bar} & \text{foo} & \text{bar} & \text{foo} & \text{bar} & \text{foo} & \text{bar} & \text{foo} & \text{bar} & \text{foo} & \text{bar} & \text{foo} \\
\text{B} & 2.241830 & -1.028115 & -2.363137 & \text{NaN} & \text{NaN} & 2.001971 \\
& -0.676843 & 0.005518 & \text{NaN} & 0.867024 & 0.316495 & \text{NaN} \\
& -1.077692 & 1.399070 & 1.177566 & \text{NaN} & \text{NaN} & 0.352360 \\
\end{array}
\]

In [64]: pd.pivot_table(df, values=['D', 'E'], index=['B'], columns=['A', 'C'], aggfunc=np.sum)
Out[64]:
\[
\begin{array}{cccc}
\text{D} & \text{E} & \\
\text{A} & \text{one} & \text{three} & \text{two} & \text{one} \\
& \text{three} & \text{two} \\
\text{C} & \text{bar} & \text{foo} & \text{bar} & \text{foo} & \text{bar} & \text{foo} & \text{bar} & \text{foo} \\
& \text{bar} & \text{foo} & \text{bar} & \text{foo} \\
\text{B} & \\
\end{array}
\]

2.8. Reshaping and pivot tables
The result object is a DataFrame having potentially hierarchical indexes on the rows and columns. If the values column name is not given, the pivot table will include all of the data that can be aggregated in an additional level of hierarchy in the columns:

```python
In [65]: pd.pivot_table(df, index=['A', 'B'], columns=['C'])
Out[65]:

<table>
<thead>
<tr>
<th></th>
<th>bar</th>
<th>foo</th>
<th>bar</th>
<th>foo</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>one</td>
<td>1.120915</td>
<td>-0.514058</td>
<td>1.393057</td>
<td>-0.021605</td>
</tr>
<tr>
<td>B</td>
<td>-0.338421</td>
<td>0.002759</td>
<td>0.684140</td>
<td>-0.551692</td>
</tr>
<tr>
<td>C</td>
<td>-0.538846</td>
<td>0.699535</td>
<td>-0.988442</td>
<td>0.747859</td>
</tr>
<tr>
<td>three</td>
<td>-1.181568</td>
<td>NaN</td>
<td>0.961289</td>
<td>NaN</td>
</tr>
<tr>
<td>B</td>
<td>NaN</td>
<td>0.433512</td>
<td>NaN</td>
<td>-1.064372</td>
</tr>
<tr>
<td>C</td>
<td>0.588783</td>
<td>NaN</td>
<td>-0.131830</td>
<td>NaN</td>
</tr>
<tr>
<td>two</td>
<td>NaN</td>
<td>1.000985</td>
<td>NaN</td>
<td>0.064245</td>
</tr>
<tr>
<td>B</td>
<td>0.158248</td>
<td>NaN</td>
<td>-0.097147</td>
<td>NaN</td>
</tr>
<tr>
<td>C</td>
<td>NaN</td>
<td>0.176180</td>
<td>NaN</td>
<td>0.436241</td>
</tr>
</tbody>
</table>
```

Also, you can use `Grouper` for index and columns keywords. For detail of `Grouper`, see Grouping with a Grouper specification.

```python
In [66]: pd.pivot_table(df, values='D', index=pd.Grouper(freq='M', key='F'),
                  columns='C')
```

You can render a nice output of the table omitting the missing values by calling `to_string` if you wish:

```python
In [67]: table = pd.pivot_table(df, index=['A', 'B'], columns=['C'])
In [68]: print(table.to_string(na_rep=''))
```

(continues on next page)
Note that `pivot_table` is also available as an instance method on DataFrame, i.e. `DataFrame.pivot_table()`.

Adding margins

If you pass `margins=True` to `pivot_table`, special All columns and rows will be added with partial group aggregates across the categories on the rows and columns:

```python
In [69]: df.pivot_table(index=['A', 'B'], columns='C', margins=True, aggfunc=np.std)
Out[69]:
      D   bar    foo  All    bar    foo  All
   C
  A  B
one  A  1.804346  1.210272  1.569879  0.179483  0.418374  0.858005
  B  0.690376  1.353355  0.898998  1.083825  0.968138  1.101401
  C  0.273641  0.418926  0.771139  0.446140  1.422136
three  A  0.794212  0.794212  2.049040  0.442998  0.442998  0.442998
      NaN  0.363548  0.363548  NaN  1.625237  1.625237
      NaN  3.915454  3.915454  1.035215  NaN  1.035215
two  A  NaN  0.442998  0.442998  NaN  0.447104  0.447104
  B  0.202765  NaN  0.202765  0.560757  NaN  0.560757
  C  NaN  1.819408  1.819408  NaN  0.650439  0.650439
All  1.556686  0.952552  1.246608  1.250924  0.899904  1.059389
```

2.8.6 Cross tabulations

Use `crosstab()` to compute a cross-tabulation of two (or more) factors. By default `crosstab` computes a frequency table of the factors unless an array of values and an aggregation function are passed.

It takes a number of arguments

- `index`: array-like, values to group by in the rows.
- `columns`: array-like, values to group by in the columns.
- `values`: array-like, optional, array of values to aggregate according to the factors.
- `aggfunc`: function, optional, If no values array is passed, computes a frequency table.
- `rownames`: sequence, default None, must match number of row arrays passed.
- `colnames`: sequence, default None, if passed, must match number of column arrays passed.
- `margins`: boolean, default False, Add row/column margins (subtotals)
- `normalize`: boolean, {'all', 'index', 'columns'}, or {0,1}, default False. Normalize by dividing all values by the sum of values.
Any Series passed will have their name attributes used unless row or column names for the cross-tabulation are specified.

For example:

```python
In [70]: foo, bar, dull, shiny, one, two = 'foo', 'bar', 'dull', 'shiny', 'one', 'two'
In [71]: a = np.array([foo, foo, bar, bar, foo, foo], dtype=object)
In [72]: b = np.array([one, one, two, one, two, one], dtype=object)
In [73]: c = np.array([dull, dull, shiny, dull, dull, shiny], dtype=object)
In [74]: pd.crosstab(a, [b, c], rownames=['a'], colnames=['b', 'c'])
Out[74]:
        b  one two
    c dull     shiny dull     shiny
  a   bar     1   0   0   1
    foo     2   1   1   0
```

If `crosstab` receives only two Series, it will provide a frequency table.

```python
In [75]: df = pd.DataFrame({'A': [1, 2, 2, 2, 2], 'B': [3, 3, 4, 4, 4], 'C': [1, 1, np.nan, 1, 1]})
In [76]: df
Out[76]:
        A  B  C
 0     1  3  1.0
 1     2  3  1.0
 2     2  4  NaN
 3     2  4  1.0
 4     2  4  1.0
In [77]: pd.crosstab(df['A'], df['B'])
Out[77]:
        B  3  4
    A  1  1  0
     2  1  3
```

crosstab can also be implemented to Categorical data.

```python
In [78]: foo = pd.Categorical(['a', 'b'], categories=['a', 'b', 'c'])
In [79]: bar = pd.Categorical(['d', 'e'], categories=['d', 'e', 'f'])
In [80]: pd.crosstab(foo, bar)
Out[80]:
     col_0  d  e
  row_0
  a   1  0
  b   0  1
```

If you want to include all of data categories even if the actual data does not contain any instances of a particular category, you should set `dropna=False`.
For example:

```
In [81]: pd.crosstab(foo, bar, dropna=False)
Out[81]:
col_0  d  e  f
row_0
a     1  0  0
b     0  1  0
c     0  0  0
```

**Normalization**

Frequency tables can also be normalized to show percentages rather than counts using the `normalize` argument:

```
In [82]: pd.crosstab(df['A'], df['B'], normalize=True)
Out[82]:
B   3  4
A
1  0.2 0.0
2  0.2 0.6
```

`normalize` can also normalize values within each row or within each column:

```
In [83]: pd.crosstab(df['A'], df['B'], normalize='columns')
Out[83]:
B   3  4
A
1  0.5 0.0
2  0.5 1.0
```

crosstab can also be passed a third `Series` and an aggregation function (`aggfunc`) that will be applied to the values of the third `Series` within each group defined by the first two `Series`:

```
In [84]: pd.crosstab(df['A'], df['B'], values=df['C'], aggfunc=np.sum)
Out[84]:
B  3  4
A
1 1.0 NaN
2 1.0 2.0
```

**Adding margins**

Finally, one can also add margins or normalize this output.

```
In [85]: pd.crosstab(df['A'], df['B'], values=df['C'], aggfunc=np.sum, normalize=True,
                margins=True)
.....:
Out[85]:
B    3  4  All
A
1  0.25 0.0 0.25
2  0.25 0.75 0.75
All 0.50 0.5 1.00
```

2.8. Reshaping and pivot tables
### 2.8.7 Tiling

The `cut()` function computes groupings for the values of the input array and is often used to transform continuous variables to discrete or categorical variables:

```python
In [86]: ages = np.array([10, 15, 13, 12, 23, 25, 28, 59, 60])
In [87]: pd.cut(ages, bins=3)
Out[87]:

[(9.95, 26.667], (9.95, 26.667], (9.95, 26.667], (9.95, 26.667], (9.95, 26.667], (9.95, 26.667],
  (26.667, 43.333], (43.333, 60.0], (43.333, 60.0]
Categories (3, interval[float64]): [(9.95, 26.667] < (26.667, 43.333] < (43.333, 60.0]
```

If the `bins` keyword is an integer, then equal-width bins are formed. Alternatively we can specify custom bin-edges:

```python
In [88]: c = pd.cut(ages, bins=[0, 18, 35, 70])
In [89]: c
Out[89]:

[(0, 18], (0, 18], (0, 18], (0, 18], (18, 35], (18, 35], (18, 35], (35, 70], (35, 70]
Categories (3, interval[int64]): [(0, 18] < (18, 35] < (35, 70]
```

If the `bins` keyword is an `IntervalIndex`, then these will be used to bin the passed data:

```python
pd.cut([25, 20, 50], bins=c.categories)
```

---

### 2.8.8 Computing indicator / dummy variables

To convert a categorical variable into a “dummy” or “indicator" DataFrame, for example a column in a DataFrame (a Series) which has k distinct values, can derive a DataFrame containing k columns of 1s and 0s using `get_dummies()`:

```python
In [90]: df = pd.DataFrame({'key': list('bbacab'), 'data1': range(6)})
In [91]: pd.get_dummies(df['key'])
Out[91]:

<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
<th>c</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>
```

Sometimes it’s useful to prefix the column names, for example when merging the result with the original DataFrame:

```python
In [92]: dummies = pd.get_dummies(df['key'], prefix='key')
In [93]: dummies
Out[93]:

<table>
<thead>
<tr>
<th></th>
<th>key_a</th>
<th>key_b</th>
<th>key_c</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>
```

(continues on next page)
In [94]: df[['data1']].join(dummies)
Out[94]:
   data1  key_a  key_b  key_c
0    0      0      0      0
1    1      0      0      0
2    2      0      0      0
3    3      1      0      0
4    4      0      0      0
5    5      0      0      0

This function is often used along with discretization functions like `cut`:

In [95]: values = np.random.randn(10)
In [96]: values
Out[96]:
array([ 0.4082, -1.0481, -0.0257, -0.9884,  0.0941,  1.2627,  1.29 ,
          0.0824, -0.0558,  0.5366])
In [97]: bins = [0, 0.2, 0.4, 0.6, 0.8, 1]
In [98]: pd.get_dummies(pd.cut(values, bins))
Out[98]:
   (0.0, 0.2] (0.2, 0.4] (0.4, 0.6] (0.6, 0.8] (0.8, 1.0]
0           0          1          0          0          0
1           0          0          0          0          0
2           0          0          0          0          0
3           0          0          0          0          0
4           1          0          0          0          0
5           0          0          0          0          0
6           0          0          0          0          0
7           1          0          0          0          0
8           0          0          0          0          0
9           0          0          1          0          0

See also `Series.str.get_dummies`

`get_dummies()` also accepts a DataFrame. By default all categorical variables (categorical in the statistical sense, those with `object` or `categorical` dtype) are encoded as dummy variables.

In [99]: df = pd.DataFrame({
    'A': ['a', 'b', 'a'],
    'B': ['c', 'c', 'b'],
    'C': [1, 2, 3])

In [100]: pd.get_dummies(df)
Out[100]:
   C  A_a  A_b  B_b  B_c
0  1    1    0    0    1
1  2    0    1    0    1
2  3    1    0    1    0

All non-object columns are included untouched in the output. You can control the columns that are encoded with the `columns` keyword.

2.8. Reshaping and pivot tables
Notice that the B column is still included in the output, it just hasn’t been encoded. You can drop B before calling get_dummies if you don’t want to include it in the output.

As with the Series version, you can pass values for the prefix and prefix_sep. By default the column name is used as the prefix, and '_' as the prefix separator. You can specify prefix and prefix_sep in 3 ways:

- string: Use the same value for prefix or prefix_sep for each column to be encoded.
- list: Must be the same length as the number of columns being encoded.
- dict: Mapping column name to prefix.

Sometimes it will be useful to only keep k-1 levels of a categorical variable to avoid collinearity when feeding the result to statistical models. You can switch to this mode by turn on drop_first.

```python
In [101]: pd.get_dummies(df, columns=['A'])
Out[101]:
         B  C       A_a      A_b
0        c  1       1       0
1        c  2       0       1
2        b  3       1       0
```

```
In [102]: simple = pd.get_dummies(df, prefix='new_prefix')
In [103]: simple
Out[103]:
             C         new_prefix_a      new_prefix_b      new_prefix_b      new_prefix_c
0       1        1          0          0          1
1       2          0          1          0          1
2       3          1          0          1          0
```

```
In [104]: from_list = pd.get_dummies(df, prefix=['from_A', 'from_B'])
In [105]: from_list
Out[105]:
             C       from_A_a       from_A_b       from_B_b       from_B_c
0       1        1          0          0          1
1       2          0          1          0          1
2       3          1          0          1          0
```

```
In [106]: from_dict = pd.get_dummies(df, prefix={'B': 'from_B', 'A': 'from_A'})
In [107]: from_dict
Out[107]:
             C       from_A_a       from_A_b       from_B_b       from_B_c
0       1        1          0          0          1
1       2          0          1          0          1
2       3          1          0          1          0
```

```
In [108]: s = pd.Series(list('abcaa'))
In [109]: pd.get_dummies(s)
Out[109]:
         a         b         c
0       1        0        0
1       0        1        0
2       0        0        1
3       1        0        0
```
When a column contains only one level, it will be omitted in the result.

```python
In [111]: df = pd.DataFrame({'A': list('aaaaa'), 'B': list('ababc')})
In [112]: pd.get_dummies(df)
Out[112]:
     A_a  B_a  B_b  B_c
0     1     1     0   0
1     1     0     1   0
2     1     1     0   0
3     1     0     1   0
4     1     0     0   1
```

By default new columns will have `np.uint8` dtype. To choose another dtype, use the `dtype` argument:

```python
In [114]: df = pd.DataFrame({'A': list('abc'), 'B': [1.1, 2.2, 3.3]})
In [115]: pd.get_dummies(df, dtype=bool).dtypes
Out[115]:
B       float64
A_a     bool
A_b     bool
A_c     bool
dtype: object
```

New in version 0.23.0.
2.8.9 Factorizing values

To encode 1-d values as an enumerated type use `factorize()`:

```python
In [116]: x = pd.Series(['A', 'A', np.nan, 'B', 3.14, np.inf])
In [117]: x
Out[117]:
0    A
1    A
2   NaN
3    B
4  3.14
5    inf
dtype: object
In [118]: labels, uniques = pd.factorize(x)
In [119]: labels
Out[119]:
array([ 0,  0, -1,  1,  2,  3])
In [120]: uniques
Out[120]: Index(['A', 'B', 3.14, inf], dtype='object')
```

Note that `factorize` is similar to `numpy.unique`, but differs in its handling of NaN:

```python
Note: The following `numpy.unique` will fail under Python 3 with a `TypeError` because of an ordering bug. See also here.
```

```python
In [1]: x = pd.Series(['A', 'A', np.nan, 'B', 3.14, np.inf])
In [2]: pd.factorize(x, sort=True)
Out[2]:
(array([2, 2, -1, 3, 0, 1]),
Index([3.14, inf, 'A', 'B'], dtype='object'))
In [3]: np.unique(x, return_inverse=True)[::-1]
Out[3]: (array([3, 3, 0, 4, 1, 2]), array([nan, 3.14, inf, 'A', 'B'], dtype=object))
```

Note: If you just want to handle one column as a categorical variable (like R’s factor), you can use `df["cat_col"] = pd.Categorical(df["col"])` or `df["cat_col"] = df["col"].astype("category")`. For full docs on `Categorical`, see the `Categorical introduction` and the `API documentation`.

2.8.10 Examples

In this section, we will review frequently asked questions and examples. The column names and relevant column values are named to correspond with how this DataFrame will be pivoted in the answers below.

```python
In [121]: np.random.seed([3, 1415])
In [122]: n = 20
In [123]: cols = np.array(['key', 'row', 'item', 'col'])
```

(continues on next page)
In [124]: df = cols + pd.DataFrame((np.random.randint(5, size=(n, 4))
            // [2, 1, 2, 1]).astype(str))

In [125]: df.columns = cols

In [126]: df = df.join(pd.DataFrame(np.random.rand(n, 2).round(2)).add_prefix('val'))

In [127]: df
Out[127]:
key row item col val0 val1
0 key0 row3 item1 col3 0.81 0.04
1 key1 row2 item1 col2 0.44 0.07
2 key1 row0 item1 col10 0.77 0.01
3 key0 row4 item0 col12 0.15 0.59
4 key1 row0 item2 col11 0.81 0.64
.. ... ... ... ... ... ...
15 key0 row3 item1 col11 0.31 0.23
16 key0 row0 item2 col13 0.86 0.01
17 key0 row4 item0 col13 0.64 0.21
18 key2 row2 item2 col10 0.13 0.45
19 key0 row2 item0 col14 0.37 0.70

[20 rows x 6 columns]

Pivoting with single aggregations

Suppose we wanted to pivot df such that the col values are columns, row values are the index, and the mean of val0 are the values? In particular, the resulting DataFrame should look like:

col  col0  col1  col2  col3  col4
row
row0  0.77  0.605 NaN  0.860  0.65
row2  0.13  NaN  0.395  0.500  0.25
row3  NaN  0.310  NaN  0.545  NaN
row4  NaN  0.100  0.395  0.760  0.24

This solution uses pivot_table(). Also note that aggfunc='mean' is the default. It is included here to be explicit.

In [128]: df.pivot_table(
         ...:     values='val0', index='row', columns='col', aggfunc='mean')

Out[128]:
col  col0  col1  col2  col3  col4
row
row0  0.77  0.605 NaN  0.860  0.65
row2  0.13  NaN  0.395  0.500  0.25
row3  NaN  0.310  NaN  0.545  NaN
row4  NaN  0.100  0.395  0.760  0.24

Note that we can also replace the missing values by using the fill_value parameter.
In [129]: df.pivot_table(
     .....:     values='val0', index='row', columns='col', aggfunc='mean', fill_value=0)
     .....:
Out[129]:
<table>
<thead>
<tr>
<th></th>
<th>col0</th>
<th>col1</th>
<th>col2</th>
<th>col3</th>
<th>col4</th>
</tr>
</thead>
<tbody>
<tr>
<td>row0</td>
<td>0.77</td>
<td>0.60</td>
<td>0.00</td>
<td>0.86</td>
<td>0.65</td>
</tr>
<tr>
<td>row2</td>
<td>0.13</td>
<td>0.00</td>
<td>0.39</td>
<td>0.50</td>
<td>0.25</td>
</tr>
<tr>
<td>row3</td>
<td>0.00</td>
<td>0.31</td>
<td>0.00</td>
<td>0.54</td>
<td>0.00</td>
</tr>
<tr>
<td>row4</td>
<td>0.00</td>
<td>0.10</td>
<td>0.39</td>
<td>0.76</td>
<td>0.24</td>
</tr>
</tbody>
</table>

Also note that we can pass in other aggregation functions as well. For example, we can also pass in sum.

In [130]: df.pivot_table(
     .....:     values='val0', index='row', columns='col', aggfunc='sum', fill_value=0)
     .....:
Out[130]:
<table>
<thead>
<tr>
<th></th>
<th>col0</th>
<th>col1</th>
<th>col2</th>
<th>col3</th>
<th>col4</th>
</tr>
</thead>
<tbody>
<tr>
<td>row0</td>
<td>0.77</td>
<td>1.21</td>
<td>0.00</td>
<td>0.86</td>
<td>0.65</td>
</tr>
<tr>
<td>row2</td>
<td>0.13</td>
<td>0.00</td>
<td>0.79</td>
<td>0.50</td>
<td>0.50</td>
</tr>
<tr>
<td>row3</td>
<td>0.00</td>
<td>0.31</td>
<td>0.00</td>
<td>1.09</td>
<td>0.00</td>
</tr>
<tr>
<td>row4</td>
<td>0.00</td>
<td>0.10</td>
<td>0.79</td>
<td>1.52</td>
<td>0.24</td>
</tr>
</tbody>
</table>

Another aggregation we can do is calculate the frequency in which the columns and rows occur together a.k.a. “cross tabulation”. To do this, we can pass size to the aggfunc parameter.

In [131]: df.pivot_table(index='row', columns='col', fill_value=0, aggfunc='size')
Out[131]:
<table>
<thead>
<tr>
<th></th>
<th>col0</th>
<th>col1</th>
<th>col2</th>
<th>col3</th>
<th>col4</th>
</tr>
</thead>
<tbody>
<tr>
<td>row0</td>
<td>1</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>row2</td>
<td>1</td>
<td>0</td>
<td>2</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>row3</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>row4</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>1</td>
</tr>
</tbody>
</table>

Pivoting with multiple aggregations

We can also perform multiple aggregations. For example, to perform both a sum and mean, we can pass in a list to the aggfunc argument.

In [132]: df.pivot_table(
     .....:     values='val0', index='row', columns='col', aggfunc=['mean', 'sum'])
     .....:
Out[132]:
<table>
<thead>
<tr>
<th></th>
<th>mean</th>
<th>sum</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>col0</td>
<td>col1</td>
</tr>
<tr>
<td>row0</td>
<td>0.77</td>
<td>0.605</td>
</tr>
<tr>
<td>row2</td>
<td>0.13</td>
<td>NaN</td>
</tr>
<tr>
<td>row3</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>row4</td>
<td>NaN</td>
<td>NaN</td>
</tr>
</tbody>
</table>

Note to aggregate over multiple value columns, we can pass in a list to the values parameter.
In [133]: df.pivot_table(
.....:     values=['val0', 'val1'], index='row', columns='col', aggfunc=['mean'])
.....:
Out[133]:

<table>
<thead>
<tr>
<th></th>
<th>col0</th>
<th>col1</th>
<th>col2</th>
<th>col3</th>
<th>col4</th>
</tr>
</thead>
<tbody>
<tr>
<td>val0</td>
<td>0.77</td>
<td>0.605</td>
<td>NaN</td>
<td>0.86</td>
<td>0.65</td>
</tr>
<tr>
<td>val1</td>
<td>0.65</td>
<td>0.01</td>
<td>NaN</td>
<td>0.745</td>
<td>0.01</td>
</tr>
<tr>
<td>row0</td>
<td>0.77</td>
<td>0.605</td>
<td>NaN</td>
<td>0.86</td>
<td>0.65</td>
</tr>
<tr>
<td>row2</td>
<td>0.13</td>
<td>NaN</td>
<td>0.395</td>
<td>0.500</td>
<td>0.25</td>
</tr>
<tr>
<td>row3</td>
<td>NaN</td>
<td>0.310</td>
<td>NaN</td>
<td>0.545</td>
<td>NaN</td>
</tr>
<tr>
<td>row4</td>
<td>NaN</td>
<td>0.100</td>
<td>0.395</td>
<td>0.760</td>
<td>0.24</td>
</tr>
</tbody>
</table>

Note to subdivide over multiple columns we can pass in a list to the columns parameter.

In [134]: df.pivot_table(
.....:     values=['val0'], index='row', columns=['item', 'col'], aggfunc=['mean'])
.....:
Out[134]:

<table>
<thead>
<tr>
<th></th>
<th>item0</th>
<th>item1</th>
<th>item2</th>
</tr>
</thead>
<tbody>
<tr>
<td>col0</td>
<td>NaN</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>col1</td>
<td>0.77</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>col2</td>
<td>NaN</td>
<td>0.605</td>
<td>0.86</td>
</tr>
<tr>
<td>col3</td>
<td>NaN</td>
<td>0.86</td>
<td>0.65</td>
</tr>
<tr>
<td>col4</td>
<td>NaN</td>
<td>0.65</td>
<td>NaN</td>
</tr>
<tr>
<td>row0</td>
<td>NaN</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>row2</td>
<td>0.35</td>
<td>NaN</td>
<td>0.44</td>
</tr>
<tr>
<td>row3</td>
<td>NaN</td>
<td>0.310</td>
<td>NaN</td>
</tr>
<tr>
<td>row4</td>
<td>NaN</td>
<td>0.100</td>
<td>0.64</td>
</tr>
</tbody>
</table>

2.8.11 Exploding a list-like column

New in version 0.25.0.

Sometimes the values in a column are list-like.

In [135]: keys = ['panda1', 'panda2', 'panda3']

In [136]: values = [['eats', 'shoots'], ['shoots', 'leaves'], ['eats', 'leaves']]

In [137]: df = pd.DataFrame({'keys': keys, 'values': values})

In [138]: df
Out[138]:

<table>
<thead>
<tr>
<th>keys</th>
<th>values</th>
</tr>
</thead>
<tbody>
<tr>
<td>panda1</td>
<td>[eats, shoots]</td>
</tr>
<tr>
<td>panda2</td>
<td>[shoots, leaves]</td>
</tr>
<tr>
<td>panda3</td>
<td>[eats, leaves]</td>
</tr>
</tbody>
</table>

We can ‘explode’ the values column, transforming each list-like to a separate row, by using explode(). This will replicate the index values from the original row:

In [139]: df['values'].explode()
Out[139]:

0  eats
0  shoots
1  shoots

(continues on next page)
You can also explode the column in the DataFrame.

```python
In [140]: df.explode('values')
Out[140]:
   keys  values
0  panda1   eats
0  panda1 shoots
1  panda2 shoots
1  panda2 leaves
2  panda3 eats
2  panda3 leaves
```

`Series.explode()` will replace empty lists with `np.nan` and preserve scalar entries. The dtype of the resulting `Series` is always `object`.

```python
In [141]: s = pd.Series([[1, 2, 3], 'foo', [], ['a', 'b']])
In [142]: s
Out[142]:
0   [1, 2, 3]
1      foo
2        
3   [a, b]
dtype: object
In [143]: s.explode()
Out[143]:
   0  1
   0  2
   0  3
   1  foo
   2  NaN
   3   a
   3   b
dtype: object
```

Here is a typical usecase. You have comma separated strings in a column and want to expand this.

```python
In [144]: df = pd.DataFrame([{'var1': 'a,b,c', 'var2': 1},
    ......:   {'var1': 'd,e,f', 'var2': 2}])
In [145]: df
Out[145]:
   var1  var2
0  a,b,c   1
1  d,e,f   2
```

Creating a long form DataFrame is now straightforward using explode and chained operations.
In [146]: df.assign(var1=df.var1.str.split(',')).explode('var1')
Out[146]:
   var1  var2
0   a     1
0   b     1
0   c     1
1   d     2
1   e     2
1   f     2

2.9 Working with text data

2.9.1 Text data types

New in version 1.0.0.

There are two ways to store text data in pandas:

1. object -dtype NumPy array.
2. StringDtype extension type.

We recommend using StringDtype to store text data.

Prior to pandas 1.0, object dtype was the only option. This was unfortunate for many reasons:

1. You can accidentally store a mixture of strings and non-strings in an object dtype array. It’s better to have a dedicated dtype.
2. object dtype breaks dtype-specific operations like DataFrame.select_dtypes(). There isn’t a clear way to select just text while excluding non-text but still object-dtype columns.
3. When reading code, the contents of an object dtype array is less clear than 'string'.

Currently, the performance of object dtype arrays of strings and arrays.StringArray are about the same. We expect future enhancements to significantly increase the performance and lower the memory overhead of StringArray.

**Warning:** StringArray is currently considered experimental. The implementation and parts of the API may change without warning.

For backwards-compatibility, object dtype remains the default type we infer a list of strings to

In [1]: pd.Series(['a', 'b', 'c'])
Out[1]:
0   a
1   b
2   c
dtype: object

To explicitly request string dtype, specify the dtype

In [2]: pd.Series(['a', 'b', 'c'], dtype="string")
Out[2]:
0   a

(continues on next page)
In [3]: pd.Series(['a', 'b', 'c'], dtype=pd.StringDtype())
Out[3]:
0  a
1  b
2  c
dtype: string

Or astype after the Series or DataFrame is created

In [4]: s = pd.Series(['a', 'b', 'c'])
In [5]: s
Out[5]:
0  a
1  b
2  c
dtype: object

In [6]: s.astype("string")
Out[6]:
0  a
1  b
2  c
dtype: string

Changed in version 1.1.0.

You can also use StringDtype/"string" as the dtype on non-string data and it will be converted to string dtype:

In [7]: s = pd.Series(['a', 2, np.nan], dtype="string")
In [8]: s
Out[8]:
0  a
1  2
2  <NA>
dtype: string

In [9]: type(s[1])
Out[9]: str

or convert from existing pandas data:

In [10]: sl = pd.Series([1, 2, np.nan], dtype="Int64")
In [11]: sl
Out[11]:
0  1
1  2
2  <NA>
dtype: Int64
Behavior differences

These are places where the behavior of StringDtype objects differ from object dtype:

1. For StringDtype, `string accessor methods` that return numeric output will always return a nullable integer dtype, rather than either int or float dtype, depending on the presence of NA values. Methods returning boolean output will return a nullable boolean dtype.

Both outputs are Int64 dtype. Compare that with object-dtype.
When NA values are present, the output dtype is float64. Similarly for methods returning boolean values.

```python
In [22]: s.str.isdigit()
Out[22]:
0   False
1  <NA>
2   False
dtype: boolean

In [23]: s.str.match("a")
Out[23]:
0   True
1  <NA>
2   False
dtype: boolean
```

2. Some string methods, like `Series.str.decode()` are not available on `StringArray` because `StringArray` only holds strings, not bytes.

3. In comparison operations, `arrays.StringArray` and `Series` backed by a `StringArray` will return an object with `BooleanDtype`, rather than a `bool` dtype object. Missing values in a `StringArray` will propagate in comparison operations, rather than always comparing unequal like `numpy.nan`.

Everything else that follows in the rest of this document applies equally to `string` and `object` dtype.

### 2.9.2 String methods

Series and Index are equipped with a set of string processing methods that make it easy to operate on each element of the array. Perhaps most importantly, these methods exclude missing/NA values automatically. These are accessed via the `str` attribute and generally have names matching the equivalent (scalar) built-in string methods:

```python
In [24]: s = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog', 'cat'],
                   dtype="string")

In [25]: s.str.lower()
Out[25]:
0    a
1    b
2    c
3  aaba
4   baca
5   <NA>
6   caba
7    dog
8    cat
dtype: string

In [26]: s.str.upper()
Out[26]:
0    A
```
The string methods on Index are especially useful for cleaning up or transforming DataFrame columns. For instance, you may have columns with leading or trailing whitespace:

```python
In [32]: df = pd.DataFrame(np.random.randn(3, 2),
columns=[' Column A ', ' Column B '], index=range(3))
```

```python
In [33]: df
Out[33]:
   Column A     Column B
0    0.469112  -0.282863
1   -1.509059  -1.135632
2    1.212112  -0.173215
```

Since `df.columns` is an Index object, we can use the `.str` accessor

```python
In [34]: df.columns.str.strip()
Out[34]: Index([' Column A ', ' Column B '], dtype='object')

In [35]: df.columns.str.lower()
Out[35]: Index([' column a ', ' column b '], dtype='object')
```

These string methods can then be used to clean up the columns as needed. Here we are removing leading and trailing
whitespaces, lower casing all names, and replacing any remaining whitespaces with underscores:

```
In [36]: df.columns = df.columns.str.strip().str.lower().str.replace(' ', '_')
In [37]: df
Out[37]:
   column_a  column_b
0      0.469112   -0.282863
1     -1.509059   -1.135632
2      1.212112   -0.173215
```  

**Note:** If you have a Series where lots of elements are repeated (i.e. the number of unique elements in the Series is a lot smaller than the length of the Series), it can be faster to convert the original Series to one of type category and then use .str.<method> or .dt.<property> on that. The performance difference comes from the fact that, for Series of type category, the string operations are done on the .categories and not on each element of the Series.

Please note that a Series of type category with string .categories has some limitations in comparison to Series of type string (e.g. you can't add strings to each other: s + " " + s won't work if s is a Series of type category). Also, .str methods which operate on elements of type list are not available on such a Series.

---

**Warning:** Before v.0.25.0, the .str-accessor did only the most rudimentary type checks. Starting with v.0.25.0, the type of the Series is inferred and the allowed types (i.e. strings) are enforced more rigorously.

Generally speaking, the .str accessor is intended to work only on strings. With very few exceptions, other uses are not supported, and may be disabled at a later point.

---

### 2.9.3 Splitting and replacing strings

Methods like `split` return a Series of lists:

```
In [38]: s2 = pd.Series(['a_b_c', 'c_d_e', np.nan, 'f_g_h'], dtype="string")
In [39]: s2.str.split('_')
Out[39]:
0    [a, b, c]
1    [c, d, e]
2          <NA>
3    [f, g, h]
```

Elements in the split lists can be accessed using `get` or `[]` notation:

```
In [40]: s2.str.split('_').str.get(1)
Out[40]:
0     b
1     d
2    <NA>
3     g
```

```
In [41]: s2.str.split('_').str[1]
Out[41]:
0     b
1     d
2    <NA>
3     g
```
It is easy to expand this to return a DataFrame using expand.

It is also possible to limit the number of splits:

```
rsplit is similar to split except it works in the reverse direction, i.e., from the end of the string to the beginning of the string:
```

replace by default replaces regular expressions:

```
(continues on next page)
Some caution must be taken to keep regular expressions in mind! For example, the following code will cause trouble because of the regular expression meaning of $:

```python
# Consider the following badly formatted financial data
In [48]: dollars = pd.Series(['12', '-$10', '$10,000'], dtype="string")

# This does what you'd naively expect:
In [49]: dollars.str.replace('$', '')
Out[49]:
0  12
1 -10
2 10,000
```

dtype: string

```
# But this doesn't:
In [50]: dollars.str.replace('-$', '-')
Out[50]:
0  12
1 -$10
2 $10,000
```

dtype: string

```
# We need to escape the special character (for >1 len patterns)
In [51]: dollars.str.replace(r'-\$', '-')
Out[51]:
0  12
1 -$10
2 $10,000
```

dtype: string

New in version 0.23.0.

If you do want literal replacement of a string (equivalent to `str.replace()`), you can set the optional `regex` parameter to `False`, rather than escaping each character. In this case both `pat` and `repl` must be strings:

```python
# These lines are equivalent
In [52]: dollars.str.replace(r'-\$', ' -')
Out[52]:
0  12
1 -10
2 10,000
```

dtype: string
The `replace` method can also take a callable as replacement. It is called on every `pat` using `re.sub()`. The callable should expect one positional argument (a regex object) and return a string.

```python
# Reverse every lowercase alphabetic word
In [54]: pat = r'[a-z]+'
In [55]: def repl(m):
    ....:     return m.group(0)[::-1]
In [56]: pd.Series(["foo 123", 'bar baz', np.nan],
    ....:     dtype="string").str.replace(pat, repl)
Out[56]:
0     oof 123
1     rab zab
2      <NA>
dtype: string
```

# Using regex groups
```python
In [57]: pat = r"(?P<one>\w+) (?P<two>\w+) (?P<three>\w+)"
In [58]: def repl(m):
    ....:     return m.group('two').swapcase()
In [59]: pd.Series(["Foo Bar Baz", np.nan],
    ....:     dtype="string").str.replace(pat, repl)
Out[59]:
0      bAR
1      <NA>
```

The `replace` method also accepts a compiled regular expression object from `re.compile()` as a pattern. All flags should be included in the compiled regular expression object.

```python
In [60]: import re
In [61]: regex_pat = re.compile(r'^.+a|dog', flags=re.IGNORECASE)
In [62]: s3.str.replace(regex_pat, 'XX-XX ')
Out[62]:
0     A
1     B
2     C
```
Including a flags argument when calling replace with a compiled regular expression object will raise a ValueError.

```python
In [3]: s3.str.replace(regex_pat, 'XX-XX ', flags=re.IGNORECASE)
---------------------------------------------------------------------------
ValueError: case and flags cannot be set when pat is a compiled regex
```

### 2.9.4 Concatenation

There are several ways to concatenate a Series or Index, either with itself or others, all based on `cat()`, resp. `Index.str.cat`.

#### Concatenating a single Series into a string

The content of a Series (or Index) can be concatenated:

```python
In [64]: s = pd.Series(['a', 'b', 'c', 'd'], dtype="string")
In [65]: s.str.cat(sep=',')
Out[65]: 'a,b,c,d'
```

If not specified, the keyword `sep` for the separator defaults to the empty string, `sep=''`:

```python
In [66]: s.str.cat()
Out[66]: 'abcd'
```

By default, missing values are ignored. Using `na_rep`, they can be given a representation:

```python
In [67]: t = pd.Series(['a', 'b', np.nan, 'd'], dtype="string")
In [68]: t.str.cat(sep=",")
Out[68]: 'a,b,-,d'
In [69]: t.str.cat(sep=",", na_rep='--')
Out[69]: 'a,b,--,d'
```
Concatenating a Series and something list-like into a Series

The first argument to `cat()` can be a list-like object, provided that it matches the length of the calling `Series` (or `Index`).

```
In [70]: s.str.cat(['A', 'B', 'C', 'D'])
Out[70]:
0  aA
1  bB
2  cC
3  dD
dtype: string
```

Missing values on either side will result in missing values in the result as well, unless `na_rep` is specified:

```
In [71]: s.str.cat(t)
Out[71]:
0  aa
1  bb
2  <NA>
3  dd
dtype: string

In [72]: s.str.cat(t, na_rep='-')
Out[72]:
0  aa
1  bb
2  c-
3  dd
dtype: string
```

Concatenating a Series and something array-like into a Series

New in version 0.23.0.

The parameter `others` can also be two-dimensional. In this case, the number or rows must match the lengths of the calling `Series` (or `Index`).

```
In [73]: d = pd.concat([t, s], axis=1)
```

```
In [74]: s
Out[74]:
0  a
1  b
2  c
3  d
dtype: string

In [75]: d
Out[75]:
   0  1
0  a a
1  b b
2  <NA> c
3  d d
```

(continues on next page)
Concatenating a Series and an indexed object into a Series, with alignment

New in version 0.23.0.

For concatenation with a Series or DataFrame, it is possible to align the indexes before concatenation by setting the join-keyword.

```
In [77]: u = pd.Series(['b', 'd', 'a', 'c'], index=[1, 3, 0, 2], dtype="string")
In [78]: s
Out[78]:
0 a
1 b
2 c
dtype: string
In [79]: u
Out[79]:
1 b
3 d
0 a
2 c
dtype: string
In [80]: s.str.cat(u)
Out[80]:
0 aa
1 bb
2 cc
3 dd
dtype: string
In [81]: s.str.cat(u, join='left')
Out[81]:
0 aa
1 bb
2 cc
3 dd
dtype: string
```

**Warning:** If the join keyword is not passed, the method `cat()` will currently fall back to the behavior before version 0.23.0 (i.e. no alignment), but a `FutureWarning` will be raised if any of the involved indexes differ, since this default will change to `join='left'` in a future version.
The usual options are available for join (one of 'left', 'outer', 'inner', 'right'). In particular, alignment also means that the different lengths do not need to coincide anymore.

```
In [82]: v = pd.Series(['z', 'a', 'b', 'd', 'e'], index=[-1, 0, 1, 3, 4],
    ....:       dtype="string")
    ....:
In [83]: s
Out[83]:
0   a
1   b
2   c
3   d
 dtype: string
In [84]: v
Out[84]:
-1  z
  0  a
  1  b
  3  d
  4  e
 dtype: string
In [85]: s.str.cat(v, join='left', na_rep='-')
Out[85]:
0   aa
1   bb
2   c-
3   dd
 dtype: string
In [86]: s.str.cat(v, join='outer', na_rep='-')
Out[86]:
-1  -z
  0  aa
  1  bb
  2  c-
  3  dd
  4  -e
 dtype: string
```

The same alignment can be used when others is a DataFrame:

```
In [87]: f = d.loc[[3, 2, 1, 0], :]
In [88]: s
Out[88]:
0   a
1   b
2   c
3   d
 dtype: string
In [89]: f
Out[89]:
0   1
1   2
3   d
```

(continues on next page)
Concatenating a Series and many objects into a Series

Several array-like items (specifically: Series, Index, and 1-dimensional variants of np.ndarray) can be combined in a list-like container (including iterators, dict-views, etc.).

```python
In [91]: s
Out[91]:
0  a  
1  b  
2  c  
3  d  
dtype: string

In [92]: u
Out[92]:
0  a  
1  b  
2  c  
3  d  
dtype: string

In [93]: s.str.cat([u, u.to_numpy()], join='left')
Out[93]:
0  aab  
1  bbd  
2  cca  
3  ddc  
dtype: string
```

All elements without an index (e.g. np.ndarray) within the passed list-like must match in length to the calling Series (or Index), but Series and Index may have arbitrary length (as long as alignment is not disabled with join=None):

```python
In [94]: v
Out[94]:
-1  z  
0  a  
1  b  
3  d  
4  e  
dtype: string

In [95]: s.str.cat([v, u.to_numpy()], join='outer', na_rep='-')
(continues on next page)
```
Out[95]:
-1  -z--
 0   aaab
 1   bbbd
 2    c-ca
 3    dddc
 4     -e--
dtype: string

If using join='right' on a list-like of others that contains different indexes, the union of these indexes will be used as the basis for the final concatenation:

In [96]: u.loc[[3]]
Out[96]:
3   d
dtype: string

In [97]: v.loc[[-1, 0]]
Out[97]:
-1   z
 0   a
dtype: string

In [98]: s.str.cat([u.loc[[3]], v.loc[[-1, 0]]], join='right', na_rep='-')
Out[98]:
-1   --z
 0   a-a
 3    dd-
dtype: string

2.9.5 Indexing with .str

You can use [] notation to directly index by position locations. If you index past the end of the string, the result will be a NaN.

In [99]: s = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan,
  ....:          'CABA', 'dog', 'cat'],
  ....:          dtype='string')

In [100]: s.str[0]
Out[100]:
0   A
1   B
2   C
3   A
4   B
5  <NA>
6   C
7   d
8   c
dtype: string

In [101]: s.str[1]
Out[101]:
(continues on next page)
2.9.6 Extracting substrings

Extract first match in each subject (extract)

Warning: Before version 0.23, argument expand of the `extract` method defaulted to False. When expand=False, `extract` returns a Series, Index, or DataFrame, depending on the subject and regular expression pattern. When expand=True, it always returns a DataFrame, which is more consistent and less confusing from the perspective of a user. expand=True has been the default since version 0.23.0.

The `extract` method accepts a regular expression with at least one capture group.

Extracting a regular expression with more than one group returns a DataFrame with one column per group.

```
In [102]: pd.Series(['a1', 'b2', 'c3'],
........:   dtype="string").str.extract(r'([ab])\d', expand=False)
...
Out[102]:
   0   1
0 a  1
1 b  2
2 <NA> <NA>
```

Elements that do not match return a row filled with NaN. Thus, a Series of messy strings can be “converted” into a like-indexed Series or DataFrame of cleaned-up or more useful strings, without necessitating `get()` to access tuples or `re.match` objects. The dtype of the result is always object, even if no match is found and the result only contains NaN.

Named groups like

```
In [103]: pd.Series(['a1', 'b2', 'c3'],
........:   dtype="string").str.extract(r'(\p{Letter}\p{Digit})',
........:   expand=False)
```

```
letter digit
0 a  1
1 b  2
2 <NA> <NA>
```

and optional groups like
can also be used. Note that any capture group names in the regular expression will be used for column names; otherwise capture group numbers will be used.

Extracting a regular expression with one group returns a DataFrame with one column if expand=True.

2.9. Working with text data 515
Calling on an Index with a regex with more than one capture group returns a DataFrame if expand=True.

```python
In [111]: s.index.str.extract("(?P<letter>[a-zA-Z])([0-9]+)", expand=True)
Out[111]:
   letter  digit
0   A       11
1   B       22
2   C       33
```

It raises ValueError if expand=False.

```python
>>> s.index.str.extract("(?P<letter>[a-zA-Z])([0-9]+)", expand=False)
ValueError: only one regex group is supported with Index
```

The table below summarizes the behavior of `extract(expand=False)` (input subject in first column, number of groups in regex in first row)

<table>
<thead>
<tr>
<th></th>
<th>1 group</th>
<th>&gt;1 group</th>
</tr>
</thead>
<tbody>
<tr>
<td>Index</td>
<td>Index</td>
<td>ValueError</td>
</tr>
<tr>
<td>Series</td>
<td>Series</td>
<td>DataFrame</td>
</tr>
</tbody>
</table>

### Extract all matches in each subject (extractall)

Unlike `extract` (which returns only the first match),

```python
In [112]: s = pd.Series(['ala2', 'b1', 'c1'], index=['A', 'B', 'C'],
                   dtype='string')

In [113]: s
Out[113]:
   A   a
   B   b
   C   c
   dtype: string

In [114]: two_groups = '(?P<letter>[a-z])(?P<digit>[0-9])'

In [115]: s.str.extract(two_groups, expand=True)
Out[115]:
   letter digit
   A   a   1
   B   b   1
   C   c   1
```

the `extractall` method returns every match. The result of `extractall` is always a DataFrame with a MultiIndex on its rows. The last level of the MultiIndex is named `match` and indicates the order in the subject.

```python
In [116]: s.str.extractall(two_groups)
```

(continues on next page)
When each subject string in the Series has exactly one match,

```
In [117]: s = pd.Series(['a3', 'b3', 'c2'], dtype='string')
In [118]: s
Out[118]:
0    a3
1    b3
2    c2
dtype: string
```

then `extractall(pat).xs(0, level='match')` gives the same result as `extract(pat)`.

```
In [119]: extract_result = s.str.extract(two_groups, expand=True)
In [120]: extract_result
Out[120]:
   letter digit
0    a    3
1    b    3
2    c    2
In [121]: extractall_result = s.str.extractall(two_groups)
In [122]: extractall_result
Out[122]:
   letter digit    match
0    a    3 0
1    b    3 0
2    c    2 0
In [123]: extractall_result.xs(0, level='match')
Out[123]:
   letter digit
0    a    3
1    b    3
2    c    2
```

Index also supports `.str.extractall`. It returns a DataFrame which has the same result as a Series.str.extractall with a default index (starts from 0).

```
In [124]: pd.Index(['a1a2', 'b1', 'c1']).str.extractall(two_groups)
Out[124]:
   letter digit
match
0    a    1
1    a    2
1    b    1
2    c    1
```
In [125]: pd.Series(["a1a2", "b1", "c1"], dtype="string").str.extractall(two_groups)
Out[125]:
   letter digit  match
0      a    1   True
1      a    2   False
2      b    1   False
3      c    1   False

2.9.7 Testing for strings that match or contain a pattern

You can check whether elements contain a pattern:

In [126]: pattern = r'[0-9][a-z]'

In [127]: pd.Series(['1', '2', '3a', '3b', '03c', '4dx'],
          dtype="string").str.contains(pattern)
Out[127]:
0   False
1   False
2   True
3   True
4   False
5   True
dtype: bool

Or whether elements match a pattern:

In [128]: pd.Series(['1', '2', '3a', '3b', '03c', '4dx'],
          dtype="string").str.match(pattern)
Out[128]:
0   False
1   False
2   True
3   True
4   False
5   True
dtype: bool

New in version 1.1.0.

In [129]: pd.Series(['1', '2', '3a', '3b', '03c', '4dx'],
          dtype="string").str.fullmatch(pattern)
Out[129]:
0   False
1   False
2   True
3   True
4   False
5   False
dtype: bool
Note: The distinction between `match`, `fullmatch`, and `contains` is strictness: `fullmatch` tests whether the entire string matches the regular expression; `match` tests whether there is a match of the regular expression that begins at the first character of the string; and `contains` tests whether there is a match of the regular expression at any position within the string.

The corresponding functions in the `re` package for these three match modes are `re.fullmatch`, `re.match`, and `re.search`, respectively.

Methods like `match`, `fullmatch`, `contains`, `startswith`, and `endswith` take an extra `na` argument so missing values can be considered True or False:

```python
In [130]: s4 = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog', 'cat'],
                   dtype="string")

In [131]: s4.str.contains('A', na=False)
Out[131]:
0   True
1  False
2  False
3   True
4  False
5  False
6   True
7  False
8  False
dtype: bool
```

### 2.9.8 Creating indicator variables

You can extract dummy variables from string columns. For example if they are separated by a `'|'`:

```python
In [132]: s = pd.Series(['a', 'a|b', np.nan, 'a|c'], dtype="string")

In [133]: s.str.get_dummies(sep='|')
Out[133]:
a  b  c
0  1  0  0
1  1  1  0
2  0  0  0
3  1  0  1
```

String Index also supports `get_dummies` which returns a MultiIndex.

```python
In [134]: idx = pd.Index(['a', 'a|b', np.nan, 'a|c'])

In [135]: idx.str.get_dummies(sep='|')
Out[135]:
MultiIndex([(1, 0, 0),
            (1, 1, 0),
            (0, 0, 0),
            (1, 0, 1)],
           names=['a', 'b', 'c'])
```

2.9. Working with text data
### 2.9.9 Method summary

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>cat()</code></td>
<td>Concatenate strings</td>
</tr>
<tr>
<td><code>split()</code></td>
<td>Split strings on delimiter</td>
</tr>
<tr>
<td><code>rsplit()</code></td>
<td>Split strings on delimiter working from the end of the string</td>
</tr>
<tr>
<td><code>get()</code></td>
<td>Index into each element (retrieve i-th element)</td>
</tr>
<tr>
<td><code>join()</code></td>
<td>Join strings in each element of the Series with passed separator</td>
</tr>
<tr>
<td><code>get_dummies()</code></td>
<td>Split strings on the delimiter returning DataFrame of dummy variables</td>
</tr>
<tr>
<td><code>contains()</code></td>
<td>Return boolean array if each string contains pattern/regex</td>
</tr>
<tr>
<td><code>replace()</code></td>
<td>Replace occurrences of pattern/regex/string with some other string or the return value of a callable given the occurrence</td>
</tr>
<tr>
<td><code>repeat()</code></td>
<td>Duplicate values (s.str.repeat(3) equivalent to x * 3)</td>
</tr>
<tr>
<td><code>pad()</code></td>
<td>Add whitespace to left, right, or both sides of strings</td>
</tr>
<tr>
<td><code>center()</code></td>
<td>Equivalent to str.center</td>
</tr>
<tr>
<td><code>ljust()</code></td>
<td>Equivalent to str.ljust</td>
</tr>
<tr>
<td><code>rjust()</code></td>
<td>Equivalent to str.rjust</td>
</tr>
<tr>
<td><code>zfill()</code></td>
<td>Equivalent to str.zfill</td>
</tr>
<tr>
<td><code>wrap()</code></td>
<td>Split long strings into lines with length less than a given width</td>
</tr>
<tr>
<td><code>slice()</code></td>
<td>Slice each string in the Series</td>
</tr>
<tr>
<td><code>slice_replace()</code></td>
<td>Replace slice in each string with passed value</td>
</tr>
<tr>
<td><code>count()</code></td>
<td>Count occurrences of pattern</td>
</tr>
<tr>
<td><code>startswith()</code></td>
<td>Equivalent to str.startswith(pat) for each element</td>
</tr>
<tr>
<td><code>endswith()</code></td>
<td>Equivalent to str.endswith(pat) for each element</td>
</tr>
<tr>
<td><code>findall()</code></td>
<td>Compute list of all occurrences of pattern/regex for each string</td>
</tr>
<tr>
<td><code>match()</code></td>
<td>Call re.match on each element, returning matched groups as list</td>
</tr>
<tr>
<td><code>extract()</code></td>
<td>Call re.search on each element, returning DataFrame with one row for each element and one column for each regex capture group</td>
</tr>
<tr>
<td><code>extractall()</code></td>
<td>Call re.findall on each element, returning DataFrame with one row for each match and one column for each regex capture group</td>
</tr>
<tr>
<td><code>len()</code></td>
<td>Compute string lengths</td>
</tr>
<tr>
<td><code>strip()</code></td>
<td>Equivalent to str.strip</td>
</tr>
<tr>
<td><code>rstrip()</code></td>
<td>Equivalent to str.rstrip</td>
</tr>
<tr>
<td><code>lstrip()</code></td>
<td>Equivalent to str.lstrip</td>
</tr>
<tr>
<td><code>partition()</code></td>
<td>Equivalent to str.partition</td>
</tr>
<tr>
<td><code>rpartition()</code></td>
<td>Equivalent to str.rpartition</td>
</tr>
<tr>
<td><code>lower()</code></td>
<td>Equivalent to str.lower</td>
</tr>
<tr>
<td><code>casefold()</code></td>
<td>Equivalent to str.casefold</td>
</tr>
<tr>
<td><code>upper()</code></td>
<td>Equivalent to str.upper</td>
</tr>
<tr>
<td><code>find()</code></td>
<td>Equivalent to str.find</td>
</tr>
<tr>
<td><code>rfind()</code></td>
<td>Equivalent to str.rfind</td>
</tr>
<tr>
<td><code>index()</code></td>
<td>Equivalent to str.index</td>
</tr>
<tr>
<td><code>rindex()</code></td>
<td>Equivalent to str.rindex</td>
</tr>
<tr>
<td><code>capitalize()</code></td>
<td>Equivalent to str.capitalize</td>
</tr>
<tr>
<td><code>swapcase()</code></td>
<td>Equivalent to str.swapcase</td>
</tr>
<tr>
<td><code>normalize()</code></td>
<td>Return Unicode normal form. Equivalent to unicodedata.normalize</td>
</tr>
<tr>
<td><code>translate()</code></td>
<td>Equivalent to str.translate</td>
</tr>
<tr>
<td><code>isalnum()</code></td>
<td>Equivalent to str.isalnum</td>
</tr>
</tbody>
</table>

continues on next page
In this section, we will discuss missing (also referred to as NA) values in pandas.

**Note:** The choice of using NaN internally to denote missing data was largely for simplicity and performance reasons. Starting from pandas 1.0, some optional data types start experimenting with a native NA scalar using a mask-based approach. See [here](#) for more.

See the [cookbook](#) for some advanced strategies.

### 2.10.1 Values considered “missing”

As data comes in many shapes and forms, pandas aims to be flexible with regard to handling missing data. While NaN is the default missing value marker for reasons of computational speed and convenience, we need to be able to easily detect this value with data of different types: floating point, integer, boolean, and general object. In many cases, however, the Python None will arise and we wish to also consider that “missing” or “not available” or “NA”.

**Note:** If you want to consider inf and -inf to be “NA” in computations, you can set pandas.options.mode.use_inf_as_na = True.

```python
In [1]: df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f', 'h'],
...:                     columns=['one', 'two', 'three'])
...:
In [2]: df['four'] = 'bar'
In [3]: df['five'] = df['one'] > 0
In [4]: df
Out[4]:
<table>
<thead>
<tr>
<th></th>
<th>one</th>
<th>two</th>
<th>three</th>
<th>four</th>
<th>five</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>0.469112</td>
<td>-0.282863</td>
<td>-1.509059</td>
<td>bar</td>
<td>True</td>
</tr>
<tr>
<td>c</td>
<td>-1.135632</td>
<td>1.212112</td>
<td>-0.173215</td>
<td>bar</td>
<td>False</td>
</tr>
<tr>
<td>e</td>
<td>0.119209</td>
<td>-1.044236</td>
<td>-0.861849</td>
<td>bar</td>
<td>True</td>
</tr>
<tr>
<td>f</td>
<td>-2.104569</td>
<td>-0.494929</td>
<td>1.071804</td>
<td>bar</td>
<td>False</td>
</tr>
<tr>
<td>h</td>
<td>0.721555</td>
<td>-0.706771</td>
<td>-1.039575</td>
<td>bar</td>
<td>True</td>
</tr>
</tbody>
</table>
In [5]: df2 = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])
```

(continues on next page)
To make detecting missing values easier (and across different array dtypes), pandas provides the `isna()` and `notna()` functions, which are also methods on Series and DataFrame objects:

```
In [7]: df2['one']
Out[7]:
   a   0.469112
   b   NaN
   c  -1.135632
   d   NaN
   e  0.119209
   f  -2.104569
   g   NaN
   h  0.721555
Name: one, dtype: float64
```

```
In [8]: pd.isna(df2['one'])
Out[8]:
   a  False
   b  True
   c  False
   d  True
   e  False
   f  False
   g  True
   h  False
Name: one, dtype: bool
```

```
In [9]: df2['four'].notna()
Out[9]:
   a   True
   b  False
   c   True
   d  False
   e   True
   f   True
   g  False
   h   True
Name: four, dtype: bool
```

```
In [10]: df2.isna()
Out[10]:
   one  two  three  four  five
   a   False  False  False  False  False
```
Warning: One has to be mindful that in Python (and NumPy), the `nan`'s don’t compare equal, but `None`'s do. Note that pandas/NumPy uses the fact that `np.nan != np.nan`, and treats `None` like `np.nan`.

```
In [11]: None == None  # noqa: E711
Out[11]: True

In [12]: np.nan == np.nan
Out[12]: False
```

So as compared to above, a scalar equality comparison versus a `None/np.nan` doesn’t provide useful information.

```
In [13]: df2['one'] == np.nan
Out[13]:
a   False
b   False
c   False
d   False
e   False
f   False
g   False
h   False
Name: one, dtype: bool
```

### Integer dtypes and missing data

Because `NaN` is a float, a column of integers with even one missing values is cast to floating-point dtype (see `Support for integer NA` for more). Pandas provides a nullable integer array, which can be used by explicitly requesting the dtype:

```
In [14]: pd.Series([1, 2, np.nan, 4], dtype=pd.Int64Dtype())
Out[14]:
0    1
1    2
2  <NA>
3    4
dtype: Int64
```

Alternatively, the string alias `dtype='Int64'` (note the capital "I") can be used.

See `Nullable integer data type` for more.
Datetimes

For datetime64[ns] types, NaT represents missing values. This is a pseudo-native sentinel value that can be represented by NumPy in a singular dtype (datetime64[ns]). pandas objects provide compatibility between NaT and NaN.

```
In [15]: df2 = df.copy()
In [16]: df2['timestamp'] = pd.Timestamp('20120101')
In [17]: df2
Out[17]:
     one  two  three  four   five   timestamp
  a  0.469112 -0.282863 -1.509059  bar  True 2012-01-01
  c -1.135632  1.212112 -0.173215  bar False 2012-01-01
  e  0.119209 -1.044236 -0.861849  bar  True 2012-01-01
  f -2.104569 -0.494929  1.071804  bar False 2012-01-01
  h  0.721555 -0.706771 -1.039575  bar  True 2012-01-01
In [18]: df2.loc[['a', 'c', 'h'], ['one', 'timestamp']] = np.nan
In [19]: df2
Out[19]:
     one  two  three  four   five   timestamp
  a   NaN -0.282863 -1.509059  bar  True   NaT
  c   NaN  1.212112 -0.173215  bar False   NaT
  e  0.119209 -1.044236 -0.861849  bar  True 2012-01-01
  f -2.104569 -0.494929  1.071804  bar False 2012-01-01
  h   NaN -0.706771 -1.039575  bar  True   NaT
In [20]: df2.dtypes.value_counts()
Out[20]:
        float64    3
       datetime64[ns]    1
             bool       1
              object     1
dtype: int64
```

2.10.2 Inserting missing data

You can insert missing values by simply assigning to containers. The actual missing value used will be chosen based on the dtype.

For example, numeric containers will always use NaN regardless of the missing value type chosen:

```
In [21]: s = pd.Series([1, 2, 3])
In [22]: s.loc[0] = None
In [23]: s
Out[23]:
0   NaN
1   2.0
2   3.0
dtype: float64
```

Likewise, datetime containers will always use NaT.
For object containers, pandas will use the value given:

```
In [24]: s = pd.Series(["a", "b", "c"])
In [25]: s.loc[0] = None
In [26]: s.loc[1] = np.nan
In [27]: s
Out [27]:
0  None
1  NaN
2   c
dtype: object
```

2.10.3 Calculations with missing data

Missing values propagate naturally through arithmetic operations between pandas objects.

```
In [28]: a
Out [28]:
      one    two
a   NaN -0.282863
b   NaN  1.212112
c   NaN  1.192090
```

```
In [29]: b
Out [29]:
      one    two    three
a   NaN  -0.282863  -1.509059
b   NaN  1.212112  -0.173215
c   NaN  1.192090   -0.861849
d   NaN  2.104569  -0.494929
e   NaN  -2.104569  -1.044236
f   NaN  -2.104569  -0.706771
```

```
In [30]: a + b
Out [30]:
      one    two    three
a   NaN  NaN  -0.565727
b   NaN  NaN  1.212112
c   NaN  NaN  1.192090
d   NaN  NaN  1.071804
e   NaN  NaN  -2.088472
f   NaN  NaN  1.071804
g   NaN  NaN  -1.039575
```

The descriptive statistics and computational methods discussed in the data structure overview (and listed here and here) are all written to account for missing data. For example:

- When summing data, NA (missing) values will be treated as zero.
- If the data are all NA, the result will be 0.
- Cumulative methods like cumsum() and cumprod() ignore NA values by default, but preserve them in the resulting arrays. To override this behaviour and include NA values, use skipna=False.
In [31]: df
Out[31]:
   one   two   three
a  NaN  -0.282863  -1.509059
b  NaN   1.212112  -0.173215
c  0.119209  -1.044236   -0.861849
d -2.104569  -0.494929   1.071804
e  NaN  -0.706771  -1.039575

In [32]: df['one'].sum()
Out[32]: -1.985361

In [33]: df.mean(1)
Out[33]:
a    -0.895961
b     0.519449
c    -0.595625
d    -0.509232
e    -0.873173
dtype: float64

In [34]: df.cumsum()
Out[34]:
   one   two   three
a  NaN  -0.282863  -1.509059
b  NaN  0.929249  -1.682273
c  0.119209 -0.114987 -2.544122
d -1.985361 -0.609917 -1.472318
e  NaN -1.316688 -2.511893

In [35]: df.cumsum(skipna=False)
Out[35]:
   one   two   three
a  NaN  -0.282863  -1.509059
b  NaN  0.929249  -1.682273
c  0.119209 -0.114987 -2.544122
d  NaN -0.609917 -1.472318
e  NaN -1.316688 -2.511893

2.10.4 Sum/prod of empties/nans

**Warning:** This behavior is now standard as of v0.22.0 and is consistent with the default in **numpy**; previously sum/prod of all-NA or empty Series/DataFrames would return NaN. See v0.22.0 **whatsnew** for more.

The sum of an empty or all-NA Series or column of a DataFrame is 0.

In [36]: pd.Series([np.nan]).sum()
Out[36]: 0.0

In [37]: pd.Series([], dtype="float64").sum()
Out[37]: 0.0

The product of an empty or all-NA Series or column of a DataFrame is 1.
2.10.5 NA values in GroupBy

NA groups in GroupBy are automatically excluded. This behavior is consistent with R, for example:

```python
In [40]: df
Out[40]:
   one    two    three
a  NaN -0.282863 -1.509059
b  NaN    1.212112 -0.173215
c  0.119209 -1.044236 -0.861849
d -2.104569 -0.494929  1.071804
e  NaN    0.706771 -1.039575
f  NaN       0.000000  1.509059

In [41]: df.groupby('one').mean()
Out[41]:
   two     three
one
-2.105699 -0.494929  1.071804
  0.119209 -1.044236 -0.861849
```

See the `groupby` section [here](#) for more information.

**Cleaning / filling missing data**

pandas objects are equipped with various data manipulation methods for dealing with missing data.

### 2.10.6 Filling missing values: `fillna`

`fillna()` can “fill in” NA values with non-NA data in a couple of ways, which we illustrate:

**Replace NA with a scalar value**

```python
In [42]: df2
Out[42]:
   one    two    three    four    five     timestamp
a  NaN -0.282863 -1.509059  bar  True    NaT
b  NaN    1.212112 -0.173215  bar  False    NaT
c  0.119209 -1.044236 -0.861849  bar  True  2012-01-01
d -2.104569 -0.494929  1.071804  bar  False  2012-01-01
```

```python
In [43]: df2.fillna(0)
Out[43]:
   one    two    three    four    five     timestamp
a  0.000000 -0.282863 -1.509059  bar  True       0
b  1.212112 -0.173215    0.000000  bar  False       0
c  0.119209 -1.044236 -0.861849  bar  True  2012-01-01  00:00:00
d -2.104569 -0.494929  1.071804  bar  False  2012-01-01  00:00:00
```

(continues on next page)
h  0.000000  -0.706771  -1.039575  bar  True  0

In [44]: df2['one'].fillna('missing')
Out[44]:
a       missing
b       missing
c       0.119209
d   -2.10457
Name: one, dtype: object

Fill gaps forward or backward

Using the same filling arguments as reindexing, we can propagate non-NA values forward or backward:

In [45]: df
Out[45]:
   one     two     three
a   NaN  -0.282863  -1.509059
b   NaN     1.212112  -0.173215
c   NaN  -0.119209  -1.044236
d   NaN  -0.494929   1.071804
e   NaN   1.212112  -0.173215
f   NaN   1.071804   1.071804
g   NaN -0.706771  -1.039575
h   NaN     0.706771  -1.039575

In [46]: df.fillna(method='pad')
Out[46]:
   one     two     three
a   NaN  -0.282863  -1.509059
b   NaN     1.212112  -0.173215
c   NaN  -0.119209  -1.044236
f   NaN  -0.494929   1.071804
h   NaN     0.706771  -1.039575

Limit the amount of filling

If we only want consecutive gaps filled up to a certain number of data points, we can use the limit keyword:

In [47]: df
Out[47]:
   one     two     three
a   NaN  -0.282863  -1.509059
b   NaN     1.212112  -0.173215
c   NaN  -0.119209  -1.044236
f   NaN  -0.494929   1.071804
h   NaN     0.706771  -1.039575

In [48]: df.fillna(method='pad', limit=1)
Out[48]:
   one     two     three
a   NaN  -0.282863  -1.509059
b   NaN     1.212112  -0.173215
c   NaN  -0.119209  -1.044236
f   NaN  -0.494929   1.071804
h   NaN     0.706771  -1.039575

To remind you, these are the available filling methods:
<table>
<thead>
<tr>
<th>Method</th>
<th>Action</th>
</tr>
</thead>
<tbody>
<tr>
<td>pad / ffill</td>
<td>Fill values forward</td>
</tr>
<tr>
<td>bfill / backfill</td>
<td>Fill values backward</td>
</tr>
</tbody>
</table>

With time series data, using pad/ffill is extremely common so that the “last known value” is available at every time point.

`ffill()` is equivalent to `fillna(method='ffill')` and `bfill()` is equivalent to `fillna(method='bfill')`

### 2.10.7 Filling with a PandasObject

You can also fillna using a dict or Series that is alignable. The labels of the dict or index of the Series must match the columns of the frame you wish to fill. The use case of this is to fill a DataFrame with the mean of that column.

```python
In [49]: dff = pd.DataFrame(np.random.randn(10, 3), columns=list('ABC'))
In [50]: dff.iloc[3:5, 0] = np.nan
In [51]: dff.iloc[4:6, 1] = np.nan
In [52]: dff.iloc[5:8, 2] = np.nan
In [53]: dff
  Out[53]:
     A   B   C
  0  0.271860 -0.424972  0.567020
  1  0.276232 -1.087401 -0.673690
  2  0.113648 -1.478427  0.524988
  3  NaN  0.577046  -1.715002
  4  NaN  NaN  -1.157892
  5 -1.344312  NaN  -0.293543
  6 -0.109050  1.643563  NaN
  7  0.357021  -0.674600  NaN
  8 -0.968914  -1.294524  0.413738
  9  0.276662  -0.472035 -0.013960
In [54]: dff.fillna(dff.mean())
  Out[54]:
     A   B   C
  0  0.271860 -0.424972  0.567020
  1  0.276232 -1.087401 -0.673690
  2  0.113648 -1.478427  0.524988
  3 -0.140857  0.577046 -1.715002
  4 -0.140857 -0.401419 -1.157892
  5 -1.344312 -0.401419 -0.293543
  6 -0.109050  1.643563  NaN
  7  0.357021  -0.674600  NaN
  8 -0.968914  -1.294524  0.413738
  9  0.276662  -0.472035 -0.013960
In [55]: dff.fillna(dff.mean()['B':'C'])
  Out[55]:
     A   B   C
  0  0.271860 -0.424972  0.567020
```

(continues on next page)
1 0.276232 -1.087401 -0.673690
2 0.113648 -1.478427 0.524988
3 NaN 0.577046 -1.715002
4 NaN -0.401419 -0.293543
5 -1.344312 -0.401419 -0.293543
6 -0.109050 1.643563 -0.293543
7 0.357021 -0.674600 -0.293543
8 -0.968914 -1.294524 0.413738
9 0.276662 -0.472035 -0.013960

Same result as above, but is aligning the ‘fill’ value which is a Series in this case.

In [56]: dff.where(pd.notna(dff), dff.mean(), axis='columns')
Out[56]:
      A       B       C
0  0.271860 -0.424972  0.567020
1  0.276232 -1.087401 -0.673690
2  0.113648 -1.478427  0.524988
3 -0.140857  0.577046 -1.715002
4 -0.140857 -0.401419 -1.157892
5 -1.344312 -0.401419 -0.293543
6 -0.109050  1.643563 -0.293543
7  0.357021 -0.674600 -0.293543
8 -0.968914 -1.294524  0.413738
9  0.276662 -0.472035 -0.013960

2.10.8 Dropping axis labels with missing data: dropna

You may wish to simply exclude labels from a data set which refer to missing data. To do this, use dropna():

In [57]: df
Out[57]:
     one     two     three
   NaN    0.282863 -1.509059
   NaN     1.212112 -0.173215
   NaN       0.000000    0.000000
   NaN       0.000000    0.000000
   NaN    -0.706771 -1.039575
In [58]: df.dropna(axis=0)
Out[58]:
Empty DataFrame
Columns: [one, two, three]
Index: []
In [59]: df.dropna(axis=1)
Out[59]:
     two     three
   a -0.282863 -1.509059
   c  1.212112 -0.173215
   e       0.000000    0.000000
   f       0.000000    0.000000
   h    -0.706771 -1.039575
An equivalent `dropna()` is available for Series. DataFrame.dropna has considerably more options than Series.dropna, which can be examined in the API.

### 2.10.9 Interpolation

New in version 0.23.0: The `limit_area` keyword argument was added.

Both Series and DataFrame objects have `interpolate()` that, by default, performs linear interpolation at missing data points.

```python
In [61]: ts
Out[61]:
2000-01-31    0.469112
2000-02-29     NaN
2000-03-31     NaN
2000-04-28     NaN
2000-05-31     NaN
   ...        ...
2007-12-31   -6.950267
2008-01-31  -7.904475
2008-02-29  -6.441779
2008-03-31  -8.184940
2008-04-30  -9.011531
Freq: BM, Length: 100, dtype: float64
```

```python
In [62]: ts.count()
Out[62]: 66
```

```python
In [63]: ts.plot()
Out[63]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe27754f6a0>
```
```python
In [64]: ts.interpolate()
Out[64]:
2000-01-31  0.469112
2000-02-29  0.434469
2000-03-31  0.399826
2000-04-28  0.365184
2000-05-31  0.330541
...      
2007-12-31 -6.950267
2008-01-31 -7.904475
2008-02-29 -6.441779
2008-03-31 -8.184940
2008-04-30 -9.011531
Freq: BM, Length: 100, dtype: float64
```

```python
In [65]: ts.interpolate().count()
Out[65]: 100
```

```python
In [66]: ts.interpolate().plot()
Out[66]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe2787d1820>
```
Index aware interpolation is available via the `method` keyword:

```python
In [67]: ts2
Out[67]:
2000-01-31    0.469112
2000-02-29     NaN
2002-07-31    -5.785037
2005-01-31     NaN
2008-04-30    -9.011531
dtype: float64

In [68]: ts2.interpolate()
Out[68]:
2000-01-31    0.469112
2000-02-29    -2.657962
2002-07-31    -5.785037
2005-01-31    -7.398284
2008-04-30    -9.011531
dtype: float64

In [69]: ts2.interpolate(method='time')
Out[69]:
2000-01-31    0.469112
2000-02-29    0.270241
2002-07-31    -5.785037
```

(continues on next page)
For a floating-point index, use `method='values'`:

```
In [70]: ser
Out[70]:
0.0 0.0
1.0 NaN
10.0 10.0
dtype: float64

In [71]: ser.interpolate()
Out[71]:
0.0 0.0
1.0 5.0
10.0 10.0
dtype: float64

In [72]: ser.interpolate(method='values')
Out[72]:
0.0 0.0
1.0 1.0
10.0 10.0
dtype: float64
```

You can also interpolate with a DataFrame:

```
In [73]: df = pd.DataFrame({'A': [1, 2.1, np.nan, 4.7, 5.6, 6.8],
                      'B': [.25, np.nan, np.nan, 4, 12.2, 14.4]})

In [74]: df
Out[74]:
   A    B
0  1.0  0.25
1  2.1  NaNa
2  NaNa NaNa
3  4.7  4.00
4  5.6  12.20
5  6.8  14.40

In [75]: df.interpolate()
Out[75]:
   A   B
0  1.0  0.25
1  2.1  1.50
2  3.4  2.75
3  4.7  4.00
4  5.6  12.20
5  6.8  14.40
```

The `method` argument gives access to fancier interpolation methods. If you have `scipy` installed, you can pass the name of a 1-d interpolation routine to `method`. You’ll want to consult the full `scipy` interpolation documentation and reference guide for details. The appropriate interpolation method will depend on the type of data you are working with.
• If you are dealing with a time series that is growing at an increasing rate, method='quadratic' may be appropriate.
• If you have values approximating a cumulative distribution function, then method='pchip' should work well.
• To fill missing values with goal of smooth plotting, consider method='akima'.

**Warning:** These methods require scipy.

```python
In [76]: df.interpolate(method='barycentric')
Out[76]:
    A    B
0  1.00  0.250
1  2.10  0.000
2  3.53  0.000
3  4.70  0.000
4  5.60  0.000
5  6.80  0.000

In [77]: df.interpolate(method='pchip')
Out[77]:
    A        B
0  1.000  0.2500
1  2.100  0.6728
2  3.435  1.9290
3  4.700  4.0000
4  5.600  12.2000
5  6.800  14.4000

In [78]: df.interpolate(method='akima')
Out[78]:
    A        B
0  1.000  0.2500
1  2.100 -0.8733
2  3.407  1.2070
3  4.700  4.0000
4  5.600  12.2000
5  6.800  14.4000
```

When interpolating via a polynomial or spline approximation, you must also specify the degree or order of the approximation:

```python
In [79]: df.interpolate(method='spline', order=2)
Out[79]:
    A        B
0  1.000  0.2500
1  2.100 -0.4286
2  3.407  1.2070
3  4.700  4.0000
4  5.600  12.2000
5  6.800  14.4000

In [80]: df.interpolate(method='polynomial', order=2)
Out[80]:
    A        B
0  1.000  0.2500
1  2.100 -0.4286
2  3.407  1.2070
3  4.700  4.0000
4  5.600  12.2000
5  6.800  14.4000
```

(continues on next page)
Another use case is interpolation at new values. Suppose you have 100 observations from some distribution. And let’s
suppose that you’re particularly interested in what’s happening around the middle. You can mix pandas’ `reindex` and `interpolate` methods to interpolate at the new values.

```python
In [88]: ser = pd.Series(np.sort(np.random.uniform(size=100)))

# interpolate at new_index
In [89]: new_index = ser.index | pd.Index([49.25, 49.5, 49.75, 50.25, 50.5, 50.75])

In [90]: interp_s = ser.reindex(new_index).interpolate(method='pchip')

In [91]: interp_s[49:51]
Out[91]:
   49.00    0.471410
   49.25    0.476841
   49.50    0.481780
   49.75    0.485998
   50.00    0.489266
   50.25    0.491814
   50.50    0.493995
   50.75    0.495763
   51.00    0.497074
   dtype: float64
```

**Interpolation limits**

Like other pandas fill methods, `interpolate()` accepts a `limit` keyword argument. Use this argument to limit the number of consecutive NaN values filled since the last valid observation:

```python
In [92]: ser = pd.Series([np.nan, np.nan, 5, np.nan, np.nan, ...
                ..: np.nan, 13, np.nan, np.nan])

In [93]: ser
Out[93]:
   0      NaN
   1      NaN
   2       5.0
   3      NaN
   4      NaN
   5      NaN
   6      13.0
   7      NaN
   8      NaN
   dtype: float64

# fill all consecutive values in a forward direction
In [94]: ser.interpolate()
Out[94]:
   0      NaN
   1      NaN
   2       5.0
   3       7.0
   4       9.0
   5      11.0
   6      13.0
   7      13.0
```

(continues on next page)
8  13.0
dtype: float64

# fill one consecutive value in a forward direction
In [95]: ser.interpolate(limit=1)
Out[95]:
0   NaN
1   NaN
2   5.0
3   7.0
4   NaN
5   NaN
6  13.0
7  13.0
8   NaN
dtype: float64

By default, NaN values are filled in a forward direction. Use limit_direction parameter to fill backward or from both directions.

# fill one consecutive value backwards
In [96]: ser.interpolate(limit=1, limit_direction='backward')
Out[96]:
0   NaN
1   5.0
2   5.0
3   NaN
4   NaN
5  11.0
6  13.0
7   NaN
8   NaN
dtype: float64

# fill one consecutive value in both directions
In [97]: ser.interpolate(limit=1, limit_direction='both')
Out[97]:
0   NaN
1   5.0
2   5.0
3   7.0
4   NaN
5  11.0
6  13.0
7  13.0
8   NaN
dtype: float64

# fill all consecutive values in both directions
In [98]: ser.interpolate(limit_direction='both')
Out[98]:
0   5.0
1   5.0
2   5.0
3   7.0
4   9.0

(continues on next page)
By default, NaN values are filled whether they are inside (surrounded by) existing valid values, or outside existing valid values. Introduced in v0.23 the `limit_area` parameter restricts filling to either inside or outside values.

```python
# fill one consecutive inside value in both directions
In [99]: ser.interpolate(limit_direction='both', limit_area='inside', limit=1)
Out[99]:
   0   NaN
   1   NaN
   2   5.0
   3   7.0
   4    NaN
   5   11.0
   6   13.0
   7    NaN
   8    NaN
dtype: float64

# fill all consecutive outside values backward
In [100]: ser.interpolate(limit_direction='backward', limit_area='outside')
Out[100]:
   0    5.0
   1    5.0
   2    5.0
   3   NaN
   4   NaN
   5   NaN
   6   13.0
   7    NaN
   8    NaN
dtype: float64

# fill all consecutive outside values in both directions
In [101]: ser.interpolate(limit_direction='both', limit_area='outside')
Out[101]:
   0    5.0
   1    5.0
   2    5.0
   3   NaN
   4   NaN
   5   NaN
   6   13.0
   7   13.0
   8   13.0
dtype: float64
```
2.10.10 Replacing generic values

Often times we want to replace arbitrary values with other values.

`replace()` in Series and `replace()` in DataFrame provides an efficient yet flexible way to perform such replacements.

For a Series, you can replace a single value or a list of values by another value:

```python
In [102]: ser = pd.Series([0., 1., 2., 3., 4.])
In [103]: ser.replace(0, 5)
Out[103]:
0   5.0
1   1.0
2   2.0
3   3.0
4   4.0
dtype: float64
```

You can replace a list of values by a list of other values:

```python
In [104]: ser.replace([0, 1, 2, 3, 4], [4, 3, 2, 1, 0])
Out[104]:
0   4.0
1   3.0
2   2.0
3   1.0
4   0.0
dtype: float64
```

You can also specify a mapping dict:

```python
In [105]: ser.replace({0: 10, 1: 100})
Out[105]:
0  10.0
1 100.0
2   2.0
3   3.0
4   4.0
dtype: float64
```

For a DataFrame, you can specify individual values by column:

```python
In [106]: df = pd.DataFrame({'a': [0, 1, 2, 3, 4], 'b': [5, 6, 7, 8, 9]})
In [107]: df.replace({'a': 0, 'b': 5}, 100)
Out[107]:
a   b
0  100  100
1   1   6
2   2   7
3   3   8
4   4   9
```

Instead of replacing with specified values, you can treat all given values as missing and interpolate over them:
2.10.11 String/regular expression replacement

**Note:** Python strings prefixed with the `r` character such as `r'hello world'` are so-called “raw” strings. They have different semantics regarding backslashes than strings without this prefix. Backslashes in raw strings will be interpreted as an escaped backslash, e.g., `r'\'` == `'\'`. You should read about them if this is unclear.

Replace the `.` with NaN (str -> str):

```
In [109]: d = {'a': list(range(4)), 'b': list('ab..'), 'c': ['a', 'b', np.nan, 'd']}
In [110]: df = pd.DataFrame(d)
In [111]: df.replace('.', np.nan)
```

Now do it with a regular expression that removes surrounding whitespace (regex -> regex):

```
In [112]: df.replace(r'\s*\.\s*', np.nan, regex=True)
```

Replace a few different values (list -> list):

```
In [113]: df.replace(['a', '.'], ['b', np.nan])
```

```
In [114]: df.replace([r'\.', r'(a)'], ['dot', r'\1stuff'], regex=True)
```

(continues on next page)
Only search in column 'b' (dict -> dict):

```python
In [115]: df.replace({'b': '.'}, {'b': np.nan})
Out[115]:
   a  b  c
0  0   a  a
1  1   b  b
2  2  NaN  NaN
3  3  NaN   d
```

Same as the previous example, but use a regular expression for searching instead (dict of regex -> dict):

```python
In [116]: df.replace({'b': r'\s*\.\s*'}, {'b': np.nan}, regex=True)
Out[116]:
   a  b  c
0  0   a  a
1  1   b  b
2  2  NaN  NaN
3  3  NaN   d
```

You can pass nested dictionaries of regular expressions that use regex=True:

```python
In [117]: df.replace({'b': r'\s*(\.)*'}, {'b': r'\1ty'}, regex=True)
Out[117]:
   a  b  c
0  0   a  a
1  1   b  b
2  2  .ty  NaN
3  3  .ty   d
```

Alternatively, you can pass the nested dictionary like so:

```python
In [118]: df.replace(regex={'b': {r'\s*\.\s*': np.nan}})
Out[118]:
   a  b  c
0  0   a  a
1  1   b  b
2  2  NaN  NaN
3  3  NaN   d
```

You can also use the group of a regular expression match when replacing (dict of regex -> dict of regex), this works for lists as well.

```python
In [119]: df.replace({r'\s*\.\s*': r'\1ty'}, regex=True)
Out[119]:
   a  b  c
0  0   a  a
1  1   b  b
2  2  .ty  NaN
3  3  .ty   d
```
You can pass a list of regular expressions, of which those that match will be replaced with a scalar (list of regex -> regex).

```
In [120]: df.replace([r'^\s*\s+', r'a|b'], np.nan, regex=True)
Out[120]:
   a  b  c
0  NaN NaN
1  NaN NaN
2  NaN NaN
3  NaN d
```

All of the regular expression examples can also be passed with the `to_replace` argument as the `regex` argument. In this case the `value` argument must be passed explicitly by name or `regex` must be a nested dictionary. The previous example, in this case, would then be:

```
In [121]: df.replace(regex=[r'^\s*\s+', r'a|b'], value=np.nan)
Out[121]:
   a  b  c
0  NaN NaN
1  NaN NaN
2  NaN NaN
3  NaN d
```

This can be convenient if you do not want to pass `regex=True` every time you want to use a regular expression.

**Note:** Anywhere in the above `replace` examples that you see a regular expression a compiled regular expression is valid as well.

### 2.10.12 Numeric replacement

`replace()` is similar to `fillna()`.

```
In [122]: df = pd.DataFrame(np.random.randn(10, 2))
In [123]: df[np.random.rand(df.shape[0]) > 0.5] = 1.5
In [124]: df.replace(1.5, np.nan)
Out[124]:
   0   1
0 -0.844214 -1.021415
1  0.432396 -0.323580
2  0.423825  0.799180
3  1.262614  0.751965
4  NaN      NaN
5  NaN      NaN
6 -0.498174 -1.060799
7  0.591667 -0.183257
8  1.019855 -1.482465
9  NaN      NaN
```

Replacing more than one value is possible by passing a list.

```
In [125]: df00 = df.iloc[0, 0]
```

(continues on next page)
In [126]: df.replace([1.5, df00], [np.nan, 'a'])
Out[126]:
   0   1
0  a  -1.02141
1 0.432396 -0.32358
2 0.423825  0.79918
3 1.26261  0.751965
4  NaN  NaN
5  NaN  NaN
6 -0.498174 -1.0608
7  0.591667  -0.183257
8  1.01985  -1.48247
9  NaN  NaN

In [127]: df[1].dtype
Out[127]: dtype('float64')

You can also operate on the DataFrame in place:

In [128]: df.replace(1.5, np.nan, inplace=True)

Warning: When replacing multiple bool or datetime64 objects, the first argument to replace
(to_replace) must match the type of the value being replaced. For example,

```python
>>> s = pd.Series([True, False, True])
>>> s.replace({'a string': 'new value', True: False})  # raises
TypeError: Cannot compare types 'ndarray(dtype=bool)' and 'str'
```

will raise a TypeError because one of the dict keys is not of the correct type for replacement.

However, when replacing a single object such as,

```python
In [129]: s = pd.Series([True, False, True])
In [130]: s.replace('a string', 'another string')
Out[130]:
   0  True
   1  False
   2  True
dtype: bool
```

the original NDFrame object will be returned untouched. We’re working on unifying this API, but for backwards compatibility reasons we cannot break the latter behavior. See GH6354 for more details.
Missing data casting rules and indexing

While pandas supports storing arrays of integer and boolean type, these types are not capable of storing missing data. Until we can switch to using a native NA type in NumPy, we’ve established some “casting rules”. When a reindexing operation introduces missing data, the Series will be cast according to the rules introduced in the table below.

<table>
<thead>
<tr>
<th>data type</th>
<th>Cast to</th>
</tr>
</thead>
<tbody>
<tr>
<td>integer</td>
<td>float</td>
</tr>
<tr>
<td>boolean</td>
<td>object</td>
</tr>
<tr>
<td>float</td>
<td>no cast</td>
</tr>
<tr>
<td>object</td>
<td>no cast</td>
</tr>
</tbody>
</table>

For example:

```
In [131]: s = pd.Series(np.random.randn(5), index=[0, 2, 4, 6, 7])
In [132]: s > 0
Out[132]:
0   True
2   True
4   True
6   True
7   True
dtype: bool
In [133]: (s > 0).dtype
Out[133]: dtype('bool')
In [134]: crit = (s > 0).reindex(list(range(8)))
In [135]: crit
Out[135]:
0   True
1   NaN
2   True
3   NaN
4   True
5   NaN
6   True
7   True
dtype: object
In [136]: crit.dtype
Out[136]: dtype('O')
```

Ordinarily NumPy will complain if you try to use an object array (even if it contains boolean values) instead of a boolean array to get or set values from an ndarray (e.g. selecting values based on some criteria). If a boolean vector contains NAs, an exception will be generated:

```
In [137]: reindexed = s.reindex(list(range(8))).fillna(0)
In [138]: reindexed[crit]
---------------------------------------------------------------------------
ValueError: invalid boolean value
```

(continues on next page)
However, these can be filled in using `fillna()` and it will work fine:

```
In [139]: reindexed[crit.fillna(False)]
Out[139]:
0  0.126504
1  0.000000
2  0.696198
3  0.000000
4  0.697416
5  0.000000
6  0.601516
7  0.003659
dtype: float64

In [140]: reindexed[crit.fillna(True)]
Out[140]:
0  0.126504
1  0.000000
2  0.696198
3  0.000000
4  0.697416
5  0.000000
6  0.601516
7  0.003659
dtype: float64
```

Pandas provides a nullable integer dtype, but you must explicitly request it when creating the series or column. Notice that we use a capital “I” in the `dtype="Int64"`.

```
In [141]: s = pd.Series([0, 1, np.nan, 3, 4], dtype="Int64")
In [142]: s
Out[142]:
0    0
1    1
2  <NA>
3    3
4    4
dtype: Int64
```

See `Nullable integer data type` for more.
2.10.13 Experimental NA scalar to denote missing values

Warning: Experimental: the behaviour of pd.NA can still change without warning.

New in version 1.0.0.

Starting from pandas 1.0, an experimental pd.NA value (singleton) is available to represent scalar missing values. At this moment, it is used in the nullable integer, boolean and dedicated string data types as the missing value indicator.

The goal of pd.NA is to provide a “missing” indicator that can be used consistently across data types (instead of np.nan, None or pd.NaT depending on the data type).

For example, when having missing values in a Series with the nullable integer dtype, it will use pd.NA:

```python
In [143]: s = pd.Series([1, 2, None], dtype="Int64")
In [144]: s
Out[144]:
0   1
1   2
2   <NA>
dtype: Int64
In [145]: s[2]
Out[145]: <NA>
In [146]: s[2] is pd.NA
Out[146]: True
```

Currently, pandas does not yet use those data types by default (when creating a DataFrame or Series, or when reading in data), so you need to specify the dtype explicitly. An easy way to convert to those dtypes is explained here.

Propagation in arithmetic and comparison operations

In general, missing values propagate in operations involving pd.NA. When one of the operands is unknown, the outcome of the operation is also unknown.

For example, pd.NA propagates in arithmetic operations, similarly to np.nan:

```python
In [147]: pd.NA + 1
Out[147]: <NA>
In [148]: "a" * pd.NA
Out[148]: <NA>
```

There are a few special cases when the result is known, even when one of the operands is NA.

```python
In [149]: pd.NA ** 0
Out[149]: 1
In [150]: 1 ** pd.NA
Out[150]: 1
```

In equality and comparison operations, pd.NA also propagates. This deviates from the behaviour of np.nan, where comparisons with np.nan always return False.
In [151]: pd.NA == 1
Out[151]: <NA>

In [152]: pd.NA == pd.NA
Out[152]: <NA>

In [153]: pd.NA < 2.5
Out[153]: <NA>

To check if a value is equal to pd.NA, the *isna()* function can be used:

In [154]: pd.isna(pd.NA)
Out[154]: True

An exception on this basic propagation rule are *reductions* (such as the mean or the minimum), where pandas defaults to skipping missing values. See *above* for more.

**Logical operations**

For logical operations, pd.NA follows the rules of the *three-valued logic* (or *Kleene logic*, similarly to R, SQL and Julia). This logic means to only propagate missing values when it is logically required.

For example, for the logical “or” operation (|), if one of the operands is True, we already know the result will be True, regardless of the other value (so regardless the missing value would be True or False). In this case, pd.NA does not propagate:

In [155]: True | False
Out[155]: True

In [156]: True | pd.NA
Out[156]: True

In [157]: pd.NA | True
Out[157]: True

On the other hand, if one of the operands is False, the result depends on the value of the other operand. Therefore, in this case pd.NA propagates:

In [158]: False | True
Out[158]: True

In [159]: False | False
Out[159]: False

In [160]: False | pd.NA
Out[160]: <NA>

The behaviour of the logical “and” operation (&) can be derived using similar logic (where now pd.NA will not propagate if one of the operands is already False):

In [161]: False & True
Out[161]: False

In [162]: False & False
Out[162]: False

(continues on next page)
NA in a boolean context

Since the actual value of an NA is unknown, it is ambiguous to convert NA to a boolean value. The following raises an error:

```
In [167]: bool(pd.NA)
---------------------------------------------------------------------------
TypeError Traceback (most recent call last)
<ipython-input-167-5477a57d5abb> in <module>
----> 1 bool(pd.NA)
/pandas-release/pandas/pandas/_libs/missing.pyx in pandas._libs.missing.NAType.__bool__()  # __bool__
TypeError: boolean value of NA is ambiguous
```

This also means that pd.NA cannot be used in a context where it is evaluated to a boolean, such as if condition: ... where condition can potentially be pd.NA. In such cases, isna() can be used to check for pd.NA or condition being pd.NA can be avoided, for example by filling missing values beforehand.

A similar situation occurs when using Series or DataFrame objects in if statements, see Using if/truth statements with pandas.

NumPy ufuncs

pandas.NA implements NumPy’s __array_ufunc__ protocol. Most ufuncs work with NA, and generally return NA:

```
In [168]: np.log(pd.NA)
Out[168]: <NA>

In [169]: np.add(pd.NA, 1)
Out[169]: <NA>
```

**Warning:** Currently, ufuncs involving an ndarray and NA will return an object-dtype filled with NA values.

```
In [170]: a = np.array([1, 2, 3])

In [171]: np.greater(a, pd.NA)
Out[171]: array([<NA>, <NA>, <NA>], dtype=object)
```
The return type here may change to return a different array type in the future.

See *DataFrame interoperability with NumPy functions* for more on ufuncs.

**Conversion**

If you have a DataFrame or Series using traditional types that have missing data represented using `np.nan`, there are convenience methods `convert_dtypes()` in Series and `convert_dtypes()` in DataFrame that can convert data to use the newer dtypes for integers, strings and booleans listed here. This is especially helpful after reading in data sets when letting the readers such as `read_csv()` and `read_excel()` infer default dtypes.

In this example, while the dtypes of all columns are changed, we show the results for the first 10 columns.

```python
In [172]: bb = pd.read_csv('data/baseball.csv', index_col='id')
In [173]: bb[bb.columns[:10]].dtypes
Out[173]:
player   object
year     int64
stint    int64
team     object
lg       object
g        int64
ab       int64
r         int64
h         int64
X2b       int64
dtype: object
```

```python
In [174]: bbn = bb.convert_dtypes()
In [175]: bbn[bbn.columns[:10]].dtypes
Out[175]:
player    string
year      Int64
stint     Int64
team      string
lg         string
g         Int64
ab         Int64
r          Int64
h          Int64
X2b        Int64
dtype: object
```
2.11 Categorical data

This is an introduction to pandas categorical data type, including a short comparison with R’s factor.

Categoricals are a pandas data type corresponding to categorical variables in statistics. A categorical variable takes on a limited, and usually fixed, number of possible values (categories; levels in R). Examples are gender, social class, blood type, country affiliation, observation time or rating via Likert scales.

In contrast to statistical categorical variables, categorical data might have an order (e.g. ‘strongly agree’ vs ‘agree’ or ‘first observation’ vs. ‘second observation’), but numerical operations (additions, divisions, ... ) are not possible.

All values of categorical data are either in categories or np.nan. Order is defined by the order of categories, not lexical order of the values. Internally, the data structure consists of a categories array and an integer array of codes which point to the real value in the categories array.

The categorical data type is useful in the following cases:

- A string variable consisting of only a few different values. Converting such a string variable to a categorical variable will save some memory, see here.
- The lexical order of a variable is not the same as the logical order (“one”, “two”, “three”). By converting to a categorical and specifying an order on the categories, sorting and min/max will use the logical order instead of the lexical order, see here.
- As a signal to other Python libraries that this column should be treated as a categorical variable (e.g. to use suitable statistical methods or plot types).

See also the API docs on categoricals.

2.11.1 Object creation

Series creation

Categorical Series or columns in a DataFrame can be created in several ways:

By specifying dtype="category" when constructing a Series:

```
In [1]: s = pd.Series(["a", "b", "c", "a"], dtype="category")
```

```
In [2]: s
Out[2]:
0  a
1  b
2  c
3  a
dtype: category
Categories (3, object): ['a', 'b', 'c']
```

By converting an existing Series or column to a category dtype:

```
In [3]: df = pd.DataFrame({"A": ["a", "b", "c", "a"]})
```

```
In [4]: df["B"] = df["A"].astype('category')
```

```
In [5]: df
Out[5]:
   A  B
0  a  a
```

(continues on next page)
By using special functions, such as `cut()`, which groups data into discrete bins. See the example on tiling in the docs.

```
In [6]: df = pd.DataFrame({'value': np.random.randint(0, 100, 20)})
In [7]: labels = ["{0} - {1}".format(i, i + 9) for i in range(0, 100, 10)]
In [8]: df['group'] = pd.cut(df.value, range(0, 105, 10), right=False, labels=labels)
In [9]: df.head(10)
Out[9]:
   value   group
0   65   60 - 69
1   49   40 - 49
2   56   50 - 59
3   43   40 - 49
4   43   40 - 49
5   91   90 - 99
6   32   30 - 39
7   87   80 - 89
8   36   30 - 39
9    8    0 - 9
```

By passing a `pandas.Categorical` object to a `Series` or assigning it to a `DataFrame`.

```
In [10]: raw_cat = pd.Categorical(['a', 'b', 'c', 'a'], categories=['b', 'c', 'd'], ordered=False)
In [11]: s = pd.Series(raw_cat)
In [12]: s
Out[12]:
0    NaN
1     b
2     c
3    NaN
dtype: category
Categories (3, object): [b', 'c', 'd']
In [13]: df = pd.DataFrame({'A': ['a', 'b', 'c', 'a']})
In [14]: df['B'] = raw_cat
In [15]: df
Out[15]:
   A   B
0  a   NaN
1  b     b
2  c     c
3  a   NaN
```

Categorical data has a specific category `dtype`:
DataFrame creation

Similar to the previous section where a single column was converted to categorical, all columns in a DataFrame can be batch converted to categorical either during or after construction.

This can be done during construction by specifying dtype="category" in the DataFrame constructor:

```python
In [17]: df = pd.DataFrame({'A': list('abca'), 'B': list('bccd')}, dtype="category")
```

```python
In [18]: df.dtypes
```

```
Out[18]:
A category
B category
dtype: object
```

Note that the categories present in each column differ; the conversion is done column by column, so only labels present in a given column are categories:

```python
In [19]: df['A']
```

```
Out[19]:
    0  a
    1  b
    2  c
    3  a
Name: A, dtype: category
Categories (3, object): ['a', 'b', 'c']
```

```python
In [20]: df['B']
```

```
Out[20]:
    0  b
    1  c
    2  c
    3  d
Name: B, dtype: category
Categories (3, object): ['b', 'c', 'd']
```

New in version 0.23.0.

Analogously, all columns in an existing DataFrame can be batch converted using DataFrame.astype():

```python
In [21]: df = pd.DataFrame({'A': list('abca'), 'B': list('bccd')})
```

```python
In [22]: df_cat = df.astype('category')
```

```python
In [23]: df_cat.dtypes
```

```
Out[23]:
A category
B category
dtype: object
```

This conversion is likewise done column by column:

2.11. Categorical data
In [24]: df_cat['A']
Out[24]:
0   a
1   b
2   c
3   a
Name: A, dtype: category
Categories (3, object): ['a', 'b', 'c']

In [25]: df_cat['B']
Out[25]:
0   b
1   c
2   c
3   d
Name: B, dtype: category
Categories (3, object): ['b', 'c', 'd']

Controlling behavior

In the examples above where we passed dtype='category', we used the default behavior:

1. Categories are inferred from the data.
2. Categories are unordered.

To control those behaviors, instead of passing 'category', use an instance of CategoricalDtype.

In [26]: from pandas.api.types import CategoricalDtype

In [27]: s = pd.Series(['a', 'b', 'c', 'a'])

In [28]: cat_type = CategoricalDtype(categories=['b', 'c', 'd'], ordered=True)

In [29]: s_cat = s.astype(cat_type)

In [30]: s_cat
Out[30]:
0   NaN
1   b
2   c
3   NaN
dtype: category
Categories (3, object): ['b' < 'c' < 'd']

Similarly, a CategoricalDtype can be used with a DataFrame to ensure that categories are consistent among all columns.

In [31]: from pandas.api.types import CategoricalDtype

In [32]: df = pd.DataFrame({'A': list('abca'), 'B': list('bccd'))

In [33]: cat_type = CategoricalDtype(categories=list('abcd'), ordered=True)

(continues on next page)
In [34]: df_cat = df.astype(cat_type)

In [35]: df_cat['A']
Out[35]:
0    a
1    b
2    c
3    a
Name: A, dtype: category
Categories (4, object): ['a' < 'b' < 'c' < 'd']

In [36]: df_cat['B']
Out[36]:
0    b
1    c
2    c
3    d
Name: B, dtype: category
Categories (4, object): ['a' < 'b' < 'c' < 'd']

Note: To perform table-wise conversion, where all labels in the entire DataFrame are used as categories for each column, the categories parameter can be determined programmatically by categories = pd.unique(df.to_numpy().ravel()).

If you already have codes and categories, you can use the from_codes() constructor to save the factorize step during normal constructor mode:

In [37]: splitter = np.random.choice([0, 1], 5, p=[0.5, 0.5])

In [38]: s = pd.Series(pd.Categorical.from_codes(splitter,
.....:     categories=['train', 'test']))

Regaining original data

To get back to the original Series or NumPy array, use Series.astype(original_dtype) or np.asarray(categorical):

In [39]: s = pd.Series(['a', 'b', 'c', 'a'])

In [40]: s
Out[40]:
0    a
1    b
2    c
3    a
dtype: object

In [41]: s2 = s.astype('category')

In [42]: s2
Out[42]:
(continues on next page)
Note: In contrast to R’s `factor` function, categorical data is not converting input values to strings; categories will end up the same data type as the original values.

Note: In contrast to R’s `factor` function, there is currently no way to assign/change labels at creation time. Use `categories` to change the categories after creation time.

2.11.2 CategoricalDtype

A categorical’s type is fully described by

1. categories: a sequence of unique values and no missing values
2. ordered: a boolean

This information can be stored in a `CategoricalDtype`. The `categories` argument is optional, which implies that the actual categories should be inferred from whatever is present in the data when the `pandas.Categorical` is created. The categories are assumed to be unordered by default.

```python
In [45]: from pandas.api.types import CategoricalDtype

In [46]: CategoricalDtype(['a', 'b', 'c'])
Out[46]: CategoricalDtype(categories=['a', 'b', 'c'], ordered=False)

In [47]: CategoricalDtype(['a', 'b', 'c'], ordered=True)
Out[47]: CategoricalDtype(categories=['a', 'b', 'c'], ordered=True)

In [48]: CategoricalDtype()
Out[48]: CategoricalDtype(categories=None, ordered=False)
```

A `CategoricalDtype` can be used in any place pandas expects a `dtype`. For example `pandas.read_csv()`, `pandas.DataFrame.astype()`, or in the `Series` constructor.

Note: As a convenience, you can use the string `category` in place of a `CategoricalDtype` when you want the default behavior of the categories being unordered, and equal to the set values present in the array. In other words,
Equality semantics

Two instances of `CategoricalDtype` compare equal whenever they have the same categories and order. When comparing two unordered categoricals, the order of the categories is not considered.

```
In [49]: c1 = CategoricalDtype(['a', 'b', 'c'], ordered=False)
# Equal, since order is not considered when ordered=False
In [50]: c1 == CategoricalDtype(['b', 'c', 'a'], ordered=False)
Out[50]: True

# Unequal, since the second CategoricalDtype is ordered
In [51]: c1 == CategoricalDtype(['a', 'b', 'c'], ordered=True)
Out[51]: False
```

All instances of `CategoricalDtype` compare equal to the string 'category'.

```
In [52]: c1 == 'category'
Out[52]: True
```

Warning: Since `dtype='category'` is essentially `CategoricalDtype(None, False)`, and since all instances `CategoricalDtype` compare equal to 'category', all instances of `CategoricalDtype` compare equal to a `CategoricalDtype(None, False)`, regardless of categories or ordered.

2.11.3 Description

Using `describe()` on categorical data will produce similar output to a Series or DataFrame of type string.

```
In [53]: cat = pd.Categorical(["a", "c", "c", np.nan], categories=["b", "a", "c"])
In [54]: df = pd.DataFrame({"cat": cat, "s": ["a", "c", "c", np.nan]})
In [55]: df.describe()
Out[55]:
       cat   s
count    3    3
unique   2    2
top      c  c
freq     2    2

In [56]: df["cat"].describe()
Out[56]:
count    3
unique   2
top      c
freq     2
Name: cat, dtype: object
```
2.11.4 Working with categories

Categorical data has a `categories` and a `ordered` property, which list their possible values and whether the ordering matters or not. These properties are exposed as `s.cat.categories` and `s.cat.ordered`. If you don’t manually specify categories and ordering, they are inferred from the passed arguments.

```
In [57]: s = pd.Series(["a", "b", "c", "a"], dtype="category")
In [58]: s.cat.categories
Out[58]: Index(['a', 'b', 'c'], dtype='object')
In [59]: s.cat.ordered
Out[59]: False
```

It’s also possible to pass in the categories in a specific order:

```
In [60]: s = pd.Series(pd.Categorical(["a", "b", "c", "a"],
.....:                categories=["c", "b", "a"]))
.....:
In [61]: s.cat.categories
Out[61]: Index(['c', 'b', 'a'], dtype='object')
In [62]: s.cat.ordered
Out[62]: False
```

**Note:** New categorical data are not automatically ordered. You must explicitly pass `ordered=True` to indicate an ordered Categorical.

**Note:** The result of `unique()` is not always the same as `Series.cat.categories`, because `Series.unique()` has a couple of guarantees, namely that it returns categories in the order of appearance, and it only includes values that are actually present.

```
In [63]: s = pd.Series(list('babc')).astype(CategoricalDtype(list('abcd')))  
In [64]: s
Out[64]:
0  b
1  a
2  b
3  c
dtype: category
Categories (4, object): ['a', 'b', 'c', 'd']
```

```python
def get_categories(s):
    return s.cat.categories

def get_unique(s):
    return s.unique()
```

```
In [65]: s.cat.categories
Out[65]: Index(['a', 'b', 'c', 'd'], dtype='object')
In [66]: s.unique()
Out[66]:
['b', 'a', 'c']
Categories (3, object): ['b', 'a', 'c']
```
Renaming categories

Renaming categories is done by assigning new values to the `Series.cat.categories` property or by using the `rename_categories()` method:

```python
In [67]: s = pd.Series(["a", "b", "c", "a"], dtype="category")
In [68]: s
Out[68]:
0  a
1  b
2  c
3  a
dtype: category
Categories (3, object): ['a', 'b', 'c']

In [69]: s.cat.categories = ["Group %s" % g for g in s.cat.categories]
In [70]: s
Out[70]:
0  Group a
1  Group b
2  Group c
3  Group a
dtype: category
Categories (3, object): ['Group a', 'Group b', 'Group c']

In [71]: s = s.cat.rename_categories([1, 2, 3])
In [72]: s
Out[72]:
0  1
1  2
2  3
3  1
dtype: category
Categories (3, int64): [1, 2, 3]
```

# You can also pass a dict-like object to map the renaming
```python
In [73]: s = s.cat.rename_categories({1: 'x', 2: 'y', 3: 'z'})
In [74]: s
Out[74]:
0  x
1  y
2  z
3  x
dtype: category
Categories (3, object): ['x', 'y', 'z']
```

**Note:** In contrast to R’s `factor`, categorical data can have categories of other types than string.

**Note:** Be aware that assigning new categories is an inplace operation, while most other operations under `Series.cat` per default return a new `Series` of dtype `category`.  

2.11. Categorical data 559
Categories must be unique or a `ValueError` is raised:

```python
In [75]: try:
    ....:     s.cat.categories = [1, 1, 1]
    ....:     except ValueError as e:
    ....:         print("ValueError:", str(e))
    ....:
ValueError: Categorical categories must be unique
```

Categories must also not be NaN or a `ValueError` is raised:

```python
In [76]: try:
    ....:     s.cat.categories = [1, 2, np.nan]
    ....:     except ValueError as e:
    ....:         print("ValueError:", str(e))
    ....:
ValueError: Categorical categories cannot be null
```

**Appending new categories**

Appending categories can be done by using the `add_categories()` method:

```python
In [77]: s = s.cat.add_categories([4])
In [78]: s.cat.categories
Out[78]: Index(["x", "y", "z", 4], dtype='object')
```

```python
In [79]: s
Out[79]:
0  x
1  y
2  z
3  x
```

```python
Categories (4, object): ['x', 'y', 'z', 4]
```

**Removing categories**

Removing categories can be done by using the `remove_categories()` method. Values which are removed are replaced by `np.nan`:

```python
In [80]: s = s.cat.remove_categories([4])
In [81]: s
Out[81]:
0  x
1  y
2  z
3  x
```

```python
Categories (3, object): ['x', 'y', 'z']
```
Removing unused categories

Removing unused categories can also be done:

```
In [82]: s = pd.Series(pd.Categorical(["a", "b", "a"],
   ....:     categories=["a", "b", "c", "d"]))
   ....:

In [83]: s
Out[83]:
0    a
1    b
2    a
dtype: category
Categories (4, object): ['a', 'b', 'c', 'd']

In [84]: s.cat.remove_unused_categories()
Out[84]:
0    a
1    b
2    a
dtype: category
Categories (2, object): ['a', 'b']
```

Setting categories

If you want to do remove and add new categories in one step (which has some speed advantage), or simply set the categories to a predefined scale, use `set_categories()`.

```
In [85]: s = pd.Series(["one", "two", "four", ",-"], dtype="category")

In [86]: s
Out[86]:
0    one
1    two
2    four
3    
3    NaN
dtype: category
Categories (4, object): ['-', 'four', 'one', 'two']

In [87]: s = s.cat.set_categories(["one", "two", "three", "four"])

In [88]: s
Out[88]:
0    one
1    two
2    four
3    NaN
dtype: category
Categories (4, object): ['one', 'two', 'three', 'four']
```

Note: Be aware that `Categorical.set_categories()` cannot know whether some category is omitted intentionally or because it is misspelled or (under Python3) due to a type difference (e.g., NumPy S1 dtype and Python strings). This can result in surprising behaviour!
2.11.5 Sorting and order

If categorical data is ordered (s.cat.ordered == True), then the order of the categories has a meaning and certain operations are possible. If the categorical is unordered, .min()/.max() will raise a TypeError.

```
In [89]: s = pd.Series(pd.Categorical(["a", "b", "c", "a"], ordered=False))

In [90]: s.sort_values(inplace=True)

In [91]: s = pd.Series(["a", "b", "c", "a"]).astype(CategoricalDtype(ordered=True))

In [92]: s.sort_values(inplace=True)

In [93]: s
Out[93]:
0    a
1    b
2    c
dtype: category
Categories (3, object): ['a' < 'b' < 'c']

In [94]: s.min(), s.max()
Out[94]: ('a', 'c')
```

You can set categorical data to be ordered by using as_ordered() or unordered by using as_unordered(). These will by default return a new object.

```
In [95]: s.cat.as_ordered()
Out[95]:
0    a
3    a
1    b
2    c
dtype: category
Categories (3, object): ['a' < 'b' < 'c']

In [96]: s.cat.as_unordered()
Out[96]:
0    a
3    a
1    b
2    c
dtype: category
Categories (3, object): ['a', 'b', 'c']
```

Sorting will use the order defined by categories, not any lexical order present on the data type. This is even true for strings and numeric data:

```
In [97]: s = pd.Series([1, 2, 3, 1], dtype="category")

In [98]: s = s.cat.set_categories([2, 3, 1], ordered=True)

In [99]: s
```

(continues on next page)
Reordering

Reordering the categories is possible via the `Categorical.reorder_categories()` and the `Categorical.set_categories()` methods. For `Categorical.reorder_categories()`, all old categories must be included in the new categories and no new categories are allowed. This will necessarily make the sort order the same as the categories order.

```python
In [103]: s = pd.Series([1, 2, 3, 1], dtype="category")

In [104]: s = s.cat.reorder_categories([2, 3, 1], ordered=True)

In [105]: s
Out[105]:
0  1
1  2
2  3
3  1
dtype: category
Categories (3, int64): [2 < 3 < 1]

In [106]: s.sort_values(inplace=True)

In [107]: s
Out[107]:
1  2
2  3
0  1
3  1
dtype: category
Categories (3, int64): [2 < 3 < 1]

In [108]: s.min(), s.max()
Out[108]: (2, 1)
```
Note: Note the difference between assigning new categories and reordering the categories: the first renames categories and therefore the individual values in the Series, but if the first position was sorted last, the renamed value will still be sorted last. Reordering means that the way values are sorted is different afterwards, but not that individual values in the Series are changed.

Note: If the Categorical is not ordered, Series.min() and Series.max() will raise TypeError. Numeric operations like +, -, +, / and operations based on them (e.g. Series.median(), which would need to compute the mean between two values if the length of an array is even) do not work and raise a TypeError.

Multi column sorting

A categorical dtyped column will participate in a multi-column sort in a similar manner to other columns. The ordering of the categorical is determined by the categories of that column.

```python
In [109]: dfs = pd.DataFrame({'A': pd.Categorical(list('bbeebbaa'), categories=['e', 'a', 'b'], ordered=True), 'B': [1, 2, 1, 2, 2, 1, 2, 1]})

In [110]: dfs.sort_values(by=['A', 'B'])
Out[110]:
   A B
0 b 1
1 b 2
2 e 1
3 e 2
4 b 2
5 b 1
6 a 2
7 a 1

Reordering the categories changes a future sort.

In [111]: dfs['A'] = dfs['A'].cat.reorder_categories(['a', 'b', 'e'])

In [112]: dfs.sort_values(by=['A', 'B'])
Out[112]:
   A B
0 b 1
1 b 2
2 e 1
3 e 2
4 b 2
5 b 1
6 a 2
7 a 1
2.11.6 Comparisons

Comparing categorical data with other objects is possible in three cases:

- Comparing equality (== and !=) to a list-like object (list, Series, array, ...) of the same length as the categorical data.
- All comparisons (==, !=, >, >=, <, and <=) of categorical data to another categorical Series, when ordered==True and the categories are the same.
- All comparisons of a categorical data to a scalar.

All other comparisons, especially “non-equality” comparisons of two categoricals with different categories or a categorical with any list-like object, will raise a TypeError.

Note: Any “non-equality” comparisons of categorical data with a Series, np.array, list or categorical data with different categories or ordering will raise a TypeError because custom categories ordering could be interpreted in two ways: one with taking into account the ordering and one without.

In [113]: cat = pd.Series([1, 2, 3]).astype(CategoricalDtype([3, 2, 1], ordered=True))

In [114]: cat_base = pd.Series([2, 2, 2]).astype(CategoricalDtype([3, 2, 1], ordered=True))

In [115]: cat_base2 = pd.Series([2, 2, 2]).astype(CategoricalDtype(ordered=True))

In [116]: cat
Out[116]:
0 1
1 2
2 3
dtype: category
Categories (3, int64): [3 < 2 < 1]

In [117]: cat_base
Out[117]:
0 2
1 2
2 2
dtype: category
Categories (3, int64): [3 < 2 < 1]

In [118]: cat_base2
Out[118]:
0 2
1 2
2 2
dtype: category
Categories (1, int64): [2]
Comparing to a categorical with the same categories and ordering or to a scalar works:

```
In [119]: cat > cat_base
Out[119]:
0   True
1   False
2   False
dtype: bool

In [120]: cat > 2
Out[120]:
0   True
1   False
2   False
dtype: bool
```

Equality comparisons work with any list-like object of same length and scalars:

```
In [121]: cat == cat_base
Out[121]:
0   False
1   True
2   False
dtype: bool

In [122]: cat == np.array([1, 2, 3])
Out[122]:
0   True
1   True
2   True
dtype: bool

In [123]: cat == 2
Out[123]:
0   False
1   True
2   False
dtype: bool
```

This doesn't work because the categories are not the same:

```
In [124]: try:
.....:     cat > cat_base2
.....: except TypeError as e:
.....:     print("TypeError:", str(e))
TypeError: Categoricals can only be compared if 'categories' are the same. Categories are different lengths
```

If you want to do a “non-equality” comparison of a categorical series with a list-like object which is not categorical data, you need to be explicit and convert the categorical data back to the original values:

```
In [125]: base = np.array([1, 2, 3])

In [126]: try:
.....:     cat > base
.....: except TypeError as e:
.....:     print("TypeError:", str(e))
```

(continues on next page)
.....:
TypeError: Cannot compare a Categorical for op __gt__ with type <class 'numpy.ndarray'>.
If you want to compare values, use 'np.asarray(cat) <op> other'.

In [127]: np.asarray(cat) > base
Out[127]: array([False, False, False])

When you compare two unordered categoricals with the same categories, the order is not considered:

In [128]: c1 = pd.Categorical(['a', 'b'], categories=['a', 'b'], ordered=False)
In [129]: c2 = pd.Categorical(['a', 'b'], categories=['b', 'a'], ordered=False)
In [130]: c1 == c2
Out[130]: array([ True, True])

2.11.7 Operations

Apart from Series.min(), Series.max() and Series.mode(), the following operations are possible with categorical data:

Series methods like Series.value_counts() will use all categories, even if some categories are not present in the data:

In [131]: s = pd.Series(pd.Categorical(['a', 'b', 'c', 'c'], categories=['c', 'a', 'b', 'd']))
In [132]: s.value_counts()
Out[132]:
c    2
b    1
a    1
d    0
dtype: int64

Groupby will also show “unused” categories:

In [133]: cats = pd.Categorical(['a', 'b', 'b', 'b', 'c', 'c', 'c'], categories=['a', 'b', 'c', 'd'])
In [134]: df = pd.DataFrame({"cats": cats, "values": [1, 2, 2, 2, 3, 4, 5]})
In [135]: df.groupby("cats").mean()
Out[135]:
     values
cats    
a    1.0  
b    2.0  
c    4.0  
d    NaN  

In [136]: cats2 = pd.Categorical(['a', 'a', 'b', 'b'], categories=['a', 'b', 'c'])

(continues on next page)
In [137]: df2 = pd.DataFrame({"cats": cats2,
...:                      "B": ["c", "d", "c", "d"],
...:                      "values": [1, 2, 3, 4]})

In [138]: df2.groupby(["cats", "B"]).mean()
Out[138]:
   values
cats B
  a  c  1.0
  d  2.0
  b  c  3.0
  d  4.0
  c  c  NaN
  d  NaN

Pivot tables:

In [139]: raw_cat = pd.Categorical(["a", "a", "b", "b"], categories=["a", "b", "c"])
In [140]: df = pd.DataFrame({"A": raw_cat,
...:                      "B": ["c", "d", "c", "d"],
...:                      "values": [1, 2, 3, 4]})

In [141]: pd.pivot_table(df, values='values', index=['A', 'B'])
Out[141]:
   values
   A  B
  a  c  1
  d  2
  b  c  3
  d  4

2.11.8 Data munging

The optimized pandas data access methods .loc, .iloc, .at, and .iat, work as normal. The only difference is the return type (for getting) and that only values already in categories can be assigned.

Getting

If the slicing operation returns either a DataFrame or a column of type Series, the category dtype is preserved.

In [142]: idx = pd.Index(["a", "b", "c", "d", "e", "f", "g", "h", "i", "j", "k", "l", "m", "n"])
In [143]: cats = pd.Series(["a", "b", "c", "b", "c", "c", "c"],
...:                      dtype="category", index=idx)

In [144]: values = [1, 2, 2, 2, 3, 4, 5]
In [145]: df = pd.DataFrame({"cats": cats, "values": values}, index=idx)
In [146]: df.iloc[2:4, :]
Out[146]:
    cats  values
    j      b  2
    k      b  2

In [147]: df.iloc[2:4, :].dtypes
Out[147]:
    cats    category
    values  int64
dtype: object

In [148]: df.loc["h":"j", "cats"]
Out[148]:
    h  a
    i  b
    j  b
Name: cats, dtype: category
Categories (3, object): ['a', 'b', 'c']

In [149]: df[df["cats"] == "b"]
Out[149]:
    cats  values
    i      b  2
    j      b  2
    k      b  2

An example where the category type is not preserved is if you take one single row: the resulting Series is of dtype object:

# get the complete "h" row as a Series
In [150]: df.loc["h", :]
Out[150]:
    cats  a
    values 1
Name: h, dtype: object

Returning a single item from categorical data will also return the value, not a categorical of length “1”.

In [151]: df.iat[0, 0]
Out[151]: 'a'

In [152]: df["cats"].cat.categories = ["x", "y", "z"]

In [153]: df.at["h", "cats"]  # returns a string
Out[153]: 'x'

Note: The is in contrast to R’s factor function, where factor(c(1,2,3))[1] returns a single value factor.

To get a single value Series of type category, you pass in a list with a single value:

In [154]: df.loc["h", "cats"]
Out[154]:
    h  x
String and datetime accessors

The accessors `.dt` and `.str` will work if the `s.cat.categories` are of an appropriate type:

```
In [155]: str_s = pd.Series(list('aabb'))
In [156]: str_cat = str_s.astype('category')
In [157]: str_cat
Out[157]:
0  a
1  a
2  b
3  b
dtype: category
Categories (2, object): ['a', 'b']

In [158]: str_cat.str.contains("a")
Out[158]:
0   True
1   True
2  False
3  False
dtype: bool

In [159]: date_s = pd.Series(pd.date_range('1/1/2015', periods=5))
In [160]: date_cat = date_s.astype('category')
In [161]: date_cat
Out[161]:
0  2015-01-01
1  2015-01-02
2  2015-01-03
3  2015-01-04
4  2015-01-05
dtype: category

In [162]: date_cat.dt.day
Out[162]:
0   1
1   2
2   3
3   4
4   5
dtype: int64
```

**Note:** The returned Series (or DataFrame) is of the same type as if you used the `.str.<method>` / `.dt.<method>` on a Series of that type (and not of type category!).
That means, that the returned values from methods and properties on the accessors of a `Series` and the returned values from methods and properties on the accessors of this `Series` transformed to one of type `category` will be equal:

```python
In [163]: ret_s = str_s.str.contains("a")
In [164]: ret_cat = str_cat.str.contains("a")
In [165]: ret_s.dtype == ret_cat.dtype
Out[165]: True
In [166]: ret_s == ret_cat
Out[166]:
0   True
1   True
2   True
3   True
dtype: bool
```

**Note:** The work is done on the categories and then a new `Series` is constructed. This has some performance implication if you have a `Series` of type string, where lots of elements are repeated (i.e. the number of unique elements in the `Series` is a lot smaller than the length of the `Series`). In this case it can be faster to convert the original `Series` to one of type `category` and use `.str.<method>` or `.dt.<property>` on that.

### Setting

Setting values in a categorical column (or `Series`) works as long as the value is included in the `categories`:

```python
In [167]: idx = pd.Index(["h", "i", "j", "k", "l", "m", "n"])
In [168]: cats = pd.Categorical(["a", "a", "a", "a", "a", "a", "a"],
                         categories=["a", "b"])
In [169]: values = [1, 1, 1, 1, 1, 1, 1]
In [170]: df = pd.DataFrame({'cats': cats, 'values': values}, index=idx)
In [171]: df.iloc[2:4, :] = [["b", 2], ["b", 2]]
```

```python
In [172]: df
Out[172]:
   cats  values
  h   a      1
  i   a      1
  j   b      2
  k   b      2
  l   a      1
  m   a      1
  n   a      1
```

```python
In [173]: try:
    ....:   df.iloc[2:4, :] = [["c", 3], ["c", 3]]
    ....: except ValueError as e:
(continues on next page)
```
Setting values by assigning categorical data will also check that the categories match:

```python
In [174]: df.loc["j":"k", "cats"] = pd.Categorical(["a", "a"], categories=["a", "b"])
In [175]: df
Out[175]:
   cats  values
  h    a    1
  i    a    1
  j    a    2
  k    a    2
  l    a    1
  m    a    1
  n    a    1
In [176]: try:
    .....:     df.loc["j":"k", "cats"] = pd.Categorical(["b", "b"],
    .....:          categories=["a", "b", "c"])
    .....: except ValueError as e:
    .....:     print("ValueError: ", str(e))
    .....:
ValueError: Cannot set a Categorical with another, without identical categories
```

Assigning a Categorical to parts of a column of other types will use the values:

```python
In [177]: df = pd.DataFrame({"a": [1, 1, 1, 1, 1], "b": ["a", "a", "a", "a", "a"]})
In [178]: df.loc[1:2, "a"] = pd.Categorical(["b", "b"], categories=["a", "b"])
In [179]: df.loc[2:3, "b"] = pd.Categorical(["b", "b"], categories=["a", "b"])
In [180]: df
Out[180]:
   a  b
0  1  a
1  2  b
2  3  b
3  4  a
In [181]: df.dtypes
Out[181]:
a  object
b  object
dtype: object
```
### Merging / concatenation

By default, combining `Series` or `DataFrames` which contain the same categories results in `category` dtype, otherwise results will depend on the dtype of the underlying categories. Merges that result in non-categorical dtypes will likely have higher memory usage. Use `.astype` or `union_categoricals` to ensure category results.

```python
In [182]: from pandas.api.types import union_categoricals

# same categories
In [183]: s1 = pd.Series(['a', 'b'], dtype='category')
In [184]: s2 = pd.Series(['a', 'b', 'a'], dtype='category')

In [185]: pd.concat([s1, s2])
Out[185]:
   0 a
   1 b
   0 a
   1 b
   2 a
   dtype: category
Categories (2, object): ['a', 'b']

# different categories
In [186]: s3 = pd.Series(['b', 'c'], dtype='category')

In [187]: pd.concat([s1, s3])
Out[187]:
   0 a
   1 b
   0 b
   1 c
   dtype: object

# Output dtype is inferred based on categories values
In [188]: int_cats = pd.Series([1, 2], dtype="category")
In [189]: float_cats = pd.Series([3.0, 4.0], dtype="category")

In [190]: pd.concat([int_cats, float_cats])
Out[190]:
   0 1.0
   1 2.0
   0 3.0
   1 4.0
dtype: float64

In [191]: pd.concat([s1, s3]).astype('category')
Out[191]:
   0 a
   1 b
   0 b
   1 c
dtype: category
Categories (3, object): ['a', 'b', 'c']

In [192]: union_categoricals([s1.array, s3.array])
Out[192]:
```

(continues on next page)
The following table summarizes the results of merging Categoricals:

<table>
<thead>
<tr>
<th>arg1</th>
<th>arg2</th>
<th>identical</th>
<th>result</th>
</tr>
</thead>
<tbody>
<tr>
<td>category</td>
<td>category</td>
<td>True</td>
<td>category</td>
</tr>
<tr>
<td>category (object)</td>
<td>category (object)</td>
<td>False</td>
<td>object (dtype is inferred)</td>
</tr>
<tr>
<td>category (int)</td>
<td>category (float)</td>
<td>False</td>
<td>float (dtype is inferred)</td>
</tr>
</tbody>
</table>

See also the section on `merge dtypes` for notes about preserving merge dtypes and performance.

**Unioning**

If you want to combine categoricals that do not necessarily have the same categories, the `union_categoricals()` function will combine a list-like of categoricals. The new categories will be the union of the categories being combined.

```python
In [193]: from pandas.api.types import union_categoricals
In [194]: a = pd.Categorical(["b", "c"])
In [195]: b = pd.Categorical(["a", "b"])
In [196]: union_categoricals([a, b])
Out[196]: ['b', 'c', 'a', 'b']
Categories (3, object): ['b', 'c', 'a']
```

By default, the resulting categories will be ordered as they appear in the data. If you want the categories to be lexsorted, use `sort_categories=True` argument.

```python
In [197]: union_categoricals([a, b], sort_categories=True)
Out[197]: ['b', 'c', 'a', 'b']  
Categories (3, object): ['a', 'b', 'c']
```

`union_categoricals` also works with the “easy” case of combining two categoricals of the same categories and order information (e.g. what you could also append for).

```python
In [198]: a = pd.Categorical(["a", "b"], ordered=True)
In [199]: b = pd.Categorical(["a", "b", "a"], ordered=True)
In [200]: union_categoricals([a, b])
Out[200]: ['a', 'b', 'a', 'b', 'a']  
Categories (2, object): ['a' < 'b']
```

The below raises `TypeError` because the categories are ordered and not identical.

```python
In [1]: a = pd.Categorical(["a", "b"], ordered=True)
In [2]: b = pd.Categorical(["a", "b", "c"], ordered=True)
In [3]: union_categoricals([a, b])
```
Ordered categoricals with different categories or orderings can be combined by using the `ignore_ordered=True` argument.

```python
In [201]: a = pd.Categorical(["a", "b", "c"], ordered=True)
In [202]: b = pd.Categorical(["c", "b", "a"], ordered=True)
In [203]: union_categoricals([a, b], ignore_order=True)
Out[203]:
["a", "b", "c", "c", "b", "a"]
Categories (3, object): ["a", "b", "c"]
```

`union_categoricals()` also works with a `CategoricalIndex`, or `Series` containing categorical data, but note that the resulting array will always be a plain `Categorical`:

```python
In [204]: a = pd.Series(["b", "c"], dtype='category')
In [205]: b = pd.Series(["a", "b"], dtype='category')
In [206]: union_categoricals([a, b])
Out[206]:
["b", "c", "a", "b"]
Categories (3, object): ["b", "c", "a"]
```

**Note:** `union_categoricals` may recode the integer codes for categories when combining categoricals. This is likely what you want, but if you are relying on the exact numbering of the categories, be aware.

```python
In [207]: c1 = pd.Categorical(["b", "c"])
In [208]: c2 = pd.Categorical(["a", "b"])
In [209]: c1
Out[209]:
["b", "c"]
Categories (2, object): ["b", "c"]
# "b" is coded to 0
In [210]: c1.codes
Out[210]: array([0, 1], dtype=int8)
In [211]: c2
Out[211]:
["a", "b"]
Categories (2, object): ["a", "b"]
# "b" is coded to 1
In [212]: c2.codes
Out[212]: array([0, 1], dtype=int8)
In [213]: c = union_categoricals([c1, c2])
In [214]: c
```

(continues on next page)
2.11.9 Getting data in/out

You can write data that contains category dtypes to a HDFStore. See here for an example and caveats.

It is also possible to write data to and reading data from Stata format files. See here for an example and caveats.

Writing to a CSV file will convert the data, effectively removing any information about the categorical (categories and ordering). So if you read back the CSV file you have to convert the relevant columns back to category and assign the right categories and categories ordering.

```
In [216]: import io
In [217]: s = pd.Series(pd.Categorical(["a", "b", "b", "a", "a", "d"]))
# rename the categories
In [218]: s.cat.categories = ["very good", "good", "bad"]
# reorder the categories and add missing categories
In [219]: s = s.cat.set_categories(["very bad", "bad", "medium", "good", "very good"])
In [220]: df = pd.DataFrame({"cats": s, "vals": [1, 2, 3, 4, 5, 6]})
In [221]: csv = io.StringIO()
In [222]: df.to_csv(csv)
In [223]: df2 = pd.read_csv(io.StringIO(csv.getvalue()))
In [224]: df2.dtypes
Out[224]:
            Unnamed: 0  cats
dtype: int64  object
In [225]: df2["cats"]
Out[225]:
0   very good
1       good
2       good
3  very good
4  very good
5        bad
Name: cats, dtype: object
# Redo the category
```
In [226]: df2["cats"] = df2["cats"].astype("category")

In [227]: df2["cats"].cat.set_categories(["very bad", "bad", "medium", "good", "very good"], inplace=True)

In [228]: df2.dtypes
Out[228]:

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>unnamed</td>
<td>int64</td>
<td>cats</td>
</tr>
<tr>
<td>vals</td>
<td>int64</td>
<td>dtype : object</td>
</tr>
</tbody>
</table>

In [229]: df2["cats"]
Out[229]:

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>very good</td>
</tr>
<tr>
<td>1</td>
<td>good</td>
</tr>
<tr>
<td>2</td>
<td>good</td>
</tr>
<tr>
<td>3</td>
<td>very good</td>
</tr>
<tr>
<td>4</td>
<td>very good</td>
</tr>
<tr>
<td>5</td>
<td>bad</td>
</tr>
</tbody>
</table>

Name: cats, dtype: category
Categories (5, object): ['very bad', 'bad', 'medium', 'good', 'very good']

The same holds for writing to a SQL database with to_sql.

2.11.10 Missing data

pandas primarily uses the value np.nan to represent missing data. It is by default not included in computations. See the Missing Data section.

Missing values should not be included in the Categorical’s categories, only in the values. Instead, it is understood that NaN is different, and is always a possibility. When working with the Categorical’s codes, missing values will always have a code of -1.

In [230]: s = pd.Series(["a", "b", np.nan, "a"], dtype="category")

# only two categories
In [231]: s
Out[231]:

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>a</td>
</tr>
<tr>
<td>1</td>
<td>b</td>
</tr>
<tr>
<td>2</td>
<td>NaN</td>
</tr>
<tr>
<td>3</td>
<td>a</td>
</tr>
</tbody>
</table>

dtype: category
Categories (2, object): ["a", "b"]

In [232]: s.cat.codes
Out[232]:

| 0 | 0 |
| 1 | 1 |
| 2 | -1|
| 3 | 0 |
dtype: int8
Methods for working with missing data, e.g. `isna()`, `fillna()`, `dropna()`, all work normally:

```
In [233]: s = pd.Series(['a', 'b', np.nan], dtype="category")
In [234]: s
Out[234]:
0 a
1 b
2 NaN
dtype: category
Categories (2, object): ['a', 'b']
```

```
In [235]: pd.isna(s)
Out[235]:
0  False
1  False
2   True
dtype: bool
```

```
In [236]: s.fillna("a")
Out[236]:
0   a
1   b
2   a
dtype: category
Categories (2, object): ['a', 'b']
```

### 2.11.11 Differences to R’s `factor`

The following differences to R’s factor functions can be observed:

- R’s `levels` are named `categories`.
- R’s `levels` are always of type string, while `categories` in pandas can be of any dtype.
- It’s not possible to specify labels at creation time. Use `s.cat.rename_categories(new_labels)` afterwards.
- In contrast to R’s `factor` function, using categorical data as the sole input to create a new categorical series will not remove unused categories but create a new categorical series which is equal to the passed in one!
- R allows for missing values to be included in its `levels` (pandas’ `categories`). Pandas does not allow `NaN` categories, but missing values can still be in the `values`.

### 2.11.12 Gotchas

#### Memory usage

The memory usage of a `Categorical` is proportional to the number of categories plus the length of the data. In contrast, an `object` dtype is a constant times the length of the data.

```
In [237]: s = pd.Series(['foo', 'bar'] * 1000)
# object dtype
In [238]: s.nbytes
Out[238]: 16000
```
# category dtype
In [239]: s.astype('category').nbytes
Out[239]: 2016

Note: If the number of categories approaches the length of the data, the Categorical will use nearly the same or more memory than an equivalent object dtype representation.

In [240]: s = pd.Series(['foo%04d' % i for i in range(2000)])

# object dtype
In [241]: s.nbytes
Out[241]: 16000

# category dtype
In [242]: s.astype('category').nbytes
Out[242]: 20000

**Categorical is not a numpy array**

Currently, categorical data and the underlying Categorical is implemented as a Python object and not as a low-level NumPy array dtype. This leads to some problems.

NumPy itself doesn’t know about the new dtype:

In [243]: try:
    ....:     np.dtype("category")
    ....:     except TypeError as e:
    ....:         print("TypeError: data type \"category\" not understood")
    ....:     ....:
TypeError: data type "category" not understood

In [244]: dtype = pd.Categorical(['a']).dtype

In [245]: try:
    ....:     np.dtype(dtype)
    ....:     except TypeError as e:
    ....:         print("TypeError: data type not understood")
    ....:     ....:
TypeError: data type not understood

Dtype comparisons work:

In [246]: dtype == np.str_
Out[246]: False

In [247]: np.str_ == dtype
Out[247]: False

To check if a Series contains Categorical data, use `hasattr(s, 'cat')`:

In [248]: hasattr(pd.Series(['a'], dtype='category'), 'cat')
Out[248]: True
Using NumPy functions on a Series of type category should not work as Categoricals are not numeric data (even in the case that .categories is numeric).

```python
In [250]: s = pd.Series(pd.Categorical([1, 2, 3, 4]))
In [251]: try:
....:     np.sum(s)
....: except TypeError as e:
....:     print("TypeError: ", str(e))
TypeError: Categorical cannot perform the operation sum
```

Note: If such a function works, please file a bug at https://github.com/pandas-dev/pandas!

### `dtype` in apply

Pandas currently does not preserve the dtype in apply functions: If you apply along rows you get a Series of object dtype (same as getting a row -> getting one element will return a basic type) and applying along columns will also convert to object. NaN values are unaffected. You can use `fillna` to handle missing values before applying a function.

```python
In [252]: df = pd.DataFrame({"a": [1, 2, 3, 4],
....:                     "b": ["a", "b", "c", "d"],
....:                     "cats": pd.Categorical([1, 2, 3, 2])})
In [253]: df.apply(lambda row: type(row["cats"]), axis=1)
Out[253]:
0     <class 'int'>
1     <class 'int'>
2     <class 'int'>
3     <class 'int'>
dtype: object
In [254]: df.apply(lambda col: col.dtype, axis=0)
Out[254]:
a     int64
b     object
cats  category
dtype: object
```
Categorical index

CategoricalIndex is a type of index that is useful for supporting indexing with duplicates. This is a container around a Categorical and allows efficient indexing and storage of an index with a large number of duplicated elements. See the advanced indexing docs for a more detailed explanation.

Setting the index will create a CategoricalIndex:

```
In [255]: cats = pd.Categorical([1, 2, 3, 4], categories=[4, 2, 3, 1])
In [256]: strings = ["a", "b", "c", "d"]
In [257]: values = [4, 2, 3, 1]
In [258]: df = pd.DataFrame({"strings": strings, "values": values}, index=cats)
In [259]: df.index
Out[259]: CategoricalIndex([1, 2, 3, 4], categories=[4, 2, 3, 1], ordered=False, dtype='category')
```

# This now sorts by the categories order
```
In [260]: df.sort_index()
Out[260]:
strings values
4   d   1
2   b   2
3   c   3
1   a   4
```

Side effects

Constructing a Series from a Categorical will not copy the input Categorical. This means that changes to the Series will in most cases change the original Categorical:

```
In [261]: cat = pd.Categorical([1, 2, 3, 10], categories=[1, 2, 3, 4, 10])
In [262]: s = pd.Series(cat, name="cat")
In [263]: cat
Out[263]:
[1, 2, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]
In [264]: s.iloc[0:2] = 10
In [265]: cat
Out[265]:
[10, 10, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]
In [266]: df = pd.DataFrame(s)
In [267]: df["cat"].cat.categories = [1, 2, 3, 4, 5]
In [268]: cat
Out[268]:
```
(continues on next page)
Use `copy=True` to prevent such a behaviour or simply don’t reuse `Categoricals`:

```python
In [269]: cat = pd.Categorical([1, 2, 3, 10], categories=[1, 2, 3, 4, 10])
In [270]: s = pd.Series(cat, name="cat", copy=True)
In [271]: cat
Out[271]:
[1, 2, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]
In [272]: s.iloc[0:2] = 10
In [273]: cat
Out[273]:
[1, 2, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]
```

**Note:** This also happens in some cases when you supply a NumPy array instead of a `Categorical`: using an int array (e.g. `np.array([1,2,3,4])`) will exhibit the same behavior, while using a string array (e.g. `np.array(["a","b","c","a"])`) will not.

### 2.12 Nullable integer data type

New in version 0.24.0.

**Note:** `IntegerArray` is currently experimental. Its API or implementation may change without warning.

Changed in version 1.0.0: Now uses `pandas.NA` as the missing value rather than `numpy.nan`.

In *Working with missing data*, we saw that pandas primarily uses `NaN` to represent missing data. Because `NaN` is a float, this forces an array of integers with any missing values to become floating point. In some cases, this may not matter much. But if your integer column is, say, an identifier, casting to float can be problematic. Some integers cannot even be represented as floating point numbers.

#### 2.12.1 Construction

Pandas can represent integer data with possibly missing values using `arrays.IntegerArray`. This is an extension types implemented within pandas.

```python
In [1]: arr = pd.array([1, 2, None], dtype=pd.Int64Dtype())
In [2]: arr
Out[2]:
<IntegerArray>
[1, 2, <NA>]
Length: 3, dtype: Int64
```
Or the string alias "Int64" (note the capital "I", to differentiate from NumPy's 'int64' dtype:

```
In [3]: pd.array([1, 2, np.nan], dtype="Int64")
Out[3]:
<IntegerArray>
[1, 2, <NA>]
Length: 3, dtype: Int64
```

All NA-like values are replaced with `pandas.NA`.

```
In [4]: pd.array([1, 2, np.nan, None, pd.NA], dtype="Int64")
Out[4]:
<IntegerArray>
[1, 2, <NA>, <NA>, <NA>]
Length: 5, dtype: Int64
```

This array can be stored in a `DataFrame` or `Series` like any NumPy array.

```
In [5]: pd.Series(arr)
Out[5]:
0   1
1   2
2  <NA>
dtype: Int64
```

You can also pass the list-like object to the `Series` constructor with the dtype.

```
In [6]: pd.array([1, None])
Out[6]:
<IntegerArray>
[1, <NA>]
Length: 2, dtype: Int64
```

```
In [7]: pd.array([1, 2])
Out[7]:
<IntegerArray>
[1, 2]
Length: 2, dtype: Int64
```

For backwards-compatibility, `Series` infers these as either integer or float dtype

```
In [8]: pd.Series([1, None])
Out[8]:
0  1.0
1  NaN
dtype: float64
```

```
In [9]: pd.Series([1, 2])
Out[9]:
0  1
1  2
dtype: int64
```

We recommend explicitly providing the dtype to avoid confusion.
In [10]: pd.array([1, None], dtype="Int64")
Out[10]:
<IntegerArray>
[1, <NA>]
Length: 2, dtype: Int64

In [11]: pd.Series([1, None], dtype="Int64")
Out[11]:
0   1
1  <NA>
dtype: Int64

In the future, we may provide an option for Series to infer a nullable-integer dtype.

2.12.2 Operations

Operations involving an integer array will behave similar to NumPy arrays. Missing values will be propagated, and the data will be coerced to another dtype if needed.

In [12]: s = pd.Series([1, 2, None], dtype="Int64")

# arithmetic
In [13]: s + 1
Out[13]:
0    2
1    3
2   <NA>
dtype: Int64

# comparison
In [14]: s == 1
Out[14]:
0   True
1  False
2  <NA>
dtype: boolean

# indexing
In [15]: s.iloc[1:3]
Out[15]:
1   2
2  <NA>
dtype: Int64

# operate with other dtypes
In [16]: s + s.iloc[1:3].astype('Int8')
Out[16]:
0  <NA>
1   4
2  <NA>
dtype: Int64

# coerce when needed
In [17]: s + 0.01
Out[17]:
0  1.01
1  2.01
2   NaN
dtype: float64

These dtypes can operate as part of of DataFrame.

In [18]: df = pd.DataFrame({'A': s, 'B': [1, 1, 3], 'C': list('aab'))

In [19]: df
Out[19]:
   A  B  C
0  1  1  a
1  2  1  a
2 <NA> 3  b

In [20]: df.dtypes
Out[20]:
A   Int64
B   int64
C    object
dtype: object

These dtypes can be merged & reshaped & casted.

In [21]: pd.concat([df[['A']], df[['B', 'C']]], axis=1).dtypes
Out[21]:
A   Int64
B   int64
C    object
dtype: object

In [22]: df['A'].astype(float)
Out[22]:
0   1.0
1   2.0
2   NaN
Name: A, dtype: float64

Reduction and groupby operations such as ‘sum’ work as well.

In [23]: df.sum()
Out[23]:
    A  B   C
name: None
0   3  5  aab

In [24]: df.groupby('B').A.sum()
Out[24]:
   B
0  1
1  3
2  0
Name: A, dtype: int64

2.12. Nullable integer data type
2.12.3 Scalar NA Value

`arrays.IntegerArray` uses `pandas.NA` as its scalar missing value. Slicing a single element that’s missing will return `pandas.NA`.

In [25]: a = pd.array([1, None], dtype="Int64")
In [26]: a[1]
Out[26]: <NA>

2.13 Nullable Boolean data type

New in version 1.0.0.

2.13.1 Indexing with NA values

`pandas` allows indexing with NA values in a boolean array, which are treated as `False`. Changed in version 1.0.2.

In [1]: s = pd.Series([1, 2, 3])
In [2]: mask = pd.array([True, False, pd.NA], dtype="boolean")
In [3]: s[mask]
Out[3]:
0 1
dtype: int64

If you would prefer to keep the NA values you can manually fill them with `fillna(True)`.

In [4]: s[mask.fillna(True)]
Out[4]:
0 1
2 3
dtype: int64

2.13.2 Kleene logical operations

`arrays.BooleanArray` implements Kleene Logic (sometimes called three-value logic) for logical operations like & (and), | (or) and ^ (exclusive-or). This table demonstrates the results for every combination. These operations are symmetrical, so flipping the left- and right-hand side makes no difference in the result.
When an NA is present in an operation, the output value is NA only if the result cannot be determined solely based on the other input. For example, $\text{True} \ | \ \text{NA}$ is True, because both $\text{True} \ | \ \text{True}$ and $\text{True} \ | \ \text{False}$ are True. In that case, we don’t actually need to consider the value of the NA.

On the other hand, $\text{True} \ & \ \text{NA}$ is NA. The result depends on whether the NA really is True or False, since $\text{True} \ & \ \text{True}$ is True, but $\text{True} \ & \ \text{False}$ is False, so we can’t determine the output.

This differs from how np.nan behaves in logical operations. Pandas treated np.nan is always false in the output.

In

```
In [5]: pd.Series([True, False, np.nan], dtype="object") | True
Out[5]:
0    True
1    True
2    False
dtype: bool
```

```
In [6]: pd.Series([True, False, np.nan], dtype="boolean") | True
Out[6]:
0    True
1    True
2    True
dtype: boolean
```

In and

```
In [7]: pd.Series([True, False, np.nan], dtype="object") & True
Out[7]:
0    True
1    True
2    False
dtype: bool
```

```
In [8]: pd.Series([True, False, np.nan], dtype="boolean") & True
```

(continues on next page)
2.14 Visualization

We use the standard convention for referencing the matplotlib API:

```
In [1]: import matplotlib.pyplot as plt
In [2]: plt.close('all')
```

We provide the basics in pandas to easily create decent looking plots. See the ecosystem section for visualization libraries that go beyond the basics documented here.

*Note:* All calls to `np.random` are seeded with 123456.

### 2.14.1 Basic plotting: `plot`

We will demonstrate the basics, see the *cookbook* for some advanced strategies.

The `plot` method on Series and DataFrame is just a simple wrapper around `plt.plot()`:

```
In [3]: ts = pd.Series(np.random.randn(1000),
                  index=pd.date_range('1/1/2000', periods=1000))
```

```
NameError Traceback (most recent call last)
<ipython-input-3-00eeb137fb11> in <module>
----> 1 ts = pd.Series(np.random.randn(1000),
                      index=pd.date_range('1/1/2000', periods=1000))
NameError: name 'pd' is not defined
```

```
In [4]: ts = ts.cumsum()
```

```
NameError Traceback (most recent call last)
<ipython-input-4-a7771f529bde> in <module>
----> 1 ts = ts.cumsum()
NameError: name 'ts' is not defined
```

```
In [5]: ts.plot()
```

```
NameError Traceback (most recent call last)
<ipython-input-5-8a34b37f0ce9> in <module>
----> 1 ts.plot()
NameError: name 'ts' is not defined
```
If the index consists of dates, it calls `gcf().autofmt_xdate()` to try to format the x-axis nicely as per above.

On DataFrame, `plot()` is a convenience to plot all of the columns with labels:

```python
In [6]: df = pd.DataFrame(np.random.randn(1000, 4),
                                      index=ts.index, columns=list('ABCD'))
```

```
NameError: name 'ts' is not defined
```

```python
In [7]: df = df.cumsum()
```

```
NameError: name 'pd' is not defined
```
You can plot one column versus another using the \texttt{x} and \texttt{y} keywords in \texttt{plot()}:

\begin{Verbatim}
In [10]: df3 = pd.DataFrame(np.random.randn(1000, 2), columns=['B', 'C']).cumsum()

NameError: name 'pd' is not defined
\end{Verbatim}

\begin{Verbatim}
In [11]: df3['A'] = pd.Series(list(range(len(df))))

NameError: name 'pd' is not defined
\end{Verbatim}
In [12]: df3.plot(x='A', y='B')
NameError: name 'df3' is not defined

Note: For more formatting and styling options, see formatting below.

2.14.2 Other plots

Plotting methods allow for a handful of plot styles other than the default line plot. These methods can be provided as the kind keyword argument to plot(), and include:

- 'bar' or 'barh' for bar plots
- 'hist' for histogram
- 'box' for boxplot
- 'kde' or 'density' for density plots
• `'area'` for area plots
• `'scatter'` for scatter plots
• `'hexbin'` for hexagonal bin plots
• `'pie'` for pie plots

For example, a bar plot can be created the following way:

```python
In [13]: plt.figure();
In [14]: df.iloc[5].plot(kind='bar');
```

You can also create these other plots using the methods `DataFrame.plot.<kind>` instead of providing the `kind` keyword argument. This makes it easier to discover plot methods and the specific arguments they use:

```python
In [15]: df = pd.DataFrame()

In [16]: df.plot.<TAB>  # noqa: E225, E999
df.plot.area     df.plot.barh     df.plot.density df.plot.hist     df.plot.line
               df.plot.scatter
df.plot.bar     df.plot.box     df.plot.hexbin df.plot.kde     df.plot.pie
```

In addition to these `kind`s, there are the `DataFrame.hist()`, and `DataFrame.boxplot()` methods, which use a separate interface.
Finally, there are several *plotting functions* in `pandas.plotting` that take a `Series` or `DataFrame` as an argument. These include:

- Scatter Matrix
- Andrews Curves
- Parallel Coordinates
- Lag Plot
- Autocorrelation Plot
- Bootstrap Plot
- RadViz

Plots may also be adorned with *errorbars* or *tables*.

### Bar plots

For labeled, non-time series data, you may wish to produce a bar plot:

```python
In [17]: plt.figure();
In [18]: df.iloc[5].plot.bar()
---------------------------------------------------------------------------
NameError Traceback (most recent call last)
<ipython-input-18-d1a2cddc601a> in <module>
----> 1 df.iloc[5].plot.bar()
NameError: name 'df' is not defined
In [19]: plt.axhline(0, color='k');
```
Calling a DataFrame’s `plot.bar()` method produces a multiple bar plot:

```python
In [20]: df2 = pd.DataFrame(np.random.rand(10, 4), columns=['a', 'b', 'c', 'd'])
---------------------------------------------------------------------------
NameError Traceback (most recent call last)
<ipython-input-20-6133adb252fc> in <module>
----> 1 df2 = pd.DataFrame(np.random.rand(10, 4), columns=['a', 'b', 'c', 'd'])
NameError: name 'pd' is not defined

In [21]: df2.plot.bar();
```
To produce a stacked bar plot, pass `stacked=True`:

```
In [22]: df2.plot.bar(stacked=True);
```
To get horizontal bar plots, use the `barh` method:

```python
In [23]: df2.plot.barh(stacked=True);
```
Histograms

Histograms can be drawn by using the `DataFrame.plot.hist()` and `Series.plot.hist()` methods.

```python
In [24]: df4 = pd.DataFrame({'a': np.random.randn(1000) + 1, 'b': np.random.randn(1000), 'c': np.random.randn(1000) - 1}, columns=['a', 'b', 'c'])
```

```
IndexError: Traceback (most recent call last)
<ipython-input-24-3b054428c392> in <module>(continues on next page)
2.14. Visualization 597
```
A histogram can be stacked using `stacked=True`. Bin size can be changed using the `bins` keyword.

```python
In [27]: plt.figure();

In [28]: df4.plot.hist(stacked=True, bins=20)
---------------------------------------------------------------------------
NameError Traceback (most recent call last)
<ipython-input-28-9a4bef475383> in <module>
----> 1 df4.plot.hist(stacked=True, bins=20)
NameError: name 'df4' is not defined
```
You can pass other keywords supported by `matplotlib` `hist`. For example, horizontal and cumulative histograms can be drawn by `orientation='horizontal'` and `cumulative=True`.

```python
In [29]: plt.figure();

In [30]: df4['a'].plot.hist(orientation='horizontal', cumulative=True)
---------------------------------------------------------------------------
NameError Traceback (most recent call last)
<ipython-input-30-c49999bfb88a> in <module>
----> 1 df4['a'].plot.hist(orientation='horizontal', cumulative=True)
NameError: name 'df4' is not defined
```
See the `hist` method and the `matplotlib hist documentation` for more.

The existing interface DataFrame.hist to plot histogram still can be used.

```python
In [31]: plt.figure();
In [32]: df['A'].diff().hist()
```

```
NameError Traceback (most recent call last)
<ipython-input-32-620f128ae072> in <module>
----> 1 df['A'].diff().hist()
NameError: name 'df' is not defined
```
DataFrame.hist() plots the histograms of the columns on multiple subplots:

```python
In [33]: plt.figure()
Out[33]: <Figure size 640x480 with 0 Axes>

In [34]: df.diff().hist(color='k', alpha=0.5, bins=50)
---------------------------------------------------------------------------
NameError                       Traceback (most recent call last)
<ipython-input-34-742660109dc1> in <module>
----> 1 df.diff().hist(color='k', alpha=0.5, bins=50)

NameError: name 'df' is not defined
```
The `by` keyword can be specified to plot grouped histograms:

```
In [35]: data = pd.Series(np.random.randn(1000))
NameError                               Traceback (most recent call last)
<ipython-input-35-cd9ac77fc4c4> in <module>
----> 1 data = pd.Series(np.random.randn(1000))
NameError: name 'pd' is not defined

In [36]: data.hist(by=np.random.randint(0, 4, 1000), figsize=(6, 4))
NameError                               Traceback (most recent call last)
<ipython-input-36-9248a2062b4d> in <module>
----> 1 data.hist(by=np.random.randint(0, 4, 1000), figsize=(6, 4))
NameError: name 'data' is not defined
```
Box plots

Boxplot can be drawn calling `Series.plot.box()` and `DataFrame.plot.box()`, or `DataFrame.boxplot()` to visualize the distribution of values within each column.

For instance, here is a boxplot representing five trials of 10 observations of a uniform random variable on [0,1).

```
In [37]: df = pd.DataFrame(np.random.rand(10, 5), columns=['A', 'B', 'C', 'D', 'E'])
NameError Traceback (most recent call last)
<ipython-input-37-a2f471686f35> in <module>
    1 df = pd.DataFrame(np.random.rand(10, 5), columns=['A', 'B', 'C', 'D', 'E'])
NameError: name 'pd' is not defined

In [38]: df.plot.box()
NameError Traceback (most recent call last)
<ipython-input-38-8765cf6ed5ce> in <module>
    1 df.plot.box()
NameError: name 'df' is not defined
```
Boxplot can be colorized by passing `color` keyword. You can pass a `dict` whose keys are `boxes`, `whiskers`, `medians` and `caps`. If some keys are missing in the `dict`, default colors are used for the corresponding artists. Also, boxplot has `sym` keyword to specify fliers style.

When you pass other type of arguments via `color` keyword, it will be directly passed to matplotlib for all the `boxes`, `whiskers`, `medians` and `caps` colorization.

The colors are applied to every boxes to be drawn. If you want more complicated colorization, you can get each drawn artists by passing `return_type`.

```python
In [39]: color = {'boxes': 'DarkGreen', 'whiskers': 'DarkOrange',
           ....: 'medians': 'DarkBlue', 'caps': 'Gray'}
           ....:

In [40]: df.plot.box(color=color, sym='r+')
```

```
NameError Traceback (most recent call last)
<ipython-input-40-2a54c0d52eaf> in <module>
----> 1 df.plot.box(color=color, sym='r+')

NameError: name 'df' is not defined
```
Also, you can pass other keywords supported by matplotlib `boxplot`. For example, horizontal and custom-positioned boxplot can be drawn by `vert=False` and `positions` keywords.

```python
In [41]: df.plot.box(vert=False, positions=[1, 4, 5, 6, 8])
NameError: name 'df' is not defined
```
See the `boxplot` method and the `matplotlib` boxplot documentation for more.

The existing interface `DataFrame.boxplot` to plot boxplot still can be used.

```
In [42]: df = pd.DataFrame(np.random.rand(10, 5))
NameError: name 'pd' is not defined

In [43]: plt.figure();

In [44]: bp = df.boxplot()
NameError: name 'df' is not defined
```
You can create a stratified boxplot using the `by` keyword argument to create groupings. For instance,

```python
In [45]: df = pd.DataFrame(np.random.rand(10, 2), columns=['Col1', 'Col2'])
```

```
NameError: name 'pd' is not defined
```

```python
```

```
NameError: name 'pd' is not defined
```

```python
In [47]: plt.figure();

In [48]: bp = df.boxplot(by='X')
```

```
NameError: name 'pd' is not defined
```
You can also pass a subset of columns to plot, as well as group by multiple columns:

```
In [49]: df = pd.DataFrame(np.random.rand(10, 3), columns=['Col1', 'Col2', 'Col3'])
NameError: name 'pd' is not defined
```

```
NameError: name 'pd' is not defined
```

```
NameError: name 'pd' is not defined
```
In `boxplot`, the return type can be controlled by the `return_type` keyword. The valid choices are {
"axes", "dict", "both", None}. Faceting, created by `DataFrame.boxplot` with the by keyword, will affect the output type as well:
Groupby.boxplot always returns a Series of return_type.

<table>
<thead>
<tr>
<th>return_type</th>
<th>Faceted</th>
<th>Output type</th>
</tr>
</thead>
<tbody>
<tr>
<td>None</td>
<td>No</td>
<td>axes</td>
</tr>
<tr>
<td>None</td>
<td>Yes</td>
<td>2-D ndarray of axes</td>
</tr>
<tr>
<td>'axes'</td>
<td>No</td>
<td>axes</td>
</tr>
<tr>
<td>'axes'</td>
<td>Yes</td>
<td>Series of axes</td>
</tr>
<tr>
<td>'dict'</td>
<td>No</td>
<td>dict of artists</td>
</tr>
<tr>
<td>'dict'</td>
<td>Yes</td>
<td>Series of dicts of artists</td>
</tr>
<tr>
<td>'both'</td>
<td>No</td>
<td>namedtuple</td>
</tr>
<tr>
<td>'both'</td>
<td>Yes</td>
<td>Series of namedtuples</td>
</tr>
</tbody>
</table>

**In [54]:** np.random.seed(1234)

**In [55]:** df_box = pd.DataFrame(np.random.randn(50, 2))

```
NameError Traceback (most recent call last)
<ipython-input-55-043b0e16e969> in <module>
----> 1 df_box = pd.DataFrame(np.random.randn(50, 2))

NameError: name 'pd' is not defined

In [56]: df_box['g'] = np.random.choice(['A', 'B'], size=50)

NameError: name 'df_box' is not defined

In [57]: df_box.loc[df_box['g'] == 'B', 1] += 3

NameError: name 'df_box' is not defined

In [58]: bp = df_box.boxplot(by='g')

NameError: name 'df_box' is not defined
The subplots above are split by the numeric columns first, then the value of the $g$ column. Below the subplots are first split by the value of $g$, then by the numeric columns.

```python
In [59]: bp = df_box.groupby('g').boxplot()
```

```
NameError Traceback (most recent call last)
<ipython-input-59-900c7ff9e1> in <module>
----> 1 bp = df_box.groupby('g').boxplot()

NameError: name 'df_box' is not defined
```
Area plot

You can create area plots with `Series.plot.area()` and `DataFrame.plot.area()`. Area plots are stacked by default. To produce stacked area plot, each column must be either all positive or all negative values.

When input data contains `NaN`, it will be automatically filled by 0. If you want to drop or fill by different values, use `dataframe.dropna()` or `dataframe.fillna()` before calling `plot`.

```
In [60]: df = pd.DataFrame(np.random.rand(10, 4), columns=['a', 'b', 'c', 'd'])
NameError: name 'pd' is not defined

In [61]: df.plot.area();
```
To produce an unstacked plot, pass `stacked=False`. Alpha value is set to 0.5 unless otherwise specified:

```python
In [62]: df.plot.area(stacked=False);
```
Scatter plot

Scatter plot can be drawn by using the `DataFrame.plot.scatter()` method. Scatter plot requires numeric columns for the x and y axes. These can be specified by the x and y keywords.

```
In [63]: df = pd.DataFrame(np.random.rand(50, 4), columns=['a', 'b', 'c', 'd'])
NameError: name 'pd' is not defined

In [64]: df.plot.scatter(x='a', y='b');
```
To plot multiple column groups in a single axes, repeat `plot` method specifying target `ax`. It is recommended to specify `color` and `label` keywords to distinguish each groups.

```python
In [65]: ax = df.plot.scatter(x='a', y='b', color='DarkBlue', label='Group 1');
In [66]: df.plot.scatter(x='c', y='d', color='DarkGreen', label='Group 2', ax=ax);
```
The keyword `c` may be given as the name of a column to provide colors for each point:

```python
In [67]: df.plot.scatter(x='a', y='b', c='c', s=50);
```
You can pass other keywords supported by matplotlib `scatter`. The example below shows a bubble chart using a column of the DataFrame as the bubble size.

```
In [68]: df.plot.scatter(x='a', y='b', s=df['c'] * 200);
```
See the `scatter` method and the `matplotlib scatter` documentation for more.

**Hexagonal bin plot**

You can create hexagonal bin plots with `DataFrame.plot.hexbin()`. Hexbin plots can be a useful alternative to scatter plots if your data are too dense to plot each point individually.

```python
In [69]: df = pd.DataFrame(np.random.randn(1000, 2), columns=['a', 'b'])
NameError: Traceback (most recent call last)
<ipython-input-69-e243cb9efde5> in <module>()
----> 1 df = pd.DataFrame(np.random.randn(1000, 2), columns=['a', 'b'])
NameError: name 'pd' is not defined

In [70]: df['b'] = df['b'] + np.arange(1000)
NameError: Traceback (most recent call last)
<ipython-input-70-09ef1c00dd7f> in <module>()
----> 1 df['b'] = df['b'] + np.arange(1000)
NameError: name 'df' is not defined

In [71]: df.plot.hexbin(x='a', y='b', gridsize=25)
```
A useful keyword argument is `gridsize`; it controls the number of hexagons in the x-direction, and defaults to 100. A larger `gridsize` means more, smaller bins.

By default, a histogram of the counts around each \((x, y)\) point is computed. You can specify alternative aggregations by passing values to the `C` and `reduce_C_function` arguments. `C` specifies the value at each \((x, y)\) point and `reduce_C_function` is a function of one argument that reduces all the values in a bin to a single number (e.g., `mean`, `max`, `sum`, `std`). In this example the positions are given by columns `a` and `b`, while the value is given by column `z`. The bins are aggregated with NumPy’s `max` function.

```
In [72]: df = pd.DataFrame(np.random.randn(1000, 2), columns=['a', 'b'])
```
See the `hexbin` method and the matplotlib `hexbin` documentation for more.
Pie plot

You can create a pie plot with DataFrame.plot.pie() or Series.plot.pie(). If your data includes any NaN, they will be automatically filled with 0. A ValueError will be raised if there are any negative values in your data.

```python
In [76]: series = pd.Series(3 * np.random.rand(4),
                    index=['a', 'b', 'c', 'd'], name='series')

In [77]: series.plot.pie(figsize=(6, 6))
```

For pie plots it’s best to use square figures, i.e. a figure aspect ratio 1. You can create the figure with equal width and
height, or force the aspect ratio to be equal after plotting by calling `ax.set_aspect('equal')` on the returned axes object.

Note that pie plot with DataFrame requires that you either specify a target column by the `y` argument or `subplots=True`. When `y` is specified, pie plot of selected column will be drawn. If `subplots=True` is specified, pie plots for each column are drawn as subplots. A legend will be drawn in each pie plots by default; specify `legend=False` to hide it.

```python
In [78]: df = pd.DataFrame(3 * np.random.rand(4, 2),
       index=['a', 'b', 'c', 'd'], columns=['x', 'y'])
       
NameError: name 'pd' is not defined

In [79]: df.plot.pie(subplots=True, figsize=(8, 4))
```

```
NameError: name 'df' is not defined
```
You can use the labels and colors keywords to specify the labels and colors of each wedge.

**Warning:** Most pandas plots use the label and color arguments (note the lack of “s” on those). To be consistent with `matplotlib.pyplot.pie()` you must use labels and colors.

If you want to hide wedge labels, specify labels=None. If fontsize is specified, the value will be applied to wedge labels. Also, other keywords supported by `matplotlib.pyplot.pie()` can be used.

```python
In [80]: series.plot.pie(labels=['AA', 'BB', 'CC', 'DD'], colors=['r', 'g', 'b', 'c'],
          autopct='%.2f', fontsize=20, figsize=(6, 6))
```

```python
NameError Traceback (most recent call last)
<ipython-input-80-f6a8e8e24c35> in <module>
----> 1 series.plot.pie(labels=['AA', 'BB', 'CC', 'DD'], colors=['r', 'g', 'b', 'c'],
          autopct='%.2f', fontsize=20, figsize=(6, 6))
NameError: name 'series' is not defined
```

If you pass values whose sum total is less than 1.0, matplotlib draws a semicircle.

```python
In [81]: series = pd.Series([0.1] * 4, index=['a', 'b', 'c', 'd'], name='series2')
```

(continues on next page)
NameError Traceback (most recent call last)
<ipython-input-81-80a435a1151e> in <module>
----> 1 series = pd.Series([0.1] * 4, index=['a', 'b', 'c', 'd'], name='series2')

NameError: name 'pd' is not defined

In [80]: series.plot.pie(figsize=(6, 6))

NameError: name 'series' is not defined

See the matplotlib pie documentation for more.
2.14.3 Plotting with missing data

Pandas tries to be pragmatic about plotting DataFrame or Series that contain missing data. Missing values are dropped, left out, or filled depending on the plot type.

<table>
<thead>
<tr>
<th>Plot Type</th>
<th>NaN Handling</th>
</tr>
</thead>
<tbody>
<tr>
<td>Line</td>
<td>Leave gaps at NaNs</td>
</tr>
<tr>
<td>Line (stacked)</td>
<td>Fill 0's</td>
</tr>
<tr>
<td>Bar</td>
<td>Fill 0's</td>
</tr>
<tr>
<td>Scatter</td>
<td>Drop NaNs</td>
</tr>
<tr>
<td>Histogram</td>
<td>Drop NaNs (column-wise)</td>
</tr>
<tr>
<td>Box</td>
<td>Drop NaNs (column-wise)</td>
</tr>
<tr>
<td>Area</td>
<td>Fill 0's</td>
</tr>
<tr>
<td>KDE</td>
<td>Drop NaNs (column-wise)</td>
</tr>
<tr>
<td>Hexbin</td>
<td>Drop NaNs</td>
</tr>
<tr>
<td>Pie</td>
<td>Fill 0's</td>
</tr>
</tbody>
</table>

If any of these defaults are not what you want, or if you want to be explicit about how missing values are handled, consider using `fillna()` or `dropna()` before plotting.

2.14.4 Plotting tools

These functions can be imported from `pandas.plotting` and take a Series or DataFrame as an argument.

**Scatter matrix plot**

You can create a scatter plot matrix using the `scatter_matrix` method in `pandas.plotting`:

```
In [83]: from pandas.plotting import scatter_matrix

In [84]: df = pd.DataFrame(np.random.randn(1000, 4), columns=['a', 'b', 'c', 'd'])
NameError: name 'pd' is not defined

In [85]: scatter_matrix(df, alpha=0.2, figsize=(6, 6), diagonal='kde');
```
Density plot

You can create density plots using the `Series.plot.kde()` and `DataFrame.plot.kde()` methods.

```python
In [86]: ser = pd.Series(np.random.randn(1000))
NameError: name 'pd' is not defined
```

```python
In [87]: ser.plot.kde()
NameError: name 'ser' is not defined
```
Andrews curves

Andrews curves allow one to plot multivariate data as a large number of curves that are created using the attributes of samples as coefficients for Fourier series, see the Wikipedia entry for more information. By coloring these curves differently for each class it is possible to visualize data clustering. Curves belonging to samples of the same class will usually be closer together and form larger structures.

Note: The “Iris” dataset is available here.

```python
In [88]: from pandas.plotting import andrews_curves

In [89]: data = pd.read_csv('data/iris.data')
---------------------------------------------------------------------------
NameError Traceback (most recent call last)
<ipython-input-89-ea4716c8ea20> in <module>
----> 1 data = pd.read_csv('data/iris.data')
NameError: name 'pd' is not defined

In [90]: plt.figure()
Out[90]: <Figure size 640x480 with 0 Axes>

In [91]: andrews_curves(data, 'Name')
```
Parallel coordinates

Parallel coordinates is a plotting technique for plotting multivariate data, see the Wikipedia entry for an introduction. Parallel coordinates allows one to see clusters in data and to estimate other statistics visually. Using parallel coordinates points are represented as connected line segments. Each vertical line represents one attribute. One set of connected line segments represents one data point. Points that tend to cluster will appear closer together.

```python
In [92]: from pandas.plotting import parallel_coordinates

In [93]: data = pd.read_csv('data/iris.data')
```

NameError: name 'pd' is not defined
Lag plots are used to check if a data set or time series is random. Random data should not exhibit any structure in the lag plot. Non-random structure implies that the underlying data are not random. The `lag` argument may be passed, and when `lag=1` the plot is essentially `data[:-1]` vs. `data[1:]`.

```python
In [96]: from pandas.plotting import lag_plot
In [97]: plt.figure()
Out[97]: <Figure size 640x480 with 0 Axes>
```
In [98]: spacing = np.linspace(-99 * np.pi, 99 * np.pi, num=1000)

In [99]: data = pd.Series(0.1 * np.random.rand(1000) + 0.9 * np.sin(spacing))

NameError Traceback (most recent call last)
<ipython-input-99-a1dee79fc325> in <module>
----> 1 data = pd.Series(0.1 * np.random.rand(1000) + 0.9 * np.sin(spacing))

NameError: name 'pd' is not defined

In [100]: lag_plot(data)

NameError Traceback (most recent call last)
<ipython-input-100-76d4c87cecf0> in <module>
----> 1 lag_plot(data)

NameError: name 'data' is not defined
Autocorrelation plot

Autocorrelation plots are often used for checking randomness in time series. This is done by computing autocorrelations for data values at varying time lags. If time series is random, such autocorrelations should be near zero for any and all time-lag separations. If time series is non-random then one or more of the autocorrelations will be significantly non-zero. The horizontal lines displayed in the plot correspond to 95% and 99% confidence bands. The dashed line is 99% confidence band. See the Wikipedia entry for more about autocorrelation plots.

```python
In [101]: from pandas.plotting import autocorrelation_plot

In [102]: plt.figure()
Out[102]: <Figure size 640x480 with 0 Axes>

In [103]: spacing = np.linspace(-9 * np.pi, 9 * np.pi, num=1000)

In [104]: data = pd.Series(0.7 * np.random.rand(1000) + 0.3 * np.sin(spacing))

---------------------------------------------------------------------------
NameError                                Traceback (most recent call last)
<ipython-input-104-8a50b1acf632> in <module>
----> 1 data = pd.Series(0.7 * np.random.rand(1000) + 0.3 * np.sin(spacing))

NameError: name 'pd' is not defined

In [105]: autocorrelation_plot(data)

---------------------------------------------------------------------------
NameError                                Traceback (most recent call last)
<ipython-input-105-eccad460986f> in <module>
----> 1 autocorrelation_plot(data)

NameError: name 'data' is not defined
```
Bootstrap plot

Bootstrap plots are used to visually assess the uncertainty of a statistic, such as mean, median, midrange, etc. A random subset of a specified size is selected from a data set, the statistic in question is computed for this subset and the process is repeated a specified number of times. Resulting plots and histograms are what constitutes the bootstrap plot.

```
In [106]: from pandas.plotting import bootstrap_plot

In [107]: data = pd.Series(np.random.rand(1000))
NameError: name 'pd' is not defined

In [108]: bootstrap_plot(data, size=50, samples=500, color='grey')
NameError: name 'data' is not defined
```
RadViz

RadViz is a way of visualizing multi-variate data. It is based on a simple spring tension minimization algorithm. Basically you set up a bunch of points in a plane. In our case they are equally spaced on a unit circle. Each point represents a single attribute. You then pretend that each sample in the data set is attached to each of these points by a spring, the stiffness of which is proportional to the numerical value of that attribute (they are normalized to unit interval). The point in the plane, where our sample settles to (where the forces acting on our sample are at an equilibrium) is where a dot representing our sample will be drawn. Depending on which class that sample belongs it will be colored differently. See the R package Radviz for more information.

Note: The “Iris” dataset is available here.

In [109]: from pandas.plotting import radviz

In [110]: data = pd.read_csv('data/iris.data')

---------------------------------------------------------------------------
NameError               Traceback (most recent call last)
<ipython-input-110-ea4716c8ea20> in <module>
     ----> 1 data = pd.read_csv('data/iris.data')

NameError: name 'pd' is not defined

In [111]: plt.figure()
Out[111]: <Figure size 640x480 with 0 Axes>
In [112]: radviz(data, 'Name')
---------------------------------------------------------------------------
NameError Traceback (most recent call last)
<ipython-input-112-1720a88f3922> in <module>
----> 1 radviz(data, 'Name')

NameError: name 'data' is not defined

2.14.5 Plot formatting

Setting the plot style

From version 1.5 and up, matplotlib offers a range of pre-configured plotting styles. Setting the style can be used to easily give plots the general look that you want. Setting the style is as easy as calling matplotlib.style.use(my_plot_style) before creating your plot. For example you could write matplotlib.style.use('ggplot') for ggplot-style plots.

You can see the various available style names at matplotlib.style.available and it’s very easy to try them out.
General plot style arguments

Most plotting methods have a set of keyword arguments that control the layout and formatting of the returned plot:

```python
In [113]: plt.figure();
In [114]: ts.plot(style='k--', label='Series');
```

For each kind of plot (e.g. line, bar, scatter) any additional arguments keywords are passed along to the corresponding matplotlib function (ax.plot(), ax.bar(), ax.scatter()). These can be used to control additional styling, beyond what pandas provides.

Controlling the legend

You may set the `legend` argument to `False` to hide the legend, which is shown by default.

```python
In [115]: df = pd.DataFrame(np.random.randn(1000, 4),
                         index=ts.index, columns=list('ABCD'))
```

(continues on next page)
NameError: name 'pd' is not defined

In [116]: df = df.cumsum()

---------------------------------------------------------------------------
NameError                        Traceback (most recent call last)
<ipython-input-116-08208d45ae16> in
----> 1 df = df.cumsum()

NameError: name 'df' is not defined

In [117]: df.plot(legend=False)

---------------------------------------------------------------------------
NameError                        Traceback (most recent call last)
<ipython-input-117-c885e70fbb28> in
----> 1 df.plot(legend=False)

NameError: name 'df' is not defined
Controlling the labels

New in version 1.1.0.

You may set the `xlabel` and `ylabel` arguments to give the plot custom labels for x and y axis. By default, pandas will pick up index name as xlabel, while leaving it empty for ylabel.

```
In [118]: df.plot()
NameError Traceback (most recent call last)
<ipython-input-118-848b80e64df8> in <module>
----> 1 df.plot()

NameError: name 'df' is not defined

In [119]: df.plot(xlabel="new x", ylabel="new y")
NameError Traceback (most recent call last)
<ipython-input-119-5a8534754966> in <module>
----> 1 df.plot(xlabel="new x", ylabel="new y")

NameError: name 'df' is not defined
```
Scales

You may pass `logy` to get a log-scale Y axis.

```python
In [120]: ts = pd.Series(np.random.randn(1000),
    index=pd.date_range('1/1/2000', periods=1000))

---------------------------------------------------------------------------
NameError Traceback (most recent call last)
<ipython-input-120-00eeb137fb11> in <module>
----> 1 ts = pd.Series(np.random.randn(1000),
                      index=pd.date_range('1/1/2000', periods=1000))

NameError: name 'pd' is not defined

In [121]: ts = np.exp(ts.cumsum())

---------------------------------------------------------------------------
NameError Traceback (most recent call last)
<ipython-input-121-a60c32c780a6> in <module>
----> 1 ts = np.exp(ts.cumsum())

NameError: name 'ts' is not defined

In [122]: ts.plot(logy=True)

---------------------------------------------------------------------------
NameError Traceback (most recent call last)
<ipython-input-122-9e595842ea79> in <module>
----> 1 ts.plot(logy=True)

NameError: name 'ts' is not defined
See also the \texttt{logx} and \texttt{loglog} keyword arguments.

**Plotting on a secondary y-axis**

To plot data on a secondary y-axis, use the \texttt{secondary_y} keyword:

```python
In [123]: df['A'].plot()
---------------------------------------------------------------------------
NameError                       Traceback (most recent call last)
<ipython-input-123-142941d65816> in <module>
    1 df['A'].plot()
NameError: name 'df' is not defined

In [124]: df['B'].plot(secondary_y=True, style='g')
---------------------------------------------------------------------------
NameError                       Traceback (most recent call last)
<ipython-input-124-d13b0146b561> in <module>
    1 df['B'].plot(secondary_y=True, style='g')
NameError: name 'df' is not defined
```
To plot some columns in a DataFrame, give the column names to the `secondary_y` keyword:

```python
In [125]: plt.figure()
Out[125]: <Figure size 640x480 with 0 Axes>

In [126]: ax = df.plot(secondary_y=['A', 'B'])
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-126-c7f4eaf8c12b> in <module>
----> 1 ax = df.plot(secondary_y=['A', 'B'])

NameError: name 'df' is not defined

In [127]: ax.set_ylabel('CD scale')
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-127-0396311dl2a3> in <module>
----> 1 ax.set_ylabel('CD scale')

NameError: name 'ax' is not defined

In [128]: ax.right_ax.set_ylabel('AB scale')
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-128-5ddf1e3892e0> in <module>
```

(continues on next page)
-----> 1 ax.right_ax.set_ylabel('AB scale')

NameError: name 'ax' is not defined

Note that the columns plotted on the secondary y-axis is automatically marked with “(right)” in the legend. To turn off the automatic marking, use the mark_right=False keyword:

```
In [129]: plt.figure()
Out[129]: <Figure size 640x480 with 0 Axes>

In [130]: df.plot(secondary_y=['A', 'B'], mark_right=False)

NameError: name 'df' is not defined
Custom formatters for timeseries plots

Changed in version 1.0.0.

Pandas provides custom formatters for timeseries plots. These change the formatting of the axis labels for dates and times. By default, the custom formatters are applied only to plots created by pandas with DataFrame.plot() or Series.plot(). To have them apply to all plots, including those made by matplotlib, set the option pd.options.plotting.matplotlib.register_converters = True or use pandas.plotting.register_matplotlib_converters().

Suppressing tick resolution adjustment

pandas includes automatic tick resolution adjustment for regular frequency time-series data. For limited cases where pandas cannot infer the frequency information (e.g., in an externally created twinx), you can choose to suppress this behavior for alignment purposes.

Here is the default behavior, notice how the x-axis tick labeling is performed:

In [131]: plt.figure()
Out[131]: <Figure size 640x480 with 0 Axes>

In [132]: df['A'].plot()
Using the `x_compat` parameter, you can suppress this behavior:

```
In [133]: plt.figure()
Out[133]: <Figure size 640x480 with 0 Axes>

In [134]: df['A'].plot(x_compat=True)
```
If you have more than one plot that needs to be suppressed, the `use` method in `pandas.plotting.plot_params` can be used in a *with statement*:

```python
In [135]: plt.figure()
Out[135]: <Figure size 640x480 with 0 Axes>

In [136]: with pd.plotting.plot_params.use('x_compat', True):
    ..........: df['A'].plot(color='r')
    ..........: df['B'].plot(color='g')
    ..........: df['C'].plot(color='b')
    ..........:
NameError Traceback (most recent call last)
<ipython-input-136-b939e52d1f0a> in <module>
----> 1 with pd.plotting.plot_params.use('x_compat', True):

NameError: name 'pd' is not defined
```
**Automatic date tick adjustment**

`TimedeltaIndex` now uses the native matplotlib tick locator methods, it is useful to call the automatic date tick adjustment from matplotlib for figures whose ticklabels overlap.

See the `autofmt_xdate` method and the matplotlib documentation for more.
Subplots

Each Series in a DataFrame can be plotted on a different axis with the subplots keyword:

```
In [137]: df.plot(subplots=True, figsize=(6, 6));
```

Using layout and targeting multiple axes

The layout of subplots can be specified by the layout keyword. It can accept (rows, columns). The layout keyword can be used in hist and boxplot also. If the input is invalid, a ValueError will be raised.

The number of axes which can be contained by rows x columns specified by layout must be larger than the number of required subplots. If layout can contain more axes than required, blank axes are not drawn. Similar to a NumPy array’s reshape method, you can use -1 for one dimension to automatically calculate the number of rows or columns needed, given the other.
In [138]: df.plot(subplots=True, layout=(2, 3), figsize=(6, 6), sharex=False);

The above example is identical to using:

In [139]: df.plot(subplots=True, layout=(2, -1), figsize=(6, 6), sharex=False);

The required number of columns (3) is inferred from the number of series to plot and the given number of rows (2).
You can pass multiple axes created beforehand as list-like via ax keyword. This allows more complicated layouts.
The passed axes must be the same number as the subplots being drawn.
When multiple axes are passed via the ax keyword, layout, sharex and sharey keywords don’t affect to the output. You should explicitly pass sharex=False and sharey=False, otherwise you will see a warning.

In [140]: fig, axes = plt.subplots(4, 4, figsize=(9, 9))
In [141]: plt.subplots_adjust(wspace=0.5, hspace=0.5)
In [142]: target1 = [axes[0][0], axes[1][1], axes[2][2], axes[3][3]]
In [143]: target2 = [axes[3][0], axes[2][1], axes[1][2], axes[0][3]]
In [144]: df.plot(subplots=True, ax=target1, legend=False, sharex=False, sharey=False);
Another option is passing an `ax` argument to `Series.plot()` to plot on a particular axis:
In [146]: fig, axes = plt.subplots(nrows=2, ncols=2)
In [147]: plt.subplots_adjust(wspace=0.2, hspace=0.5)
In [148]: df['A'].plot(ax=axes[0, 0]);
In [149]: axes[0, 0].set_title('A');
In [150]: df['B'].plot(ax=axes[0, 1]);
In [151]: axes[0, 1].set_title('B');
In [152]: df['C'].plot(ax=axes[1, 0]);
In [153]: axes[1, 0].set_title('C');
In [154]: df['D'].plot(ax=axes[1, 1]);
In [155]: axes[1, 1].set_title('D');
Plotting with error bars

Plotting with error bars is supported in `DataFrame.plot()` and `Series.plot()`. Horizontal and vertical error bars can be supplied to the `xerr` and `yerr` keyword arguments to `plot()`. The error values can be specified using a variety of formats:

- As a `DataFrame` or `dict` of errors with column names matching the `columns` attribute of the plotting `DataFrame` or matching the `name` attribute of the `Series`.
- As a `str` indicating which of the columns of plotting `DataFrame` contain the error values.
- As raw values (`list`, `tuple`, or `np.ndarray`). Must be the same length as the plotting `DataFrame/Series`.

Asymmetrical error bars are also supported, however raw error values must be provided in this case. For an N length `Series`, a 2xN array should be provided indicating lower and upper (or left and right) errors. For an MxN `DataFrame`, asymmetrical errors should be in an Mx2xN array.

Here is an example of one way to easily plot group means with standard deviations from the raw data.

```python
# Generate the data
In [156]: ix3 = pd.MultiIndex.from_arrays([   
          
    ['a', 'a', 'a', 'b', 'b', 'b', 'b'],   
    ['foo', 'foo', 'bar', 'bar', 'foo', 'foo', 'bar'],   
    names=['letter', 'word'])

---------------------------------------------------------------------------
NameError                      Traceback (most recent call last)
<ipython-input-156-9f015fa171f2> in 
----> 1     ix3 = pd.MultiIndex.from_arrays([   
          
    ['a', 'a', 'a', 'b', 'b', 'b', 'b'],   
    ['foo', 'foo', 'bar', 'bar', 'foo', 'foo', 'bar'],   
    names=['letter', 'word'])

NameError: name 'pd' is not defined

In [157]: df3 = pd.DataFrame({'data1': [3, 2, 4, 3, 2, 4, 3, 2],   
                          'data2': [6, 5, 7, 5, 4, 5, 6, 5]}, index=ix3)

---------------------------------------------------------------------------
NameError                      Traceback (most recent call last)
<ipython-input-157-a2b5068f0300> in 
----> 1     df3 = pd.DataFrame({'data1': [3, 2, 4, 3, 2, 4, 3, 2],   
          
    'data2': [6, 5, 7, 5, 4, 5, 6, 5]}, index=ix3)

NameError: name 'pd' is not defined

# Group by index labels and take the means and standard deviations
# for each group
In [158]: gp3 = df3.groupby(level=('letter', 'word'))

---------------------------------------------------------------------------
NameError                      Traceback (most recent call last)
<ipython-input-158-3f049b0a1791> in 
----> 1     gp3 = df3.groupby(level=('letter', 'word'))

NameError: name 'df3' is not defined

In [159]: means = gp3.mean()
```
---

NameError: name 'gp3' is not defined

In [160]: errors = gp3.std()

NameError: name 'gp3' is not defined

In [161]: means

NameError: name 'means' is not defined

In [162]: errors

NameError: name 'errors' is not defined

# Plot
In [163]: fig, ax = plt.subplots()

In [164]: means.plot.bar(yerr=errors, ax=ax, capsize=4, rot=0)

NameError: name 'means' is not defined
Plotting tables

Plotting with matplotlib table is now supported in DataFrame.plot() and Series.plot() with a table keyword. The table keyword can accept bool, DataFrame or Series. The simple way to draw a table is to specify table=True. Data will be transposed to meet matplotlib's default layout.

In [165]: fig, ax = plt.subplots(1, 1, figsize=(7, 6.5))

In [166]: df = pd.DataFrame(np.random.rand(5, 3), columns=['a', 'b', 'c'])

NameError Traceback (most recent call last)
<ipython-input-166-05c0fbdb11a1> in <module>
----> 1 df = pd.DataFrame(np.random.rand(5, 3), columns=['a', 'b', 'c'])

NameError: name 'pd' is not defined

In [167]: ax.xaxis.tick_top()  # Display x-axis ticks on top.

In [168]: df.plot(table=True, ax=ax)

NameError Traceback (most recent call last)
<ipython-input-168-8624f4234fa9> in <module>
----> 1 df.plot(table=True, ax=ax)

(continues on next page)
Also, you can pass a different DataFrame or Series to the `table` keyword. The data will be drawn as displayed in print method (not transposed automatically). If required, it should be transposed manually as seen in the example below.

```
In [169]: fig, ax = plt.subplots(1, 1, figsize=(7, 6.75))

In [170]: ax.xaxis.tick_top()  # Display x-axis ticks on top.

In [171]: df.plot(table=np.round(df.T, 2), ax=ax)
```

```
NameError Traceback (most recent call last)
<ipython-input-171-60288b063fbb> in <module>
----> 1 df.plot(table=np.round(df.T, 2), ax=ax)

NameError: name 'df' is not defined
```
There also exists a helper function `pandas.plotting.table`, which creates a table from DataFrame or Series, and adds it to an `matplotlib.Axes` instance. This function can accept keywords which the matplotlib table has.

```python
In [172]: from pandas.plotting import table
In [173]: fig, ax = plt.subplots(1, 1)
In [174]: table(ax, np.round(df.describe(), 2),
       ....:       loc='upper right', colWidths=[0.2, 0.2, 0.2])
```

NameError: name 'df' is not defined
NameError Traceback (most recent call last)
<ipython-input-174-c7487f392c87> in 
----> 1 table(ax, np.round(df.describe(), 2),
2     2 loc='upper right', colWidths=[0.2, 0.2, 0.2])

NameError: name 'df' is not defined

In [175]: df.plot(ax=ax, ylim=(0, 2), legend=None)

---------------------------------------------------------------------------
NameError Traceback (most recent call last)
<ipython-input-175-068255ff0f3e> in 
----> 1 df.plot(ax=ax, ylim=(0, 2), legend=None)

NameError: name 'df' is not defined

Note: You can get table instances on the axes using axes.tables property for further decorations. See the matplotlib table documentation for more.
Colormaps

A potential issue when plotting a large number of columns is that it can be difficult to distinguish some series due to repetition in the default colors. To remedy this, DataFrame plotting supports the use of the `colormap` argument, which accepts either a Matplotlib colormap or a string that is a name of a colormap registered with Matplotlib. A visualization of the default matplotlib colormaps is available here.

As matplotlib does not directly support colormaps for line-based plots, the colors are selected based on an even spacing determined by the number of columns in the DataFrame. There is no consideration made for background color, so some colormaps will produce lines that are not easily visible.

To use the cubehelix colormap, we can pass `colormap='cubehelix'`.

```
In [176]: df = pd.DataFrame(np.random.randn(1000, 10), index=ts.index)
In [177]: df = df.cumsum()
In [178]: plt.figure()
In [179]: df.plot(colormap='cubehelix')
```

```
NameError: name 'pd' is not defined
NameError: name 'df' is not defined
NameError: name 'df' is not defined
```
Alternatively, we can pass the colormap itself:

```python
In [180]: from matplotlib import cm
In [181]: plt.figure()
Out[181]: <Figure size 640x480 with 0 Axes>
In [182]: df.plot(colormap=cm.cubehelix)
```

```
NameError Traceback (most recent call last)
<ipython-input-182-7cdc1499f1cb> in <module>
----> 1 df.plot(colormap=cm.cubehelix)
NameError: name 'df' is not defined
```
Colormaps can also be used other plot types, like bar charts:

```python
In [183]: dd = pd.DataFrame(np.random.randn(10, 10)).applymap(abs)
NameError Traceback (most recent call last)
<ipython-input-183-2d4edaa33d2e> in <module>
----> 1 dd = pd.DataFrame(np.random.randn(10, 10)).applymap(abs)
NameError: name 'pd' is not defined

In [184]: dd = dd.cumsum()
NameError Traceback (most recent call last)
<ipython-input-184-cf596e929dc1> in <module>
----> 1 dd = dd.cumsum()
NameError: name 'dd' is not defined

In [185]: plt.figure()
Out[185]: <Figure size 640x480 with 0 Axes>

In [186]: dd.plot.bar(colormap='Greens')
NameError Traceback (most recent call last)
<ipython-input-186-d5bc68809546> in <module>
(continues on next page)```
Parallel coordinates charts:

```python
In [187]: plt.figure()
Out[187]: <Figure size 640x480 with 0 Axes>

In [188]: parallel_coordinates(data, 'Name', colormap='gist_rainbow')
```

```
NameError Traceback (most recent call last)
<ipython-input-188-a0c62c912a5a> in <module>
----> 1 parallel_coordinates(data, 'Name', colormap='gist_rainbow')

NameError: name 'data' is not defined
```
Andrews curves charts:

In [189]: plt.figure()
Out[189]: <Figure size 640x480 with 0 Axes>

In [190]: andrews_curves(data, 'Name', colormap='winter')
---------------------------------------------------------------------------
NameError Traceback (most recent call last)
<ipython-input-190-3fe5a5a07312> in <module>
      ----> 1 andrews_curves(data, 'Name', colormap='winter')
NameError: name 'data' is not defined
2.14.6 Plotting directly with matplotlib

In some situations it may still be preferable or necessary to prepare plots directly with matplotlib, for instance when a certain type of plot or customization is not (yet) supported by pandas. Series and DataFrame objects behave like arrays and can therefore be passed directly to matplotlib functions without explicit casts.

pandas also automatically registers formatters and locators that recognize date indices, thereby extending date and time support to practically all plot types available in matplotlib. Although this formatting does not provide the same level of refinement you would get when plotting via pandas, it can be faster when plotting a large number of points.

```python
In [191]: price = pd.Series(np.random.randn(150).cumsum(),
                      index=pd.date_range('2000-1-1', periods=150, freq='B'))

In [192]: ma = price.rolling(20).mean()
```

(continues on next page)
<ipython-input-192-7dcf1e53fe5c> in <module>
    1 ma = price.rolling(20).mean()

NameError: name 'price' is not defined

In [193]: mstd = price.rolling(20).std()

NameError Traceback (most recent call last)
<ipython-input-193-e2f8c3d51887> in <module>
----> 1 mstd = price.rolling(20).std()

NameError: name 'price' is not defined

In [194]: plt.figure()  
Out[194]: <Figure size 640x480 with 0 Axes>

In [195]: plt.plot(price.index, price, 'k')
NameError Traceback (most recent call last)
<ipython-input-195-7bb1b226415a> in <module>
----> 1 plt.plot(price.index, price, 'k')

NameError: name 'price' is not defined

In [196]: plt.plot(ma.index, ma, 'b')
NameError Traceback (most recent call last)
<ipython-input-196-3728ccc65de7> in <module>
----> 1 plt.plot(ma.index, ma, 'b')

NameError: name 'ma' is not defined

In [197]: plt.fill_between(mstd.index, ma - 2 * mstd, ma + 2 * mstd, 
     ...: color='b', alpha=0.2)
     ...:

NameError Traceback (most recent call last)
<ipython-input-197-ba00db352f3f> in <module>
----> 1 plt.fill_between(mstd.index, ma - 2 * mstd, ma + 2 * mstd, 
     2 color='b', alpha=0.2)

NameError: name 'mstd' is not defined
2.14.7 Plotting backends

Starting in version 0.25, pandas can be extended with third-party plotting backends. The main idea is letting users select a plotting backend different than the provided one based on Matplotlib.

This can be done by passing `backend.module` as the argument `backend` in `plot` function. For example:

```python
>>> Series([1, 2, 3]).plot(backend='backend.module')
```

Alternatively, you can also set this option globally, so you don’t need to specify the keyword in each `plot` call. For example:

```python
>>> pd.set_option('plotting.backend', 'backend.module')
>>> pd.Series([1, 2, 3]).plot()
```

Or:

```python
>>> pd.options.plotting.backend = 'backend.module'
>>> pd.Series([1, 2, 3]).plot()
```

This would be more or less equivalent to:

```python
>>> import backend.module
>>> backend.module.plot(pd.Series([1, 2, 3]))
```
The backend module can then use other visualization tools (Bokeh, Altair, hvplot,...) to generate the plots. Some libraries implementing a backend for pandas are listed on the ecosystem ecosystem.visualization page.

Developers guide can be found at [https://pandas.pydata.org/docs/dev/development/extending.html#plotting-backends](https://pandas.pydata.org/docs/dev/development/extending.html#plotting-backends)

## 2.15 Computational tools

### 2.15.1 Statistical functions

#### Percent change

Series and DataFrame have a method `pct_change()` to compute the percent change over a given number of periods (using `fill_method` to fill NA/null values before computing the percent change).

```python
In [1]: ser = pd.Series(np.random.randn(8))

In [2]: ser.pct_change()
Out[2]:
   0   NaN
   1 -1.602976
   2   4.334938
   3 -0.247456
   4 -2.067345
   5 -1.142903
   6 -1.688214
   7 -9.759729
   dtype: float64

In [3]: df = pd.DataFrame(np.random.randn(10, 4))

In [4]: df.pct_change(periods=3)
Out[4]:
     0       1       2       3
0 NaN     NaN     NaN     NaN
1 NaN     NaN     NaN     NaN
2 NaN     NaN     NaN     NaN
3 -0.218320 -1.054001  1.987147 -0.510183
4 -0.439121 -1.816454  0.649715 -4.822809
5 -0.127833 -3.042065 -5.866604 -1.776977
6 -2.596833 -1.959538 -2.111697 -3.798900
7 -0.117826 -2.169058  0.036094 -0.067696
8  2.492606 -1.357320 -1.205802 -1.558697
9 -1.012977  2.324558 -1.003744 -0.371806
```
### Covariance

*Series.cov()* can be used to compute covariance between series (excluding missing values).

```python
In [5]: s1 = pd.Series(np.random.randn(1000))
In [6]: s2 = pd.Series(np.random.randn(1000))
In [7]: s1.cov(s2)
Out[7]: 0.0006801088174310875
```

Analogously, *DataFrame.cov()* to compute pairwise covariances among the series in the DataFrame, also excluding NA/null values.

**Note:** Assuming the missing data are missing at random this results in an estimate for the covariance matrix which is unbiased. However, for many applications this estimate may not be acceptable because the estimated covariance matrix is not guaranteed to be positive semi-definite. This could lead to estimated correlations having absolute values which are greater than one, and/or a non-invertible covariance matrix. See *Estimation of covariance matrices* for more details.

```python
In [8]: frame = pd.DataFrame(np.random.randn(1000, 5),
                        columns=['a', 'b', 'c', 'd', 'e'])
In [9]: frame.cov()
Out[9]:
   a        b        c        d        e
a 1.000882 -0.003177 -0.002698 -0.006889 0.031912
b -0.003177 1.024721 0.000191 0.009212 0.000857
c -0.002698 0.000191 0.950735 -0.031743 -0.005087
d -0.006889 0.009212 -0.031743 1.002983 -0.047952
e 0.031912 0.000857 -0.005087 -0.047952 1.042487
```

*DataFrame.cov* also supports an optional *min_periods* keyword that specifies the required minimum number of observations for each column pair in order to have a valid result.

```python
In [10]: frame = pd.DataFrame(np.random.randn(20, 3), columns=['a', 'b', 'c'])
In [11]: frame.loc[frame.index[:5], 'a'] = np.nan
In [12]: frame.loc[frame.index[5:10], 'b'] = np.nan
In [13]: frame.cov()
Out[13]:
   a  b  c
a 1.123670 -0.412851 0.018169
b -0.412851 1.154141 0.305260
c 0.018169 0.305260 1.301149
In [14]: frame.cov(min_periods=12)
Out[14]:
   a  b  c
a 1.123670 NaN 0.018169
b  NaN 1.154141 0.305260
c 0.018169 0.305260 1.301149
```

2.15. Computational tools
Correlation

Correlation may be computed using the `corr()` method. Using the `method` parameter, several methods for computing correlations are provided:

<table>
<thead>
<tr>
<th>Method name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>pearson</td>
<td>Standard correlation coefficient</td>
</tr>
<tr>
<td>kendall</td>
<td>Kendall Tau correlation coefficient</td>
</tr>
<tr>
<td>spearman</td>
<td>Spearman rank correlation coefficient</td>
</tr>
</tbody>
</table>

All of these are currently computed using pairwise complete observations. Wikipedia has articles covering the above correlation coefficients:

- Pearson correlation coefficient
- Kendall rank correlation coefficient
- Spearman’s rank correlation coefficient

**Note:** Please see the caveats associated with this method of calculating correlation matrices in the covariance section.

In [15]: frame = pd.DataFrame(np.random.randn(1000, 5),
                          columns=['a', 'b', 'c', 'd', 'e'])

In [16]: frame.iloc[::2] = np.nan

# Series with Series
In [17]: frame['a'].corr(frame['b'])
Out[17]: 0.013479040400098775

In [18]: frame['a'].corr(frame['b'], method='spearman')
Out[18]: -0.007289885159540637

# Pairwise correlation of DataFrame columns
In [19]: frame.corr()
Out[19]:

<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>e</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>1.000000</td>
<td>0.013479</td>
<td>-0.049269</td>
<td>-0.042239</td>
<td>-0.028525</td>
</tr>
<tr>
<td>b</td>
<td>0.013479</td>
<td>1.000000</td>
<td>-0.020433</td>
<td>-0.011139</td>
<td>0.005654</td>
</tr>
<tr>
<td>c</td>
<td>-0.049269</td>
<td>-0.020433</td>
<td>1.000000</td>
<td>0.018587</td>
<td>-0.054269</td>
</tr>
<tr>
<td>d</td>
<td>-0.042239</td>
<td>-0.011139</td>
<td>0.018587</td>
<td>1.000000</td>
<td>-0.017060</td>
</tr>
<tr>
<td>e</td>
<td>-0.028525</td>
<td>0.005654</td>
<td>-0.054269</td>
<td>-0.017060</td>
<td>1.000000</td>
</tr>
</tbody>
</table>

Note that non-numeric columns will be automatically excluded from the correlation calculation.

Like `cov`, `corr` also supports the optional `min_periods` keyword:

In [20]: frame = pd.DataFrame(np.random.randn(20, 3), columns=['a', 'b', 'c'])

In [21]: frame.loc[frame.index[:5], 'a'] = np.nan

In [22]: frame.loc[frame.index[5:10], 'b'] = np.nan

In [23]: frame.corr()
Out[23]:

<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
<th>c</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>1.000000</td>
<td>-0.121111</td>
<td>0.069544</td>
</tr>
<tr>
<td>b</td>
<td>-0.121111</td>
<td>1.000000</td>
<td>0.051742</td>
</tr>
<tr>
<td>c</td>
<td>0.069544</td>
<td>0.051742</td>
<td>1.000000</td>
</tr>
</tbody>
</table>

In[24]: frame.corr(min_periods=12)

Out[24]:

<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
<th>c</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>1.000000</td>
<td>NaN</td>
<td>0.069544</td>
</tr>
<tr>
<td>b</td>
<td>NaN</td>
<td>1.000000</td>
<td>0.051742</td>
</tr>
<tr>
<td>c</td>
<td>0.069544</td>
<td>0.051742</td>
<td>1.000000</td>
</tr>
</tbody>
</table>

New in version 0.24.0.

The `method` argument can also be a callable for a generic correlation calculation. In this case, it should be a single function that produces a single value from two ndarray inputs. Suppose we wanted to compute the correlation based on histogram intersection:

```python
# histogram intersection
In [25]: def histogram_intersection(a, b):
    ....:     return np.minimum(np.true_divide(a, a.sum()),
    ....:                          np.true_divide(b, b.sum())).sum()
    ....:

In [26]: frame.corr(method=histogram_intersection)

Out[26]:

<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
<th>c</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>1.000000</td>
<td>-6.404882</td>
<td>-2.058431</td>
</tr>
<tr>
<td>b</td>
<td>-6.404882</td>
<td>1.000000</td>
<td>-19.255743</td>
</tr>
<tr>
<td>c</td>
<td>-2.058431</td>
<td>-19.255743</td>
<td>1.000000</td>
</tr>
</tbody>
</table>

A related method `corrwith()` is implemented on DataFrame to compute the correlation between like-labeled Series contained in different DataFrame objects.

In[27]: index = ['a', 'b', 'c', 'd', 'e']

In[28]: columns = ['one', 'two', 'three', 'four']

In[29]: df1 = pd.DataFrame(np.random.randn(5, 4), index=index, columns=columns)

In[30]: df2 = pd.DataFrame(np.random.randn(4, 4), index=index[:4], columns=columns)

In[31]: df1.corrwith(df2)

Out[31]:

<table>
<thead>
<tr>
<th></th>
<th>one</th>
<th>two</th>
<th>three</th>
<th>four</th>
</tr>
</thead>
<tbody>
<tr>
<td>one</td>
<td>-0.125501</td>
<td>-0.493244</td>
<td>0.344056</td>
<td>0.004183</td>
</tr>
<tr>
<td>two</td>
<td>-0.493244</td>
<td>0.344056</td>
<td>0.004183</td>
<td>-0.125501</td>
</tr>
<tr>
<td>three</td>
<td>0.344056</td>
<td>0.004183</td>
<td>-0.125501</td>
<td>-0.493244</td>
</tr>
<tr>
<td>four</td>
<td>0.004183</td>
<td>-0.125501</td>
<td>-0.493244</td>
<td>0.344056</td>
</tr>
</tbody>
</table>

dtype: float64

In[32]: df2.corrwith(df1, axis=1)

Out[32]:

<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>-0.675817</td>
<td>0.458296</td>
<td>0.190809</td>
<td>-0.186275</td>
</tr>
<tr>
<td>b</td>
<td>0.458296</td>
<td>0.458296</td>
<td>0.458296</td>
<td>0.458296</td>
</tr>
<tr>
<td>c</td>
<td>0.190809</td>
<td>0.190809</td>
<td>0.190809</td>
<td>0.190809</td>
</tr>
<tr>
<td>d</td>
<td>-0.186275</td>
<td>-0.186275</td>
<td>-0.186275</td>
<td>-0.186275</td>
</tr>
</tbody>
</table>
The `rank()` method produces a data ranking with ties being assigned the mean of the ranks (by default) for the group:

```python
In [33]: s = pd.Series(np.random.randn(5), index=list('abcde'))
In [34]: s['d'] = s['b']  # so there's a tie
In [35]: s.rank()
Out[35]:
    a 5.0
    b 2.5
    c 1.0
    d 2.5
    e 4.0
```

dtype: float64

`rank()` is also a DataFrame method and can rank either the rows (`axis=0`) or the columns (`axis=1`). NaN values are excluded from the ranking.

```python
In [36]: df = pd.DataFrame(np.random.randn(10, 6))
In [38]: df.rank(1)
Out[38]:
        0     1     2     3    
0  4.00  3.00  1.50  5.00
1  2.00  6.00  4.50  1.00
2  1.00  6.00  3.50  5.00
3  4.00  5.00  1.50  3.00
4  5.00  3.00  1.50  4.00
5  1.00  2.00  5.00  NaN
6  4.00  5.00  3.00  1.00
7  2.00  5.00  3.00  4.00
8  2.00  5.00  3.00  4.00
9  2.00  3.00  1.00  4.00
```

rank optionally takes a parameter `ascending` which by default is true; when false, data is reverse-ranked, with larger values assigned a smaller rank.

`rank` supports different tie-breaking methods, specified with the `method` parameter:

- **average**: average rank of tied group
- **min**: lowest rank in the group
- **max**: highest rank in the group
- **first**: ranks assigned in the order they appear in the array

### 2.15.2 Window functions

For working with data, a number of window functions are provided for computing common window or rolling statistics. Among these are count, sum, mean, median, correlation, variance, covariance, standard deviation, skewness, and kurtosis.

The `rolling()` and `expanding()` functions can be used directly from DataFrameGroupBy objects, see the groupby docs.

**Note:** The API for window statistics is quite similar to the way one works with GroupBy objects, see the documentation [here](#).

We work with `rolling`, `expanding` and exponentially weighted data through the corresponding objects, `Rolling`, `Expanding` and `ExponentialMovingWindow`.

```python
In [40]: s = pd.Series(np.random.randn(1000),
                   index=pd.date_range('1/1/2000', periods=1000))

In [41]: s = s.cumsum()

In [42]: r = s.rolling(window=60)

In [43]: r
Out[43]: Rolling [window=60, center=False, axis=0]
```

These are created from methods on `Series` and `DataFrame`.

These object provide tab-completion of the available methods and properties.
Generally these methods all have the same interface. They all accept the following arguments:

- `window`: size of moving window
- `min_periods`: threshold of non-null data points to require (otherwise result is NA)
- `center`: boolean, whether to set the labels at the center (default is False)

We can then call methods on these rolling objects. These return like-indexed objects:

```
In [45]: r.mean()
Out[45]:
          2000-01-01   NaN
          2000-01-02   NaN
          2000-01-03   NaN
          2000-01-04   NaN
          2000-01-05   NaN
       ...       ...
          2002-09-22  -62.914971
          2002-09-23  -63.061867
          2002-09-24  -63.213876
          2002-09-25  -63.375074
          2002-09-26  -63.539734
Freq: D, Length: 1000, dtype: float64
```

```
In [46]: s.plot(style='k--')
Out[46]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe295cb7ca0>
```

```
In [47]: r.mean().plot(style='k')
Out[47]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe295cb7ca0>
```
They can also be applied to DataFrame objects. This is really just syntactic sugar for applying the moving window operator to all of the DataFrame's columns:

```
In [48]: df = pd.DataFrame(np.random.randn(1000, 4),
                   index=pd.date_range('1/1/2000', periods=1000),
                   columns=['A', 'B', 'C', 'D'])

In [49]: df = df.cumsum()

In [50]: df.rolling(window=60).sum().plot(subplots=True)
Out[50]:
array([<matplotlib.axes._subplots.AxesSubplot object at 0x7fe295cfe2b0>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x7fe294b9e2e0>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x7fe294b3e550>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x7fe294b6a610>],
      dtype=object)
```
Method summary

We provide a number of common statistical functions:

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>count()</td>
<td>Number of non-null observations</td>
</tr>
<tr>
<td>sum()</td>
<td>Sum of values</td>
</tr>
<tr>
<td>mean()</td>
<td>Mean of values</td>
</tr>
<tr>
<td>median()</td>
<td>Arithmetic median of values</td>
</tr>
<tr>
<td>min()</td>
<td>Minimum</td>
</tr>
<tr>
<td>max()</td>
<td>Maximum</td>
</tr>
<tr>
<td>std()</td>
<td>Sample standard deviation</td>
</tr>
<tr>
<td>var()</td>
<td>Sample variance</td>
</tr>
<tr>
<td>skew()</td>
<td>Sample skewness (3rd moment)</td>
</tr>
<tr>
<td>kurt()</td>
<td>Sample kurtosis (4th moment)</td>
</tr>
<tr>
<td>quantile()</td>
<td>Sample quantile (value at %)</td>
</tr>
<tr>
<td>apply()</td>
<td>Generic apply</td>
</tr>
<tr>
<td>cov()</td>
<td>Sample covariance (binary)</td>
</tr>
<tr>
<td>corr()</td>
<td>Sample correlation (binary)</td>
</tr>
</tbody>
</table>

Note: Please note that std() and var() use the sample variance formula by default, i.e. the sum of squared
differences is divided by \(\text{window\_size - 1}\) and not by \(\text{window\_size}\) during averaging. In statistics, we use sample when the dataset is drawn from a larger population that we don’t have access to. Using it implies that the data in our window is a random sample from the population, and we are interested not in the variance inside the specific window but in the variance of some general window that our windows represent. In this situation, using the sample variance formula results in an unbiased estimator and so is preferred.

Usually, we are instead interested in the variance of each window as we slide it over the data, and in this case we should specify \(\text{ddof=0}\) when calling these methods to use population variance instead of sample variance. Using sample variance under the circumstances would result in a biased estimator of the variable we are trying to determine.

The same caveats apply to using any supported statistical sample methods.

**Rolling apply**

The `apply()` function takes an extra `func` argument and performs generic rolling computations. The `func` argument should be a single function that produces a single value from an ndarray input. Suppose we wanted to compute the mean absolute deviation on a rolling basis:

```python
In [51]: def mad(x):
   ....:     return np.fabs(x - x.mean()).mean()
   ....:

In [52]: s.rolling(window=60).apply(mad, raw=True).plot(style='k')
```

Out[52]: `<matplotlib.axes._subplots.AxesSubplot at 0x7fe2949df2b0>`
New in version 1.0.

Additionally, `apply()` can leverage Numba if installed as an optional dependency. The apply aggregation can be executed using Numba by specifying `engine='numba'` and `engine_kwargs` arguments (raw must also be set to True). Numba will be applied in potentially two routines:

1. If `func` is a standard Python function, the engine will JIT the passed function. `func` can also be a JITed function in which case the engine will not JIT the function again.

2. The engine will JIT the for loop where the apply function is applied to each window.

The `engine_kwargs` argument is a dictionary of keyword arguments that will be passed into the `numba.jit` decorator. These keyword arguments will be applied to both the passed function (if a standard Python function) and the apply for loop over each window. Currently only nogil, nopython, and parallel are supported, and their default values are set to False, True and False respectively.

**Note:** In terms of performance, the first time a function is run using the Numba engine will be slow as Numba will have some function compilation overhead. However, the compiled functions are cached, and subsequent calls will be fast. In general, the Numba engine is performant with a larger amount of data points (e.g. 1+ million).

```python
In [1]: data = pd.Series(range(1_000_000))
In [2]: roll = data.rolling(10)
In [3]: def f(x):
   ...:     return np.sum(x) + 5
   ...:
# Run the first time, compilation time will affect performance
In [4]: %timeit -r 1 -n 1 roll.apply(f, engine='numba', raw=True) # noqa: E225
1.23 s ± 0 ns per loop (mean ± std. dev. of 1 run, 1 loop each)
# Function is cached and performance will improve
In [5]: %timeit roll.apply(f, engine='numba', raw=True)
188 ms ± 1.93 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)
In [6]: %timeit roll.apply(f, engine='cython', raw=True)
3.92 s ± 59 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

### Rolling windows

Passing `win_type` to `.rolling` generates a generic rolling window computation, that is weighted according the `win_type`. The following methods are available:

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>sum()</code></td>
<td>Sum of values</td>
</tr>
<tr>
<td><code>mean()</code></td>
<td>Mean of values</td>
</tr>
</tbody>
</table>

The weights used in the window are specified by the `win_type` keyword. The list of recognized types are the `scipy.signal window functions`:

- boxcar
- triang
- blackman
- hamming
- bartlett

---

674 Chapter 2. User Guide
• parzen
• bohman
• blackmanharris
• nuttall
• barthann
• kaiser (needs beta)
• gaussian (needs std)
• general_gaussian (needs power, width)
• slepian (needs width)
• exponential (needs tau).

```
In [53]: ser = pd.Series(np.random.randn(10),
                   index=pd.date_range('1/1/2000', periods=10))

In [54]: ser.rolling(window=5, win_type='triang').mean()
Out[54]:
2000-01-01     NaN
2000-01-02     NaN
2000-01-03     NaN
2000-01-04     NaN
2000-01-05  -1.037870
2000-01-06  -0.767705
2000-01-07  -0.383197
2000-01-08  -0.395513
2000-01-09  -0.558440
2000-01-10  -0.672416
Freq: D, dtype: float64
```

Note that the boxcar window is equivalent to mean().

```
In [55]: ser.rolling(window=5, win_type='boxcar').mean()
Out[55]:
2000-01-01     NaN
2000-01-02     NaN
2000-01-03     NaN
2000-01-04     NaN
2000-01-05  -0.841164
2000-01-06  -0.779948
2000-01-07  -0.565487
2000-01-08  -0.502815
2000-01-09  -0.553755
2000-01-10  -0.472211
Freq: D, dtype: float64
```

```
In [56]: ser.rolling(window=5).mean()
Out[56]:
2000-01-01     NaN
2000-01-02     NaN
2000-01-03     NaN
2000-01-04  -0.841164
2000-01-05  -0.841164
Freq: D, dtype: float64
```

(continues on next page)
For some windowing functions, additional parameters must be specified:

```
ser.rolling(window=5, win_type='gaussian').mean(std=0.1)
```

```
2000-01-01    NaN
2000-01-02    NaN
2000-01-03    NaN
2000-01-04    NaN
2000-01-05   -1.309989
2000-01-06   -1.153000
2000-01-07    0.606382
2000-01-08   -0.681101
2000-01-09   -0.289724
2000-01-10   -0.996632
Freq: D, dtype: float64
```

**Note:** For .sum() with a win_type, there is no normalization done to the weights for the window. Passing custom weights of [1, 1, 1] will yield a different result than passing weights of [2, 2, 2], for example. When passing a win_type instead of explicitly specifying the weights, the weights are already normalized so that the largest weight is 1.

In contrast, the nature of the .mean() calculation is such that the weights are normalized with respect to each other. Weights of [1, 1, 1] and [2, 2, 2] yield the same result.

### Time-aware rolling

It is possible to pass an offset (or convertible) to a .rolling() method and have it produce variable sized windows based on the passed time window. For each time point, this includes all preceding values occurring within the indicated time delta.

This can be particularly useful for a non-regular time frequency index.

```
dft = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]},
                   index=pd.date_range('20130101 09:00:00',
                                      periods=5,
                                      freq='s'))
```

```
dft
```

```
   B
2013-01-01  09:00:00  0.0
2013-01-01  09:00:01  1.0
2013-01-01  09:00:02  2.0
2013-01-01  09:00:03  NaN
2013-01-01  09:00:04  4.0
```
This is a regular frequency index. Using an integer window parameter works to roll along the window frequency.

```
In [60]: dft.rolling(2).sum()
Out[60]:
   B
2013-01-01 09:00:00 NaN
2013-01-01 09:00:01 1.0
2013-01-01 09:00:02 3.0
2013-01-01 09:00:03 NaN
2013-01-01 09:00:04 NaN
```

```
In [61]: dft.rolling(2, min_periods=1).sum()
Out[61]:
   B
2013-01-01 09:00:00 0.0
2013-01-01 09:00:01 1.0
2013-01-01 09:00:02 3.0
2013-01-01 09:00:03 2.0
2013-01-01 09:00:04 4.0
```

Specifying an offset allows a more intuitive specification of the rolling frequency.

```
In [62]: dft.rolling('2s').sum()
Out[62]:
   B
2013-01-01 09:00:00 0.0
2013-01-01 09:00:01 1.0
2013-01-01 09:00:02 3.0
2013-01-01 09:00:03 2.0
2013-01-01 09:00:04 4.0
```

Using a non-regular, but still monotonic index, rolling with an integer window does not impart any special calculation.

```
In [63]: dft = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]},
                   index=pd.Index([pd.Timestamp('20130101 09:00:00'),
                                    pd.Timestamp('20130101 09:00:02'),
                                    pd.Timestamp('20130101 09:00:03'),
                                    pd.Timestamp('20130101 09:00:05'),
                                    pd.Timestamp('20130101 09:00:06')],
                   name='foo'))
```

```
In [64]: dft
Out[64]:
   B
foo
2013-01-01 09:00:00 0.0
2013-01-01 09:00:02 1.0
2013-01-01 09:00:03 2.0
2013-01-01 09:00:05 NaN
2013-01-01 09:00:06 4.0
```

```
In [65]: dft.rolling(2).sum()
Out[65]:
   B
foo
2013-01-01 09:00:00 NaN
2013-01-01 09:00:02 1.0
```

(continues on next page)
Using the time-specification generates variable windows for this sparse data.

```
In [66]: dft.rolling('2s').sum()
Out[66]:
          B
2013-01-01 09:00:00  0.0
2013-01-01 09:00:02  1.0
2013-01-01 09:00:03  3.0
2013-01-01 09:00:05  NaN
2013-01-01 09:00:06  4.0
```

Furthermore, we now allow an optional `on` parameter to specify a column (rather than the default of the index) in a DataFrame.

```
In [67]: dft = dft.reset_index()
In [68]: dft
Out[68]:
     foo  B
0 2013-01-01 09:00:00  0.0
1 2013-01-01 09:00:02  1.0
2 2013-01-01 09:00:03  2.0
3 2013-01-01 09:00:05  NaN
4 2013-01-01 09:00:06  4.0
```

```
In [69]: dft.rolling('2s', on='foo').sum()
Out[69]:
          B
0 2013-01-01 09:00:00  0.0
1 2013-01-01 09:00:02  1.0
2 2013-01-01 09:00:03  3.0
3 2013-01-01 09:00:05  NaN
4 2013-01-01 09:00:06  4.0
```

**Custom window rolling**

New in version 1.0.

In addition to accepting an integer or offset as a `window` argument, `rolling` also accepts a `BaseIndexer` subclass that allows a user to define a custom method for calculating window bounds. The `BaseIndexer` subclass will need to define a `get_window_bounds` method that returns a tuple of two arrays, the first being the starting indices of the windows and second being the ending indices of the windows. Additionally, `num_values`, `min_periods`, `center`, `closed` and will automatically be passed to `get_window_bounds` and the defined method must always accept these arguments.

For example, if we have the following DataFrame:

```
In [70]: use_expanding = [True, False, True, False, True]
In [71]: use_expanding
```
and we want to use an expanding window where `use_expanding` is `True` otherwise a window of size 1, we can create the following `BaseIndexer` subclass:

```python
In [2]: from pandas.api.indexers import BaseIndexer
   ...: class CustomIndexer(BaseIndexer):
   ...:     def get_window_bounds(self, num_values, min_periods, center, closed):
   ...:         start = np.empty(num_values, dtype=np.int64)
   ...:         end = np.empty(num_values, dtype=np.int64)
   ...:         for i in range(num_values):
   ...:             if self.use_expanding[i]:
   ...:                 start[i] = 0
   ...:                 end[i] = i + 1
   ...:             else:
   ...:                 start[i] = i
   ...:                 end[i] = i + self.window_size
   ...:         return start, end
   ...

In [3]: indexer = CustomIndexer(window_size=1, use_expanding=use_expanding)

In [4]: df.rolling(indexer).sum()
```

```
Out[4]:
values
0  0.0
1  1.0
2  3.0
3  3.0
4 10.0
```

You can view other examples of `BaseIndexer` subclasses here

New in version 1.1.

One subclass of note within those examples is the `VariableOffsetWindowIndexer` that allows rolling operations over a non-fixed offset like a `BusinessDay`.

```python
In [74]: from pandas.api.indexers import VariableOffsetWindowIndexer

In [75]: df = pd.DataFrame(range(10), index=pd.date_range('2020', periods=10))

In [76]: offset = pd.offsets.BDay(1)
```

```
(continues on next page)
```
For some problems knowledge of the future is available for analysis. For example, this occurs when each data point is a
full time series read from an experiment, and the task is to extract underlying conditions. In these cases it can be useful
to perform forward-looking rolling window computations. FixedForwardWindowIndexer class is available for
this purpose. This BaseIndexer subclass implements a closed fixed-width forward-looking rolling window, and
we can use it as follows:

**Rolling window endpoints**

The inclusion of the interval endpoints in rolling window calculations can be specified with the closed parameter:

<table>
<thead>
<tr>
<th>closed</th>
<th>Description</th>
<th>Default for</th>
</tr>
</thead>
<tbody>
<tr>
<td>right</td>
<td>close right endpoint</td>
<td>time-based windows</td>
</tr>
<tr>
<td>left</td>
<td>close left endpoint</td>
<td>fixed windows</td>
</tr>
<tr>
<td>both</td>
<td>close both endpoints</td>
<td></td>
</tr>
<tr>
<td>neither</td>
<td>open endpoints</td>
<td></td>
</tr>
</tbody>
</table>

For example, having the right endpoint open is useful in many problems that require that there is no contamination
from present information back to past information. This allows the rolling window to compute statistics “up to that
point in time”, but not including that point in time.
Currently, this feature is only implemented for time-based windows. For fixed windows, the closed parameter cannot be set and the rolling window will always have both endpoints closed.

**Iteration over window:**

New in version 1.1.0.

Rolling and Expanding objects now support iteration. Be noted that min_periods is ignored in iteration.

**Time-aware rolling vs. resampling**

Using `.rolling()` with a time-based index is quite similar to `resampling`. They both operate and perform reductive operations on time-indexed pandas objects.

When using `.rolling()` with an offset. The offset is a time-delta. Take a backwards-in-time looking window, and aggregate all of the values in that window (including the end-point, but not the start-point). This is the new value at that point in the result. These are variable sized windows in time-space for each point of the input. You will get a same sized result as the input.
When using `.resample()` with an offset. Construct a new index that is the frequency of the offset. For each frequency bin, aggregate points from the input within a backwards-in-time looking window that fall in that bin. The result of this aggregation is the output for that frequency point. The windows are fixed size in the frequency space. Your result will have the shape of a regular frequency between the min and the max of the original input object.

To summarize, `.rolling()` is a time-based window operation, while `.resample()` is a frequency-based window operation.

**Centering windows**

By default the labels are set to the right edge of the window, but a `center` keyword is available so the labels can be set at the center.

```python
In [88]: ser.rolling(window=5).mean()
Out[88]:
2000-01-01    NaN
2000-01-02    NaN
2000-01-03    NaN
2000-01-04    NaN
2000-01-05   -0.841164
2000-01-06   -0.779948
2000-01-07   -0.565487
2000-01-08   -0.502815
2000-01-09   -0.553755
2000-01-10   -0.472211
Freq: D, dtype: float64
```

```python
In [89]: ser.rolling(window=5, center=True).mean()
Out[89]:
2000-01-01    NaN
2000-01-02    NaN
2000-01-03  -0.841164
2000-01-04  -0.779948
2000-01-05  -0.565487
2000-01-06  -0.502815
2000-01-07  -0.553755
2000-01-08  -0.472211
2000-01-09    NaN
2000-01-10    NaN
Freq: D, dtype: float64
```

**Binary window functions**

cov() and corr() can compute moving window statistics about two Series, or any combination of DataFrame/Series or DataFrame/DataFrame/DataFrame. Here is the behavior in each case:

- two Series: compute the statistic for the pairing.
- DataFrame/Series: compute the statistics for each column of the DataFrame with the passed Series, thus returning a DataFrame.
- DataFrame/DataFrame: by default compute the statistic for matching column names, returning a DataFrame. If the keyword argument `pairwise=True` is passed then computes the statistic for each pair of columns, returning a MultiIndexed DataFrame whose index are the dates in question (see the next section).

For example:
Computing rolling pairwise covariances and correlations

In financial data analysis and other fields it’s common to compute covariance and correlation matrices for a collection of time series. Often one is also interested in moving-window covariance and correlation matrices. This can be done by passing the `pairwise` keyword argument, which in the case of DataFrame inputs will yield a MultiIndexed DataFrame whose index are the dates in question. In the case of a single DataFrame argument the `pairwise` argument can even be omitted:

**Note:** Missing values are ignored and each entry is computed using the pairwise complete observations. Please see the covariance section for caveats associated with this method of calculating covariance and correlation matrices.

In [94]:
```python
covs = (df[['B', 'C', 'D']].rolling(window=50)
....: .cov(df[['A', 'B', 'C']], pairwise=True))
....:
```

In [95]:
```python
covs.loc['2002-09-22':]
```

Out [95]:
```
<table>
<thead>
<tr>
<th></th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002-09-22</td>
<td>1.367467</td>
<td>8.676734</td>
<td>-8.047366</td>
</tr>
<tr>
<td>2002-09-23</td>
<td>3.067315</td>
<td>0.865946</td>
<td>-1.052533</td>
</tr>
<tr>
<td>2002-09-24</td>
<td>0.910343</td>
<td>8.669065</td>
<td>-8.443062</td>
</tr>
<tr>
<td>2002-09-25</td>
<td>2.625456</td>
<td>0.565152</td>
<td>-0.907654</td>
</tr>
<tr>
<td>2002-09-26</td>
<td>0.463332</td>
<td>8.514509</td>
<td>-9.162599</td>
</tr>
</tbody>
</table>
```

(continues on next page)
In [96]: correls = df.rolling(window=50).corr()

In [97]: correls.loc['2002-09-22':]

Out[97]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002-09-22</td>
<td>1.000000</td>
<td>0.186397</td>
<td>0.744551</td>
<td>-0.769767</td>
</tr>
<tr>
<td>2002-09-23</td>
<td>1.000000</td>
<td>0.134723</td>
<td>0.743113</td>
<td>-0.758758</td>
</tr>
</tbody>
</table>

You can efficiently retrieve the time series of correlations between two columns by reshaping and indexing:

In [98]: correls.unstack(1)[('A', 'C')].plot()
Once the Rolling, Expanding or ExponentialMovingWindow objects have been created, several methods are available to perform multiple computations on the data. These operations are similar to the aggregating API, groupby API, and resample API.

We can aggregate by passing a function to the entire DataFrame, or select a Series (or multiple Series) via standard __getitem__.

We can aggregate by passing a function to the entire DataFrame, or select a Series (or multiple Series) via standard __getitem__.

```python
In [99]: dfa = pd.DataFrame(np.random.randn(1000, 3),
                     index=pd.date_range('1/1/2000', periods=1000),
                     columns=['A', 'B', 'C'])

In [100]: r = dfa.rolling(window=60, min_periods=1)

In [101]: r.aggregate(np.sum)
```

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01</td>
<td>-0.289838</td>
<td>-0.370545</td>
</tr>
</tbody>
</table>
As you can see, the result of the aggregation will have the selected columns, or all columns if none are selected.
Applying multiple functions

With windowed Series you can also pass a list of functions to do aggregation with, outputting a DataFrame:

```python
In [105]: r['A'].agg([np.sum, np.mean, np.std])
Out[105]:
                      sum        mean       std
2000-01-01 -0.289838   -0.289838    NaN
2000-01-02 -0.216612   -0.108306   0.256725
2000-01-03  1.154661   0.384887   0.873311
2000-01-04  2.969393   0.742348  1.009734
2000-01-05  4.690630   0.938126   0.977914
...       ...        ...        ...
2002-09-22  2.860036   0.047667  1.132051
2002-09-23  3.510163   0.058503  1.142913
2002-09-24  6.524983   0.108750  1.144204
2002-09-25  6.409626   0.106827  1.142913
2002-09-26  5.093787   0.084896  1.151416
[1000 rows x 3 columns]
```

On a windowed DataFrame, you can pass a list of functions to apply to each column, which produces an aggregated result with a hierarchical index:

```python
In [106]: r.agg([np.sum, np.mean])
Out[106]:
                      A       B       C
sum         mean     mean     mean
2000-01-01 -0.289838 -0.370545 -1.284206
2000-01-02 -0.216612 -0.169415 -1.000819
2000-01-03  1.154661 -1.566620 -0.522207
2000-01-04  2.969393 -0.816179 -0.454045
2000-01-05  4.690630 -0.543442 -0.534342
...       ...        ...        ...
2002-09-22  2.860036 -0.154506  6.415245
2002-09-23  3.510163  6.151439  5.177219
2002-09-24  6.524983 -0.169468  5.792639
2002-09-25  6.409626 -0.165937  5.704050
2002-09-26  5.093787 -0.117909  6.905823
[1000 rows x 6 columns]
```

Passing a dict of functions has different behavior by default, see the next section.

Applying different functions to DataFrame columns

By passing a dict to `aggregate` you can apply a different aggregation to the columns of a DataFrame:

```python
In [107]: r.agg({'A': np.sum, 'B': lambda x: np.std(x, ddof=1)})
Out[107]:
                     A       B
2000-01-01  -0.289838 NaN
2000-01-02  -0.216612  0.660747
2000-01-03   1.154661  0.689929
2000-01-04   2.969393  1.072199
2000-01-05   4.690630  0.939657
...       ...        ...
2002-09-22   2.860036  0.547667
2002-09-23   3.510163  0.105603
2002-09-24   6.524983  0.082050
2002-09-25   6.409626  0.108827
2002-09-26   5.093787  0.084896
[1000 rows x 2 columns]
```

(continues on next page)
The function names can also be strings. In order for a string to be valid it must be implemented on the windowed object.

```python
In [108]: r.agg({'A': 'sum', 'B': 'std'})
Out[108]:
   A     B
2000-01-01 -0.289838 NaN
2000-01-02 -0.216612  0.660747
2000-01-03  1.154661  0.689929
2000-01-04  2.969393  1.072199
2000-01-05  4.690630  0.939657
2002-09-22  2.860036  1.113208
2002-09-23  3.510163  1.132381
2002-09-24  6.524983  1.080963
2002-09-25  6.409626  1.082911
2002-09-26  5.093787  1.136199
[1000 rows x 2 columns]
```

Furthermore you can pass a nested dict to indicate different aggregations on different columns.

```python
In [109]: r.agg({'A': ['sum', 'std'], 'B': ['mean', 'std']})
Out[109]:
   A B
   sum std mean std
2000-01-01 -0.289838 NaN -0.370545 NaN
2000-01-02 -0.216612  0.256725 -0.837764  0.660747
2000-01-03  1.154661  0.873311 -0.544672  0.689929
2000-01-04  2.969393  1.009734 -1.000819  1.072199
2000-01-05  4.690630  0.977914 -0.936403  0.939657
2002-09-22  2.860036  1.132051 -0.154506  1.113208
2002-09-23  3.510163  1.132381 -0.135857  1.132381
2002-09-24  6.524983  1.080963 -0.169468  1.080963
2002-09-25  6.409626  1.082911 -0.165937  1.082911
2002-09-26  5.093787  1.136199 -0.117909  1.136199
[1000 rows x 4 columns]
```
2.15.4 Expanding windows

A common alternative to rolling statistics is to use an *expanding* window, which yields the value of the statistic with all the data available up to that point in time.

These follow a similar interface to `.rolling`, with the `.expanding` method returning an `Expanding` object.

As these calculations are a special case of rolling statistics, they are implemented in pandas such that the following two calls are equivalent:

```python
In [110]: df.rolling(window=len(df), min_periods=1).mean()[:5]
Out[110]:
          A        B        C        D
2000-01-01  0.314226 -0.001675  0.071823  0.892566
2000-01-02  0.654522 -0.171495  0.179278  0.853361
2000-01-03  0.708733 -0.064489 -0.238271  1.371111
2000-01-04  0.987613  0.163472 -0.919693  1.566485
2000-01-05  1.426971  0.288267 -1.358877  1.808650
```

```python
In [111]: df.expanding(min_periods=1).mean()[:5]
Out[111]:
          A        B        C        D
2000-01-01  0.314226 -0.001675  0.071823  0.892566
2000-01-02  0.654522 -0.171495  0.179278  0.853361
2000-01-03  0.708733 -0.064489 -0.238271  1.371111
2000-01-04  0.987613  0.163472 -0.919693  1.566485
2000-01-05  1.426971  0.288267 -1.358877  1.808650
```

These have a similar set of methods to `.rolling` methods.

**Method summary**

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>count()</td>
<td>Number of non-null observations</td>
</tr>
<tr>
<td>sum()</td>
<td>Sum of values</td>
</tr>
<tr>
<td>mean()</td>
<td>Mean of values</td>
</tr>
<tr>
<td>median()</td>
<td>Arithmetic median of values</td>
</tr>
<tr>
<td>min()</td>
<td>Minimum</td>
</tr>
<tr>
<td>max()</td>
<td>Maximum</td>
</tr>
<tr>
<td>std()</td>
<td>Sample standard deviation</td>
</tr>
<tr>
<td>var()</td>
<td>Sample variance</td>
</tr>
<tr>
<td>skew()</td>
<td>Sample skewness (3rd moment)</td>
</tr>
<tr>
<td>kurt()</td>
<td>Sample kurtosis (4th moment)</td>
</tr>
<tr>
<td>quantile()</td>
<td>Sample quantile (value at %)</td>
</tr>
<tr>
<td>apply()</td>
<td>Generic apply</td>
</tr>
<tr>
<td>cov()</td>
<td>Sample covariance (binary)</td>
</tr>
<tr>
<td>corr()</td>
<td>Sample correlation (binary)</td>
</tr>
</tbody>
</table>

**Note:** Using sample variance formulas for `std()` and `var()` comes with the same caveats as using them with rolling windows. See *this section* for more information.

The same caveats apply to using any supported statistical sample methods.
Aside from not having a `window` parameter, these functions have the same interfaces as their `.rolling` counterparts. Like above, the parameters they all accept are:

- `min_periods`: threshold of non-null data points to require. Defaults to minimum needed to compute statistic. No NaNs will be output once `min_periods` non-null data points have been seen.
- `center`: boolean, whether to set the labels at the center (default is False).

**Note:** The output of the `.rolling` and `.expanding` methods do not return a NaN if there are at least `min_periods` non-null values in the current window. For example:

```python
In [112]: sn = pd.Series([1, 2, np.nan, 3, np.nan, 4])
In [113]: sn
Out[113]:
0    1.0
1    2.0
2  NaN
3    3.0
4  NaN
5    4.0
dtype: float64
In [114]: sn.rolling(2).max()
Out[114]:
0  NaN
1  2.0
2  NaN
3  NaN
4  NaN
5  NaN
dtype: float64
In [115]: sn.rolling(2, min_periods=1).max()
Out[115]:
0    1.0
1    2.0
2    2.0
3    3.0
4    3.0
5    4.0
dtype: float64
```

In case of expanding functions, this differs from `cumsum()`, `cumprod()`, `cummax()`, and `cummin()`, which return NaN in the output wherever a NaN is encountered in the input. In order to match the output of `cumsum` with expanding, use `fillna()`:

```python
In [116]: sn.expanding().sum()
Out[116]:
0    1.0
1    3.0
2    3.0
3    6.0
4    6.0
5   10.0
dtype: float64
In [117]: sn.cumsum()
```

(continues on next page)
Out[117]:
0  1.0
1  3.0
2  NaN
3  6.0
4  NaN
5  10.0
dtype: float64

In [118]: sn.cumsum().fillna(method='ffill')
Out[118]:
0  1.0   
1  3.0   
2  3.0   
3  6.0   
4  6.0   
5  10.0  
dtype: float64

An expanding window statistic will be more stable (and less responsive) than its rolling window counterpart as the increasing window size decreases the relative impact of an individual data point. As an example, here is the mean() output for the previous time series dataset:

In [119]: s.plot(style='k--')
Out[119]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe29462b1f0>

In [120]: s.expanding().mean().plot(style='k')
Out[120]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe29462b1f0>
2.15.5 Exponentially weighted windows

A related set of functions are exponentially weighted versions of several of the above statistics. A similar interface to .rolling and .expanding is accessed through the .ewm method to receive an ExponentialMovingWindow object. A number of expanding EW (exponentially weighted) methods are provided:

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean()</td>
<td>EW moving average</td>
</tr>
<tr>
<td>var()</td>
<td>EW moving variance</td>
</tr>
<tr>
<td>std()</td>
<td>EW moving standard deviation</td>
</tr>
<tr>
<td>corr()</td>
<td>EW moving correlation</td>
</tr>
<tr>
<td>cov()</td>
<td>EW moving covariance</td>
</tr>
</tbody>
</table>

In general, a weighted moving average is calculated as

\[ y_t = \frac{\sum_{i=0}^{t} w_t x_{t-i}}{\sum_{i=0}^{t} w_i}, \]

where \( x_t \) is the input, \( y_t \) is the result and the \( w_i \) are the weights.

The EW functions support two variants of exponential weights. The default, adjust=True, uses the weights \( w_i = \)
\[(1 - \alpha)^t \text{ which gives} \]
\[
y_t = \frac{x_t + (1 - \alpha)x_{t-1} + (1 - \alpha)^2x_{t-2} + \ldots + (1 - \alpha)^t x_0}{1 + (1 - \alpha) + (1 - \alpha)^2 + \ldots + (1 - \alpha)^t}
\]

When `adjust=False` is specified, moving averages are calculated as
\[
y_0 = x_0 \\
y_t = (1 - \alpha)y_{t-1} + \alpha x_t,
\]
which is equivalent to using weights
\[
w_i = \begin{cases} 
\alpha(1 - \alpha)^i & \text{if } i < t \\
(1 - \alpha)^i & \text{if } i = t.
\end{cases}
\]

**Note:** These equations are sometimes written in terms of \(\alpha' = 1 - \alpha\), e.g.
\[
y_t = \alpha'y_{t-1} + (1 - \alpha')x_t.
\]

The difference between the above two variants arises because we are dealing with series which have finite history. Consider a series of infinite history, with `adjust=True`:
\[
y_t = \frac{x_t + (1 - \alpha)x_{t-1} + (1 - \alpha)^2x_{t-2} + \ldots}{1 - (1 - \alpha)}
\]
Noting that the denominator is a geometric series with initial term equal to 1 and a ratio of \(1 - \alpha\) we have
\[
y_t = x_t + (1 - \alpha)x_{t-1} + (1 - \alpha)^2x_{t-2} + \ldots \alpha \\
= \alpha x_t + [(1 - \alpha)x_{t-1} + (1 - \alpha)^2x_{t-2} + \ldots] \alpha \\
= \alpha x_t + (1 - \alpha)[x_{t-1} + (1 - \alpha)x_{t-2} + \ldots] \alpha \\
= \alpha x_t + (1 - \alpha)y_{t-1}
\]
which is the same expression as `adjust=False` above and therefore shows the equivalence of the two variants for infinite series. When `adjust=False`, we have \(y_0 = x_0\) and \(y_t = \alpha x_t + (1 - \alpha)y_{t-1}\). Therefore, there is an assumption that \(x_0\) is not an ordinary value but rather an exponentially weighted moment of the infinite series up to that point.

One must have \(0 < \alpha \leq 1\), and while it is possible to pass \(\alpha\) directly, it’s often easier to think about either the **span**, **center of mass (com)** or **half-life** of an EW moment:
\[
\alpha = \begin{cases} 
\frac{2}{s+1}, & \text{for span } s \geq 1 \\
\frac{1}{1+c}, & \text{for center of mass } c \geq 0 \\
1 - \exp\left(-\frac{s}{h}\right), & \text{for half-life } h > 0
\end{cases}
\]

One must specify precisely one of **span**, **center of mass**, **half-life** and **alpha** to the EW functions:

- **Span** corresponds to what is commonly called an “N-day EW moving average”.
- **Center of mass** has a more physical interpretation and can be thought of in terms of span: \(c = (s - 1)/2\).
- **Half-life** is the period of time for the exponential weight to reduce to one half.
- **Alpha** specifies the smoothing factor directly.
You can also specify `halflife` in terms of a timedelta convertible unit to specify the amount of time it takes for an observation to decay to half its value when also specifying a sequence of `times`.

```python
In [121]: df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]})

In [122]: df
Out[122]:
   B
0  0
1  1
2  2
3  NaN
4  4

In [123]: times = ['2020-01-01', '2020-01-03', '2020-01-10', '2020-01-15', '2020-01-17']

In [124]: df.ewm(halflife='4 days', times=pd.DatetimeIndex(times)).mean()
Out[124]:
   B
0  0.000000
1  0.585786
2  1.523889
3  1.523889
4  3.233686
```

The following formula is used to compute exponentially weighted mean with an input vector of times:

\[
y_t = \frac{\sum_{i=0}^{t} 0.5^{\frac{t-i}{\lambda}} x_{t-i}}{0.5^{\frac{t}{\lambda}}}
\]

Here is an example for a univariate time series:

```python
In [125]: s.plot(style='k--')
Out[125]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe294526e20>

In [126]: s.ewm(span=20).mean().plot(style='k')
Out[126]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe294526e20>
```
ExponentialMovingWindow has a min_periods argument, which has the same meaning it does for all the .expanding and .rolling methods: no output values will be set until at least min_periods non-null values are encountered in the (expanding) window.

ExponentialMovingWindow also has an ignore_na argument, which determines how intermediate null values affect the calculation of the weights. When ignore_na=False (the default), weights are calculated based on absolute positions, so that intermediate null values affect the result. When ignore_na=True, weights are calculated by ignoring intermediate null values. For example, assuming adjust=True, if ignore_na=False, the weighted average of 3, NaN, 5 would be calculated as

\[
\frac{(1 - \alpha)^2 \cdot 3 + 1 \cdot 5}{(1 - \alpha)^2 + 1}.
\]

Whereas if ignore_na=True, the weighted average would be calculated as

\[
\frac{(1 - \alpha) \cdot 3 + 1 \cdot 5}{(1 - \alpha) + 1}.
\]

The var(), std(), and cov() functions have a bias argument, specifying whether the result should contain biased or unbiased statistics. For example, if bias=True, ewmvar(x) is calculated as ewmvar(x) = ewma(x**2) - ewma(x)**2; whereas if bias=False (the default), the biased variance statistics are scaled by debiasing factors

\[
\frac{\left(\sum_{i=0}^{t} w_i\right)^2}{\left(\sum_{i=0}^{t} w_i^2\right)^2 - \sum_{i=0}^{t} w_i^2}.
\]
(For \( w_i = 1 \), this reduces to the usual \( N/(N-1) \) factor, with \( N = t + 1 \).) See Weighted Sample Variance on Wikipedia for further details.

2.16 Group by: split-apply-combine

By “group by” we are referring to a process involving one or more of the following steps:

- **Splitting** the data into groups based on some criteria.
- **Applying** a function to each group independently.
- **Combining** the results into a data structure.

Out of these, the split step is the most straightforward. In fact, in many situations we may wish to split the data set into groups and do something with those groups. In the apply step, we might wish to do one of the following:

- **Aggregation**: compute a summary statistic (or statistics) for each group. Some examples:
  - Compute group sums or means.
  - Compute group sizes / counts.
- **Transformation**: perform some group-specific computations and return a like-indexed object. Some examples:
  - Standardize data (zscore) within a group.
  - Filling NAs within groups with a value derived from each group.
- **Filtration**: discard some groups, according to a group-wise computation that evaluates True or False. Some examples:
  - Discard data that belongs to groups with only a few members.
  - Filter out data based on the group sum or mean.
- Some combination of the above: GroupBy will examine the results of the apply step and try to return a sensibly combined result if it doesn’t fit into either of the above two categories.

Since the set of object instance methods on pandas data structures are generally rich and expressive, we often simply want to invoke, say, a DataFrame function on each group. The name GroupBy should be quite familiar to those who have used a SQL-based tool (or *itertools*), in which you can write code like:

```sql
SELECT Column1, Column2, mean(Column3), sum(Column4)
FROM SomeTable
GROUP BY Column1, Column2
```

We aim to make operations like this natural and easy to express using pandas. We’ll address each area of GroupBy functionality then provide some non-trivial examples / use cases.

See the *cookbook* for some advanced strategies.
2.16.1 Splitting an object into groups

Pandas objects can be split on any of their axes. The abstract definition of grouping is to provide a mapping of labels to group names. To create a GroupBy object (more on what the GroupBy object is later), you may do the following:

```
In [1]: df = pd.DataFrame([('bird', 'Falconiformes', 389.0),
                         ('bird', 'Psittaciformes', 24.0),
                         ('mammal', 'Carnivora', 80.2),
                         ('mammal', 'Primates', np.nan),
                         ('mammal', 'Carnivora', 58)],
                        index=['falcon', 'parrot', 'lion', 'monkey', 'leopard'],
                        columns=('class', 'order', 'max_speed'))
In [2]: df
Out[2]:
          class  order       max_speed
    falcon  bird  Falconiformes     389.0
    parrot  bird  Psittaciformes     24.0
    lion  mammal  Carnivora       80.2
  monkey  mammal     Primates        NaN
  leopard  mammal  Carnivora      58.0

# default is axis=0
In [3]: grouped = df.groupby('class')
In [4]: grouped = df.groupby('order', axis='columns')
In [5]: grouped = df.groupby(['class', 'order'])
```

The mapping can be specified many different ways:

- A Python function, to be called on each of the axis labels.
- A list or NumPy array of the same length as the selected axis.
- A dict or Series, providing a label -> group name mapping.
- For DataFrame objects, a string indicating a column to be used to group. Of course `df.groupby('A')` is just syntactic sugar for `df.groupby(df['A'])`, but it makes life simpler.
- For DataFrame objects, a string indicating an index level to be used to group.
- A list of any of the above things.

Collectively we refer to the grouping objects as the keys. For example, consider the following DataFrame:

```
In [6]: df = pd.DataFrame({'A': ['foo', 'bar', 'foo', 'bar', 'foo', 'bar', 'foo', 'bar'],
                       'B': ['one', 'one', 'two', 'three', 'two', 'two', 'one', 'three'],
                       'C': np.random.randn(8),
                       'D': np.random.randn(8)})
```

Note: A string passed to `groupby` may refer to either a column or an index level. If a string matches both a column name and an index level name, a `ValueError` will be raised.
On a DataFrame, we obtain a GroupBy object by calling `groupby()`. We could naturally group by either the A or B columns, or both:

```python
In [8]: grouped = df.groupby('A')
In [9]: grouped = df.groupby(['A', 'B'])
```

New in version 0.24.

If we also have a MultiIndex on columns A and B, we can group by all but the specified columns:

```python
In [10]: df2 = df.set_index(['A', 'B'])
In [11]: grouped = df2.groupby(level=df2.index.names.difference(['B']))
In [12]: grouped.sum()
```

These will split the DataFrame on its index (rows). We could also split by the columns:

```python
In [13]: def get_letter_type(letter):
    ...:     if letter.lower() in 'aeiou':
    ...:         return 'vowel'
    ...:     else:
    ...:         return 'consonant'
    ...:
In [14]: grouped = df.groupby(get_letter_type, axis=1)
```

pandas Index objects support duplicate values. If a non-unique index is used as the group key in a groupby operation, all values for the same index value will be considered to be in one group and thus the output of aggregation functions will only contain unique index values:

```python
In [15]: lst = [1, 2, 3, 1, 2, 3]
In [16]: s = pd.Series([1, 2, 3, 10, 20, 30], lst)
In [17]: grouped = s.groupby(level=0)
In [18]: grouped.first()
```
Note that **no splitting occurs** until it’s needed. Creating the GroupBy object only verifies that you’ve passed a valid mapping.

**Note:** Many kinds of complicated data manipulations can be expressed in terms of GroupBy operations (though can’t be guaranteed to be the most efficient). You can get quite creative with the label mapping functions.

### GroupBy sorting

By default the group keys are sorted during the groupby operation. You may however pass `sort=False` for potential speedups:

```python
In [21]: df2 = pd.DataFrame({'X': ['B', 'B', 'A', 'A'], 'Y': [1, 2, 3, 4]})

In [22]: df2.groupby(['X']).sum()
Out[22]:
   Y  
  X
  A   7
  B   3

In [23]: df2.groupby(['X'], sort=False).sum()
Out[23]:
   Y  
  X
  B   3
  A   7
```

Note that `groupby` will preserve the order in which **observations** are sorted **within** each group. For example, the groups created by `groupby()` below are in the order they appeared in the original DataFrame:

```python
In [24]: df3 = pd.DataFrame({'X': ['A', 'B', 'A', 'B'], 'Y': [1, 4, 3, 2]})

In [25]: df3.groupby(['X']).get_group('A')
```

(continues on next page)
X Y
0 A 1
2 A 3

In [26]: df3.groupby(['X']).get_group('B')
Out[26]:
   X  Y
1  B  4
3  B  2

New in version 1.1.0.

**GroupBy dropna**

By default NA values are excluded from group keys during the groupby operation. However, in case you want to include NA values in group keys, you could pass dropna=False to achieve it.

In [27]: df_list = [[1, 2, 3], [1, None, 4], [2, 1, 3], [1, 2, 2]]
In [28]: df_dropna = pd.DataFrame(df_list, columns=["a", "b", "c"])
In [29]: df_dropna
Out[29]:
     a  b  c
0  1  2.0 3
1  1   NaN 4
2  2  1.0 3
3  1  2.0 2

# Default `dropna` is set to True, which will exclude NaNs in keys
In [30]: df_dropna.groupby(by="b", dropna=True).sum()
Out[30]:
     a  c
b
1.0  2  3
2.0  2  5

# In order to allow NaN in keys, set `dropna` to False
In [31]: df_dropna.groupby(by="b", dropna=False).sum()
Out[31]:
     a  c
b
1.0  2  3
2.0  2  5
NaN  1  4

The default setting of dropna argument is True which means NA are not included in group keys.
GroupBy object attributes

The `groups` attribute is a dict whose keys are the computed unique groups and corresponding values being the axis labels belonging to each group. In the above example we have:

```python
In [32]: df.groupby('A').groups
Out[32]: {'bar': [1, 3, 5], 'foo': [0, 2, 4, 6, 7]}

In [33]: df.groupby(get_letter_type, axis=1).groups
Out[33]: {'consonant': ['B', 'C', 'D'], 'vowel': ['A']}
```

Calling the standard Python `len` function on the GroupBy object just returns the length of the `groups` dict, so it is largely just a convenience:

```python
In [34]: grouped = df.groupby(['A', 'B'])
In [35]: grouped.groups
Out[35]: {('bar', 'one'): [1], ('bar', 'three'): [3], ('bar', 'two'): [5], ('foo', 'one'): [0, 6], ('foo', 'three'): [7], ('foo', 'two'): [2, 4]}
In [36]: len(grouped)
Out[36]: 6
```

GroupBy will tab complete column names (and other attributes):

```python
In [37]: df
Out[37]:
   height  weight  gender
2000-01-01  42.849980  157.500553  male
2000-01-02  49.607315  177.340407  male
2000-01-03  56.293531  171.524640  male
2000-01-04  48.421077  144.251986  female
2000-01-05  46.556882  152.526206  male
2000-01-06  68.448851  168.272968  female
2000-01-07  70.757698  136.431469  male
2000-01-08  58.909500  176.499753  female
2000-01-09  76.435631  174.094104  female
2000-01-10  45.306120  177.540920  male

In [38]: gb = df.groupby('gender')
In [39]: gb.<TAB>  # noqa: E225, E999
```

2.16. Group by: split-apply-combine
GroupBy with MultiIndex

With `hierarchically-indexed data`, it’s quite natural to group by one of the levels of the hierarchy.

Let’s create a Series with a two-level `MultiIndex`.

```python
arrays = [['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux'],
          ['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two']]

index = pd.MultiIndex.from_arrays(arrays, names=['first', 'second'])

s = pd.Series(np.random.randn(8), index=index)

s
```

```
first second
bar one  -0.919854
  two  -0.042379
baz one  1.247642
  two  -0.009920
foo one  0.290213
  two  0.495767
qux one  0.362949
  two  1.548106
dtype: float64
```

We can then group by one of the levels in `s`.

```python
grouped = s.groupby(level=0)

grouped.sum()
```

```
first
bar  -0.962232
baz  1.237723
foo  0.785980
qux  1.911055
dtype: float64
```

If the `MultiIndex` has names specified, these can be passed instead of the level number:

```python
s.groupby(level='second').sum()
```

```
second
one  0.980950
two  1.991575
dtype: float64
```

The aggregation functions such as `sum` will take the level parameter directly. Additionally, the resulting index will be named according to the chosen level:

```python
s.sum(level='second')
```

```
second
one  0.980950
two  1.991575
dtype: float64
```
Grouping with multiple levels is supported.

```python
In [48]: s
Out[48]:
first  second  third
bar   doo     one   -1.131345
       two      -0.089329
baz   bee     one    0.337863
       two     -0.945867
foo   bop     one   -0.932132
       two     1.956030
qux   bop     one    0.017587
       two    -0.016692
dtype: float64
```

```python
In [49]: s.groupby(level=['first', 'second']).sum()
Out[49]:
first  second
bar   doo     -1.220674
baz   bee    -0.608004
foo   bop     1.023898
qux   bop     0.000895
dtype: float64
```

Index level names may be supplied as keys.

```python
In [50]: s.groupby(['first', 'second']).sum()
Out[50]:
first  second
bar   doo     -1.220674
baz   bee    -0.608004
foo   bop     1.023898
qux   bop     0.000895
dtype: float64
```

More on the `sum` function and aggregation later.

**Grouping DataFrame with Index levels and columns**

A DataFrame may be grouped by a combination of columns and index levels by specifying the column names as strings and the index levels as `pd.Grouper` objects.

```python
In [51]: arrays = [['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux'],
                   ['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two']]
In [52]: index = pd.MultiIndex.from_arrays(arrays, names=['first', 'second'])
In [53]: df = pd.DataFrame({'A': [1, 1, 1, 1, 2, 2, 3, 3],
                         'B': np.arange(8)},
                         index=index)
In [54]: df
Out[54]:
   A  B
first second
(continues on next page)
The following example groups `df` by the second index level and the A column.

```
In [55]: df.groupby([pd.Grouper(level=1), 'A']).sum()
Out[55]:
    B
second A
  one  1  2
       2  4
       3  6
  two  1  4
       2  5
       3  7
```

Index levels may also be specified by name.

```
In [56]: df.groupby([pd.Grouper(level='second'), 'A']).sum()
Out[56]:
    B
second A
  one  1  2
       2  4
       3  6
  two  1  4
       2  5
       3  7
```

Index level names may be specified as keys directly to `groupby`.

```
In [57]: df.groupby(['second', 'A']).sum()
Out[57]:
    B
second A
  one  1  2
       2  4
       3  6
  two  1  4
       2  5
       3  7
```
DataFrame column selection in GroupBy

Once you have created the GroupBy object from a DataFrame, you might want to do something different for each of the columns. Thus, using [ ] similar to getting a column from a DataFrame, you can do:

```python
In [58]: grouped = df.groupby(['A'])
In [59]: grouped_C = grouped['C']
In [60]: grouped_D = grouped['D']
```

This is mainly syntactic sugar for the alternative and much more verbose:

```python
In [61]: df['C'].groupby(df['A'])
Out[61]: <pandas.core.groupby.generic.SeriesGroupBy object at 0x7fe294531430>
```

Additionally this method avoids recomputing the internal grouping information derived from the passed key.

### 2.16.2 Iterating through groups

With the GroupBy object in hand, iterating through the grouped data is very natural and functions similarly to `itertools.groupby()`:

```python
In [62]: grouped = df.groupby('A')
In [63]: for name, group in grouped:
       ....:     print(name)
       ....:     print(group)
       ....:
bar
   A   B   C   D
  1 bar one 0.254161 1.511763
  3 bar three 0.215897 -0.990582
  5 bar two -0.077118 1.211526
foo
   A   B   C   D
  0 foo one -0.575247 1.346061
  2 foo two -1.143704 1.627081
  4 foo two 1.193555 -0.441652
  6 foo one -0.408530 0.268520
  7 foo three -0.862495 0.024580
```

In the case of grouping by multiple keys, the group name will be a tuple:

```python
In [64]: for name, group in df.groupby(['A', 'B']):
       ....:     print(name)
       ....:     print(group)
       ....:
('bar', 'one')
   A   B   C   D
  1 bar one 0.254161 1.511763
('bar', 'three')
   A   B   C   D
  3 bar three 0.215897 -0.990582
('bar', 'two')
   A   B   C   D
```

(continues on next page)
See *Iterating through groups*.

### 2.16.3 Selecting a group

A single group can be selected using `get_group()`:

```python
In [65]: grouped.get_group('bar')
Out[65]:
     A    B    C    D
   --- --- --- ---
   bar 0.25 1.51 1.11 1.21
```

Or for an object grouped on multiple columns:

```python
In [66]: df.groupby(['A', 'B']).get_group(('bar', 'one'))
Out[66]:
     A    B    C    D
   --- --- --- ---
   bar 0.25 1.51 1.11 1.21
```

### 2.16.4 Aggregation

Once the GroupBy object has been created, several methods are available to perform a computation on the grouped data. These operations are similar to the *aggregating API*, *window functions API*, and *resample API*.

An obvious one is aggregation via the `aggregate()` or equivalently `agg()` method:

```python
In [67]: grouped = df.groupby('A')

In [68]: grouped.aggregate(np.sum)
Out[68]:
     C    D
   --- ---
   bar 0.39 1.73
   foo -1.79 2.82
```

```python
In [69]: grouped = df.groupby(['A', 'B'])

In [70]: grouped.aggregate(np.sum)
Out[70]:
       C    D
     --- ---
     bar 0.39 1.73
     foo -1.79 2.82
```

(continues on next page)
As you can see, the result of the aggregation will have the group names as the new index along the grouped axis. In the case of multiple keys, the result is a `MultiIndex` by default, though this can be changed by using the `as_index` option:

```python
In [71]: grouped = df.groupby(['A', 'B'], as_index=False)
In [72]: grouped.aggregate(np.sum)
Out[72]:
   A    B    C   D
0  bar  one  0.254161  1.511763
1  bar  three  0.215897 -0.990582
2  bar  two  -0.077118  1.211526
3  foo  one  -0.983776  1.614581
4  foo  three  -0.862495  0.024580
5  foo  two   0.049851  1.185429
```

Note that you could use the `reset_index` DataFrame function to achieve the same result as the column names are stored in the resulting `MultiIndex`:

```python
In [73]: df.groupby('A', as_index=False).sum()
Out[73]:
   A    C   D
0  bar  0.392940  1.732707
1  foo -1.796421  2.824590
```

Another simple aggregation example is to compute the size of each group. This is included in GroupBy as the `size` method. It returns a Series whose index are the group names and whose values are the sizes of each group.

```python
In [74]: grouped.size()
Out[74]:
   A    B  size
0  bar  one   1
1  bar  three  1
2  bar  two   1
3  foo  one   2
4  foo  three  1
5  foo  two   2
```

2.16. Group by: split-apply-combine 707
In [76]: grouped.describe()
Out[76]:
   C ... D
  count mean  std  min  25%  50%  75% ... mean
  std  min  25%  50%  75%  max
0  1.0  0.254161 NaN 0.254161 0.254161 0.254161 ... 1.511763
   NaN 1.511763 1.511763 1.511763 1.511763 1.511763
1  1.0  0.215897 NaN 0.215897 0.215897 0.215897 ... -0.990582
   NaN -0.990582 -0.990582 -0.990582 -0.990582 -0.990582
2  1.0 -0.077118 NaN -0.077118 -0.077118 -0.077118 ... 1.211526
   NaN 1.211526 1.211526 1.211526 1.211526 1.211526
3  2.0 -0.491888 0.117887 -0.575247 -0.533567 -0.491888 ... 0.807291 0.
   NaN 0.537905 0.807291 1.076676 1.346061
4  1.0 -0.862495 NaN -0.862495 -0.862495 -0.862495 ... 0.024580
   NaN 0.024580 0.024580 0.024580 0.024580 0.024580
5  2.0  0.024925 1.652692 -1.143704 -0.559389 0.024925 ... 0.592714 1.
   NaN 0.592714 0.592714 1.109898 1.627081
[6 rows x 16 columns]

Note: Aggregation functions will not return the groups that you are aggregating over if they are named columns, when as_index=True, the default. The grouped columns will be the indices of the returned object.

Passing as_index=False will return the groups that you are aggregating over, if they are named columns.

Aggregating functions are the ones that reduce the dimension of the returned objects. Some common aggregating functions are tabulated below:

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean()</td>
<td>Compute mean of groups</td>
</tr>
<tr>
<td>sum()</td>
<td>Compute sum of group values</td>
</tr>
<tr>
<td>size()</td>
<td>Compute group sizes</td>
</tr>
<tr>
<td>count()</td>
<td>Compute count of group</td>
</tr>
<tr>
<td>std()</td>
<td>Standard deviation of groups</td>
</tr>
<tr>
<td>var()</td>
<td>Compute variance of groups</td>
</tr>
<tr>
<td>sem()</td>
<td>Standard error of the mean of groups</td>
</tr>
<tr>
<td>describe()</td>
<td>Generates descriptive statistics</td>
</tr>
<tr>
<td>first()</td>
<td>Compute first of group values</td>
</tr>
<tr>
<td>last()</td>
<td>Compute last of group values</td>
</tr>
<tr>
<td>nth()</td>
<td>Take nth value, or a subset if n is a list</td>
</tr>
<tr>
<td>min()</td>
<td>Compute min of group values</td>
</tr>
<tr>
<td>max()</td>
<td>Compute max of group values</td>
</tr>
</tbody>
</table>

The aggregating functions above will exclude NA values. Any function which reduces a Series to a scalar value is an aggregation function and will work, a trivial example is `df.groupby('A').agg(lambda ser: 1)`. Note that `nth()` can act as a reducer or a filter, see [here](#).
Applying multiple functions at once

With grouped Series you can also pass a list or dict of functions to do aggregation with, outputting a DataFrame:

```python
In [77]: grouped = df.groupby('A')
In [78]: grouped['C'].agg([np.sum, np.mean, np.std])
Out[78]:
         sum    mean   std
A
  bar  0.392940 0.130980 0.181231
  foo -1.796421 -0.359284  0.912265
```

On a grouped DataFrame, you can pass a list of functions to apply to each column, which produces an aggregated result with a hierarchical index:

```python
In [79]: grouped.agg([np.sum, np.mean, np.std])
Out[79]:
     C         D
   sum    mean   std     sum    mean   std
A
  bar  0.392940 0.130980 0.181231 1.732707 0.577569 1.366330
  foo -1.796421 -0.359284  0.912265 2.824590  0.564918  0.884785
```

The resulting aggregations are named for the functions themselves. If you need to rename, then you can add in a chained operation for a Series like this:

```python
In [80]: (grouped['C'].agg([np.sum, np.mean, np.std])
       ....: .rename(columns={'sum': 'foo',
       ....:                     'mean': 'bar',
       ....:                     'std': 'baz'}))
Out[80]:
     foo    bar    baz
A
  bar  0.392940 0.130980 0.181231
  foo -1.796421 -0.359284  0.912265
```

For a grouped DataFrame, you can rename in a similar manner:

```python
In [81]: (grouped.agg([np.sum, np.mean, np.std])
       ....: .rename(columns={'sum': 'foo',
       ....:                     'mean': 'bar',
       ....:                     'std': 'baz'}))
Out[81]:
     foo    bar    baz
A
  bar  0.392940 0.130980 0.181231 1.732707 0.577569 1.366330
  foo -1.796421 -0.359284  0.912265 2.824590  0.564918  0.884785
```

Note: In general, the output column names should be unique. You can’t apply the same function (or two functions with the same name) to the same column.
Pandas does allow you to provide multiple lambdas. In this case, pandas will mangle the name of the (nameless) lambda functions, appending \_<i> to each subsequent lambda.

Named aggregation

New in version 0.25.0.

To support column-specific aggregation with control over the output column names, pandas accepts the special syntax in \texttt{GroupBy.agg()}, known as “named aggregation”, where

- The keywords are the output column names
- The values are tuples whose first element is the column to select and the second element is the aggregation to apply to that column. Pandas provides the pandas.NamedAgg namedtuple with the fields ['column', 'aggfunc'] to make it clearer what the arguments are. As usual, the aggregation can be a callable or a string alias.
pandas: powerful Python data analysis toolkit, Release 1.1.1

```
<table>
<thead>
<tr>
<th></th>
<th>9.1</th>
<th>9.5</th>
<th>8.90</th>
</tr>
</thead>
<tbody>
<tr>
<td>cat</td>
<td>6.0</td>
<td>34.0</td>
<td>102.75</td>
</tr>
</tbody>
</table>
```

pandas.NamedAgg is just a namedtuple. Plain tuples are allowed as well.

```
In [87]: animals.groupby("kind").agg(
    ....:     min_height=('height', 'min'),
    ....:     max_height=('height', 'max'),
    ....:     average_weight=('weight', np.mean),
    ....:     )
Out[87]:
       min_height  max_height  average_weight
kind
   cat    9.1     9.5          8.90
   dog    6.0    34.0        102.75
```

If your desired output column names are not valid python keywords, construct a dictionary and unpack the keyword arguments

```
In [88]: animals.groupby("kind").agg(**{
    ....:     'total weight': pd.NamedAgg(column='weight', aggfunc=sum),
    ....:     })
Out[88]:
       total weight
kind
   cat        17.8
   dog        205.5
```

Additional keyword arguments are not passed through to the aggregation functions. Only pairs of (column, aggfunc) should be passed as **kwargs. If your aggregation functions requires additional arguments, partially apply them with functools.partial().

**Note:** For Python 3.5 and earlier, the order of **kwargs in a functions was not preserved. This means that the output column ordering would not be consistent. To ensure consistent ordering, the keys (and so output columns) will always be sorted for Python 3.5.

Named aggregation is also valid for Series groupby aggregations. In this case there’s no column selection, so the values are just the functions.

```
In [89]: animals.groupby("kind").height.agg(
    ....:     min_height='min',
    ....:     max_height='max',
    ....:     )
Out[89]:
       min_height  max_height
kind
   cat     9.1    9.5
   dog     6.0   34.0
```

2.16. Group by: split-apply-combine
Applying different functions to DataFrame columns

By passing a dict to `aggregate` you can apply a different aggregation to the columns of a DataFrame:

```python
In [90]: grouped.agg({'C': np.sum,
   ....:       'D': lambda x: np.std(x, ddof=1)})
   ....:
Out[90]:
    C    D
   A bar 0.392940 1.366330
      foo -1.796421 0.884785
```

The function names can also be strings. In order for a string to be valid it must be either implemented on GroupBy or available via dispatching:

```python
In [91]: grouped.agg({'C': 'sum', 'D': 'std'})
Out[91]:
    C    D
   A bar 0.392940 1.366330
      foo -1.796421 0.884785
```

Cython-optimized aggregation functions

Some common aggregations, currently only `sum`, `mean`, `std`, and `sem`, have optimized Cython implementations:

```python
In [92]: df.groupby('A').sum()
Out[92]:
   C    D
  A bar 0.392940 1.732707
     foo -1.796421 2.824590

In [93]: df.groupby(['A', 'B']).mean()
Out[93]:
   C    D
  A B
bar one 0.254161 1.511763
     three 0.215897 -0.990582
     two -0.077118 1.211526
foo one -0.491888 0.807291
     three -0.862495 0.024580
     two 0.024925 0.592714
```

Of course `sum` and `mean` are implemented on pandas objects, so the above code would work even without the special versions via dispatching (see below).
2.16.5 Transformation

The `transform` method returns an object that is indexed the same (same size) as the one being grouped. The transform function must:

- Return a result that is either the same size as the group chunk or broadcastable to the size of the group chunk (e.g., a scalar, `grouped.transform(lambda x: x.iloc[-1])`).
- Operate column-by-column on the group chunk. The transform is applied to the first group chunk using `chunk.apply`.
- Not perform in-place operations on the group chunk. Group chunks should be treated as immutable, and changes to a group chunk may produce unexpected results. For example, when using `fillna`, `inplace` must be `False` (`grouped.transform(lambda x: x.fillna(inplace=False))`).
- (Optionally) operates on the entire group chunk. If this is supported, a fast path is used starting from the second chunk.

For example, suppose we wished to standardize the data within each group:

```
In [94]: index = pd.date_range('10/1/1999', periods=1100)
In [95]: ts = pd.Series(np.random.normal(0.5, 2, 1100), index)
In [96]: ts = ts.rolling(window=100, min_periods=100).mean().dropna()
In [97]: ts.head()
Out[97]:
2000-01-08  0.779333
2000-01-09  0.778852
2000-01-10  0.786476
2000-01-11  0.782797
2000-01-12  0.798110
Freq: D, dtype: float64
In [98]: ts.tail()
Out[98]:
2002-09-30  0.660294
2002-10-01  0.631095
2002-10-02  0.709213
2002-10-03  0.719369
2002-10-04  0.719369
Freq: D, dtype: float64
```

```python
transformed = (ts.groupby(lambda x: x.year)
               .transform(lambda x: (x - x.mean()) / x.std()))
```

We would expect the result to now have mean 0 and standard deviation 1 within each group, which we can easily check:

```
# Original Data
In [100]: grouped = ts.groupby(lambda x: x.year)
In [101]: grouped.mean()
Out[101]:
2000    0.442441
2001    0.526246
2002    0.459365
```

(continues on next page)
dtype: float64

In [102]: grouped.std()
Out[102]:
2000    0.131752
2001    0.210945
2002    0.128753
dtype: float64

# Transformed Data
In [103]: grouped_trans = transformed.groupby(lambda x: x.year)

In [104]: grouped_trans.mean()
Out[104]:
2000    1.168208e-15
2001    1.454544e-15
2002    1.726657e-15
dtype: float64

In [105]: grouped_trans.std()
Out[105]:
2000     1.0
2001     1.0
2002     1.0
dtype: float64

We can also visually compare the original and transformed data sets.

In [106]: compare = pd.DataFrame({'Original': ts, 'Transformed': transformed})

In [107]: compare.plot()
Out[107]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe293fba520>
Transformation functions that have lower dimension outputs are broadcast to match the shape of the input array.

```python
In [108]: ts.groupby(lambda x: x.year).transform(lambda x: x.max() - x.min())
```

```text
Out[108]:
2000-01-08  0.623893
2000-01-09  0.623893
2000-01-10  0.623893
2000-01-11  0.623893
2000-01-12  0.623893
...
2002-09-30  0.558275
2002-10-01  0.558275
2002-10-02  0.558275
2002-10-03  0.558275
2002-10-04  0.558275
Freq: D, Length: 1001, dtype: float64
```

Alternatively, the built-in methods could be used to produce the same outputs.

```python
In [109]: max = ts.groupby(lambda x: x.year).transform('max')
```

```python
In [110]: min = ts.groupby(lambda x: x.year).transform('min')
```

```python
In [111]: max - min
```

(continues on next page)
Another common data transform is to replace missing data with the group mean.

```python
In [112]: data_df
Out[112]:
   A         B        C
0  1.539708 -1.166480  0.533026
1  1.302092 -0.505754   NaN
2 -0.371983  1.104803 -1.161657
3 -1.309622  1.118697 -1.161657
4 -1.924296  0.396437  0.812436
   ...     ...      ...
995 -0.093110  0.683847 -0.774753
996 -0.185043  1.438572   NaN
997 -0.394469 -0.642343  0.011374
998 -1.174126  1.857148   NaN
999  0.234564  0.517098  0.393534
```

```python
In [113]: countries = np.array(['US', 'UK', 'GR', 'JP'])
In [114]: key = countries[np.random.randint(0, 4, 1000)]
In [115]: grouped = data_df.groupby(key)
```

We can verify that the group means have not changed in the transformed data and that the transformed data contains no NAs.

```python
In [116]: grouped.mean()  # original group means
Out[116]:
   A         B        C
GR  209  217  189
JP  240  255  217
UK  216  231  193
US  239  250  217
```

```python
In [117]: transformed = grouped.transform(lambda x: x.fillna(x.mean()))
```

```python
In [118]: grouped_trans = transformed.groupby(key)
In [119]: grouped.mean()  # original group means
Out[119]:
   A         B        C
GR  209  217  189
JP  240  255  217
UK  216  231  193
US  239  250  217
```
A   B   C
GR -0.098371 -0.015420  0.068053
JP  0.069025  0.023100 -0.077324
UK  0.034069 -0.052580 -0.116525
US  0.058664 -0.020399  0.028603

In [120]: grouped_trans.mean()  # transformation did not change group means
Out[120]:

A   B   C
GR -0.098371 -0.015420  0.068053
JP  0.069025  0.023100 -0.077324
UK  0.034069 -0.052580 -0.116525
US  0.058664 -0.020399  0.028603

In [121]: grouped.count()  # original has some missing data points
Out[121]:

A   B   C
GR 209 217 189
JP 240 255 217
UK 216 231 193
US 239 250 217

In [122]: grouped_trans.count()  # counts after transformation
Out[122]:

A   B   C
GR 228 228 228
JP 267 267 267
UK 247 247 247
US 258 258 258

In [123]: grouped_trans.size()  # Verify non-NA count equals group size
Out[123]:

GR   228
JP   267
UK   247
US   258
dtype: int64

Note: Some functions will automatically transform the input when applied to a GroupBy object, but returning an object of the same shape as the original. Passing as_index=False will not affect these transformation methods.

For example: fillna, ffill, bfill, shift..

In [124]: grouped.ffill()
Out[124]:

A    B    C
0 1.539708 -1.166480  0.533026
1 1.302092 -0.505754  0.533026
2 -0.371983 1.104803 -0.651520
3 -1.309622 1.118697 -1.161657
4 -1.924296 0.396437  0.812436
...  ...  ...  ...
995 -0.093110 0.683847 -0.774753
996 -0.185043 1.438572 -0.774753
997 -0.394469 -0.642343  0.011374
998 -1.174126 1.857148 -0.774753

(continues on next page)
Window and resample operations

It is possible to use `resample()`, `expanding()` and `rolling()` as methods on groupbys. The example below will apply the `rolling()` method on the samples of the column B based on the groups of column A.

```python
                        'B': np.arange(20)})
In [126]: df_re.groupby('A').rolling(4).B.mean()
```

```
Out[126]:
    A  B
0  1  0
1  1  1
2  1  2
3  1  3
4  1  4
...  ...  ...
15  5  15
16  5  16
17  5  17
18  5  18
19  5  19
```

```
[20 rows x 2 columns]
```

The `expanding()` method will accumulate a given operation (`sum()` in the example) for all the members of each particular group.

```python
In [127]: df_re.groupby('A').expanding().sum()
```

```
Out[127]:
     A     B
  A  B
0  1  NaN
1  1  NaN
2  2  NaN
3  1  1.5
4  1  2.5
...  ...  ...
5  15  13.5
16  14.5
17  15.5
18  16.5
19  17.5
Name: B, Length: 20, dtype: float64
```
Suppose you want to use the `resample()` method to get a daily frequency in each group of your dataframe and wish to complete the missing values with the `ffill()` method.

```python
In [129]: df_re = pd.DataFrame({'date': pd.date_range(start='2016-01-01', periods=4, freq='W'),
                        'group': [1, 1, 2, 2],
                        'val': [5, 6, 7, 8]}).set_index('date')

In [130]: df_re.groupby('group').resample('1D').ffill()
```

```
<table>
<thead>
<tr>
<th>group</th>
<th>date</th>
<th>val</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2016-01-03</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>2016-01-04</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>2016-01-05</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>2016-01-06</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>2016-01-07</td>
<td>5</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>2</td>
<td>2016-01-20</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>2016-01-21</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>2016-01-22</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>2016-01-23</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>2016-01-24</td>
<td>8</td>
</tr>
</tbody>
</table>
```

[16 rows x 2 columns]
2.16.6 Filtration

The `filter` method returns a subset of the original object. Suppose we want to take only elements that belong to groups with a group sum greater than 2.

```
In [132]: sf = pd.Series([1, 1, 2, 3, 3, 3])
In [133]: sf.groupby(sf).filter(lambda x: x.sum() > 2)
Out[133]:
      3
3  3
4  3
5  3
dtype: int64
```

The argument of `filter` must be a function that, applied to the group as a whole, returns `True` or `False`.

Another useful operation is filtering out elements that belong to groups with only a couple members.

```
In [134]: dff = pd.DataFrame({'A': np.arange(8), 'B': list('aabbbbcc'))
In [135]: dff.groupby('B').filter(lambda x: len(x) > 2)
Out[135]:
     A B
2  2.0 b
3  3.0 b
4  4.0 b
5  5.0 b
```

Alternatively, instead of dropping the offending groups, we can return a like-indexed objects where the groups that do not pass the filter are filled with NaNs.

```
In [136]: dff.groupby('B').filter(lambda x: len(x) > 2, dropna=False)
Out[136]:
     A B
0   NaN NaN
1   NaN NaN
2  2.0 b
3  3.0 b
4  4.0 b
5  5.0 b
6   NaN NaN
7   NaN NaN
```

For DataFrames with multiple columns, filters should explicitly specify a column as the filter criterion.

```
In [137]: dff['C'] = np.arange(8)
In [138]: dff.groupby('B').filter(lambda x: len(x['C']) > 2)
Out[138]:
      A  B  C
2  2.0  b  2
3  3.0  b  3
4  4.0  b  4
5  5.0  b  5
```

**Note:** Some functions when applied to a groupby object will act as a `filter` on the input, returning a reduced shape of the original (and potentially eliminating groups), but with the index unchanged. Passing `as_index=False` will not
affect these transformation methods.

For example: `head`, `tail`.

```python
In [139]: dff.groupby('B').head(2)
Out[139]:
   A  B  C
0  0  a  0
1  1  a  1
2  2  b  2
3  3  b  3
6  6  c  6
7  7  c  7
```

### 2.16.7 Dispatching to instance methods

When doing an aggregation or transformation, you might just want to call an instance method on each data group. This is pretty easy to do by passing lambda functions:

```python
In [140]: grouped = df.groupby('A')
In [141]: grouped.agg(lambda x: x.std())
Out[141]:
       C      D
A
bar  0.181231  1.366330
foo   0.912265  0.884785
```

But, it’s rather verbose and can be untidy if you need to pass additional arguments. Using a bit of metaprogramming cleverness, GroupBy now has the ability to “dispatch” method calls to the groups:

```python
In [142]: grouped.std()
Out[142]:
       C      D
A
bar  0.181231  1.366330
foo   0.912265  0.884785
```

What is actually happening here is that a function wrapper is being generated. When invoked, it takes any passed arguments and invokes the function with any arguments on each group (in the above example, the `std` function). The results are then combined together much in the style of `agg` and `transform` (it actually uses `apply` to infer the gluing, documented next). This enables some operations to be carried out rather succinctly:

```python
In [143]: tsdf = pd.DataFrame(np.random.randn(1000, 3),
   index=pd.date_range('1/1/2000', periods=1000),
   columns=['A', 'B', 'C'])
   ...
In [144]: tsdf.iloc[::2] = np.nan
In [145]: grouped = tsdf.groupby(lambda x: x.year)
In [146]: grouped.fillna(method='pad')
Out[146]:
       A      B      C
0  bar  0.181231  1.366330
   foo   0.912265  0.884785
```

(continues on next page)
In this example, we chopped the collection of time series into yearly chunks then independently called `fillna` on the groups.

The `nlargest` and `nsmallest` methods work on Series style groupbys:

```python
In [147]: s = pd.Series([9, 8, 7, 5, 19, 1, 4.2, 3.3])
In [148]: g = pd.Series(list('abababab'))
In [149]: gb = s.groupby(g)

In [150]: gb.nlargest(3)
Out[150]:
   A  B  C
a  4  19
  0  9
  2  7
b 1  8
  3  5
  7  3
dtype: float64

In [151]: gb.nsmallest(3)
Out[151]:
   A  B  C
a  6  4.2
  2  7
  0  9
b  5  1.0
  7  3.3
  3  5.0
dtype: float64
```

### 2.16.8 Flexible apply

Some operations on the grouped data might not fit into either the aggregate or transform categories. Or, you may simply want GroupBy to infer how to combine the results. For these, use the `apply` function, which can be substituted for both `aggregate` and `transform` in many standard use cases. However, `apply` can handle some exceptional use cases, for example:

```python
In [152]: df
Out[152]:
   A  B  C  D
0  A  B  C  D
1  A  B  C  D
2  A  B  C  D
```
0 foo one -0.575247 1.346061
1 bar one 0.254161 1.511763
2 foo two -1.143704 1.627081
3 bar three 0.215897 -0.990582
4 foo two 1.193555 -0.441652
5 bar two -0.077118 1.211526
6 foo one -0.408530 0.268520
7 foo three -0.862495 0.024580

In [153]: grouped = df.groupby('A')

# could also just call .describe()
In [154]: grouped['C'].apply(lambda x: x.describe())
Out[154]:
     A
bar  count   3.000000
       mean  0.130980
       std  0.181231
       min -0.077118
       25%  0.069390
       ...
foo  min -1.143704
       25% -0.862495
       50% -0.575247
       75% -0.408530
       max  1.193555
Name: C, Length: 16, dtype: float64

The dimension of the returned result can also change:

In [155]: grouped = df.groupby('A')['C']

In [156]: def f(group):
       ....:     return pd.DataFrame({'original': group,
       ....:                        'demeaned': group - group.mean()})
       ....:

In [157]: grouped.apply(f)
Out[157]:
   original  demeaned
   0 -0.575247 -0.215962
   1  0.254161  0.123181
   2 -1.143704 -0.784420
   3  0.215897  0.084917
   4  1.193555  1.552839
   5 -0.077118 -0.208098
   6 -0.408530 -0.049245
   7 -0.862495 -0.053211

apply on a Series can operate on a returned value from the applied function, that is itself a series, and possibly upcast the result to a DataFrame:

In [158]: def f(x):
       ....:     return pd.Series([x, x ** 2], index=['x', 'x^2'])
       ....:
In [159]: s = pd.Series(np.random.rand(5))

In [160]: s
Out[160]:
0   0.321438
1   0.493496
2   0.139505
3   0.910103
4   0.194158
dtype: float64

In [161]: s.apply(f)
Out[161]:
x   x^2
0  0.321438  0.103323
1  0.493496  0.243538
2  0.139505  0.019462
3  0.910103  0.828287
4  0.194158  0.037697

declare: apply can act as a reducer, transformer, or filter function, depending on exactly what is passed to it. So depending on the path taken, and exactly what you are grouping. Thus the grouped columns(s) may be included in the output as well as set the indices.

2.16.9 Numba Accelerated Routines

New in version 1.1.

If Numba is installed as an optional dependency, the transform and aggregate methods support engine='numba' and engine_kwargs arguments. The engine_kwargs argument is a dictionary of keyword arguments that will be passed into the numba.jit decorator. These keyword arguments will be applied to the passed function. Currently only nogil, nopython, and parallel are supported, and their default values are set to False, True and False respectively.

The function signature must start with values, index exactly as the data belonging to each group will be passed into values, and the group index will be passed into index.

Warning: When using engine='numba', there will be no “fall back” behavior internally. The group data and group index will be passed as numpy arrays to the JITed user defined function, and no alternative execution attempts will be tried.

Note: In terms of performance, the first time a function is run using the Numba engine will be slow as Numba will have some function compilation overhead. However, the compiled functions are cached, and subsequent calls will be fast. In general, the Numba engine is performant with a larger amount of data points (e.g. 1+ million).

In [1]: N = 10 ** 3

In [2]: data = (0: [str(i) for i in range(100)] * N, 1: list(range(100)) * N)
In [3]: df = pd.DataFrame(data, columns=[0, 1])

In [4]: def f_numba(values, index):
   ...:     total = 0
   ...:     for i, value in enumerate(values):
   ...:         if i % 2:
   ...:             total += value + 5
   ...:         else:
   ...:             total += value * 2
   ...:     return total

In [5]: def f_cython(values):
   ...:     total = 0
   ...:     for i, value in enumerate(values):
   ...:         if i % 2:
   ...:             total += value + 5
   ...:         else:
   ...:             total += value * 2
   ...:     return total

In [6]: groupby = df.groupby(0)
# Run the first time, compilation time will affect performance
In [7]: %timeit -r 1 -n 1 groupby.aggregate(f_numba, engine='numba')  # noqa: E225
2.14 s ± 0 ns per loop (mean ± std. dev. of 1 run, 1 loop each)
# Function is cached and performance will improve
In [8]: %timeit groupby.aggregate(f_numba, engine='numba')
4.93 ms ± 32.3 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)
In [9]: %timeit groupby.aggregate(f_cython, engine='cython')
18.6 ms ± 84.8 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)

2.16.10 Other useful features

Automatic exclusion of “nuisance” columns

Again consider the example DataFrame we’ve been looking at:

In [162]: df
Out[162]:
    A     B     C       D
   0 foo  one  -0.575247  1.346061
   1 bar  one   0.254161  1.511763
   2 foo  two  -1.143704  1.627081
   3 bar three  0.215897 -0.990582
   4 foo  two   1.193555 -0.441652
   5 bar  two  -0.077118  1.211526
   6 foo  one  -0.408530  0.268520
   7 foo three  -0.862495  0.024580

Suppose we wish to compute the standard deviation grouped by the A column. There is a slight problem, namely that we don’t care about the data in column B. We refer to this as a “nuisance” column. If the passed aggregation function can’t be applied to some columns, the troublesome columns will be (silently) dropped. Thus, this does not pose any problems:

2.16. Group by: split-apply-combine
In [163]: df.groupby('A').std()
Out[163]:
      C    D
A  bar  0.181231  1.366330
   foo  0.912265  0.884785

Note that `df.groupby('A').colname.std()` is more efficient than `df.groupby('A').std()`. `colname`, so if the result of an aggregation function is only interesting over one column (here `colname`), it may be filtered before applying the aggregation function.

Note: Any object column, also if it contains numerical values such as Decimal objects, is considered as a “nuisance” columns. They are excluded from aggregate functions automatically in groupby.

If you do wish to include decimal or object columns in an aggregation with other non-nuisance data types, you must do so explicitly.

In [164]: from decimal import Decimal
In [165]: df_dec = pd.DataFrame(
    ..........:     {'id': [1, 2, 1, 2],
    ..........:         'int_column': [1, 2, 3, 4],
    ..........:         'dec_column': [Decimal('0.50'), Decimal('0.15'),
    ..........:                         Decimal('0.25'), Decimal('0.40')]
    ..........:     )
# Decimal columns can be sum'd explicitly by themselves...
In [166]: df_dec.groupby(['id'])[['dec_column']].sum()
Out[166]:
       dec_column
    id
1   0.75
2   0.55

# ...but cannot be combined with standard data types or they will be excluded
In [167]: df_dec.groupby(['id'])[['int_column', 'dec_column']].sum()
Out[167]:
   int_column
    id
1   4
2   6

# Use .agg function to aggregate over standard and “nuisance” data types
# at the same time
In [168]: df_dec.groupby(['id']).agg({'int_column': 'sum', 'dec_column': 'sum'})
Out[168]:
    int_column  dec_column
    id
1   4          0.75
2   6          0.55
Handling of (un)observed Categorical values

When using a `Categorical` grouper (as a single grouper, or as part of multiple groupers), the `observed` keyword controls whether to return a cartesian product of all possible groupers values (observed=False) or only those that are observed groupers (observed=True).

Show all values:

```
In [169]: pd.Series([1, 1, 1]).groupby(pd.Categorical(['a', 'a', 'a'], categories=['a', 'b']), observed=False).count()
Out[169]:
    a  3
   b  0
dtype: int64
```

Show only the observed values:

```
In [170]: pd.Series([1, 1, 1]).groupby(pd.Categorical(['a', 'a', 'a'], categories=['a', 'b']), observed=True).count()
Out[170]:
    a  3
dtype: int64
```

The returned dtype of the grouped will always include all of the categories that were grouped.

```
in [171]: s = pd.Series([1, 1, 1]).groupby(pd.Categorical(['a', 'a', 'a'], categories=['a', 'b']), observed=False).count()
in [172]: s.index.dtype
Out[172]: CategoricalDtype(categories=['a', 'b'], ordered=False)
```

NA and NaT group handling

If there are any NaN or NaT values in the grouping key, these will be automatically excluded. In other words, there will never be an “NA group” or “NaT group”. This was not the case in older versions of pandas, but users were generally discarding the NA group anyway (and supporting it was an implementation headache).

Grouping with ordered factors

Categorical variables represented as instance of pandas’s `Categorical` class can be used as group keys. If so, the order of the levels will be preserved:

```
in [173]: data = pd.Series(np.random.randn(100))
in [174]: factor = pd.qcut(data, [0, .25, .5, .75, 1.])
in [175]: data.groupby(factor).mean()
Out[175]:
   (-2.645, -0.523]    -1.362896
```

(continues on next page)
Grouping with a grouper specification

You may need to specify a bit more data to properly group. You can use the `pd.Grouper` to provide this local control.

```python
In [176]: import datetime

In [177]: df = pd.DataFrame({'Branch': 'A A A A A A A B'.split(),
                         'Buyer': 'Carl Mark Carl Carl Joe Joe Joe Carl'.split(),
                         'Quantity': [1, 3, 5, 1, 8, 1, 9, 3],
                         'Date': [
                                     datetime.datetime(2013, 1, 1, 13, 0),
                                     datetime.datetime(2013, 1, 1, 13, 5),
                                     datetime.datetime(2013, 10, 1, 20, 0),
                                     datetime.datetime(2013, 10, 2, 10, 0),
                                     datetime.datetime(2013, 10, 1, 20, 0),
                                     datetime.datetime(2013, 10, 2, 10, 0),
                                     datetime.datetime(2013, 10, 1, 20, 0),
                                     datetime.datetime(2013, 12, 2, 12, 0),
                                     datetime.datetime(2013, 12, 2, 14, 0)]})

In [178]: df
Out[178]:
   Branch Buyer      Quantity     Date
0     A   Carl         1 2013-01-01 13:00:00
1     A   Mark         3 2013-01-01 13:05:00
2     A   Carl         5 2013-10-01 20:00:00
3     A   Carl         1 2013-10-02 10:00:00
4     A   Joe          8 2013-10-01 20:00:00
5     A   Joe          1 2013-10-02 10:00:00
6     A   Joe          9 2013-12-02 12:00:00
7     B   Carl         3 2013-12-02 14:00:00

Groupby a specific column with the desired frequency. This is like resampling.

```python
In [179]: df.groupby([pd.Grouper(freq='1M', key='Date'), 'Buyer']).sum()
Out[179]:
          Quantity
Date Buyer
2013-01-31 Carl   1
                Mark   3
2013-10-31 Carl   6
                Joe   9
2013-12-31 Carl   3
                Joe   9
```

You have an ambiguous specification in that you have a named index and a column that could be potential groupers.
In [180]: df = df.set_index('Date')

In [181]: df['Date'] = df.index + pd.offsets.MonthEnd(2)

In [182]: df.groupby([pd.Grouper(freq='6M', key='Date'), 'Buyer']).sum()

Out[182]:

<table>
<thead>
<tr>
<th>Date</th>
<th>Buyer</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013-02-28</td>
<td>Carl</td>
</tr>
<tr>
<td></td>
<td>Mark</td>
</tr>
<tr>
<td>2014-02-28</td>
<td>Carl</td>
</tr>
<tr>
<td></td>
<td>Joe</td>
</tr>
</tbody>
</table>

In [183]: df.groupby([pd.Grouper(freq='6M', level='Date'), 'Buyer']).sum()

Out[183]:

<table>
<thead>
<tr>
<th>Date</th>
<th>Buyer</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013-01-31</td>
<td>Carl</td>
</tr>
<tr>
<td></td>
<td>Mark</td>
</tr>
<tr>
<td>2014-01-31</td>
<td>Carl</td>
</tr>
<tr>
<td></td>
<td>Joe</td>
</tr>
</tbody>
</table>

Taking the first rows of each group

Just like for a DataFrame or Series you can call head and tail on a groupby:

In [184]: df = pd.DataFrame([[1, 2], [1, 4], [5, 6]], columns=['A', 'B'])

In [185]: df

Out[185]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>6</td>
</tr>
</tbody>
</table>

In [186]: g = df.groupby('A')

In [187]: g.head(1)

Out[187]:

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

In [188]: g.tail(1)

Out[188]:

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>5</td>
</tr>
</tbody>
</table>
Taking the nth row of each group

To select from a DataFrame or Series the nth item, use `nth()`. This is a reduction method, and will return a single row (or no row) per group if you pass an int for n:

```
In [189]: df = pd.DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=['A', 'B'])
In [190]: g = df.groupby('A')
In [191]: g.nth(0)
Out[191]:
   A   B
0  1  NaN
5  6.0
In [192]: g.nth(-1)
Out[192]:
   A   B
0  1  4.0
5  6.0
In [193]: g.nth(1)
Out[193]:
   A   B
0  1  4.0
```

If you want to select the nth not-null item, use the `dropna` kwarg. For a DataFrame this should be either 'any' or 'all' just like you would pass to `dropna`:

```
# nth(0) is the same as g.first()
In [194]: g.nth(0, dropna='any')
Out[194]:
   A   B
0  1  4.0
5  6.0
In [195]: g.first()
Out[195]:
   A   B
0  1  4.0
5  6.0
# nth(-1) is the same as g.last()
In [196]: g.nth(-1, dropna='any')  # NaNs denote group exhausted when using dropna
Out[196]:
   A   B
0  1  4.0
5  6.0
In [197]: g.last()
Out[197]:
   B
```

(continues on next page)
As with other methods, passing `as_index=False`, will achieve a filtration, which returns the grouped row.

```python
In [199]: df = pd.DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=['A', 'B'])
In [200]: g = df.groupby('A', as_index=False)
In [201]: g.nth(0)
Out[201]:
   A  B
0 1  NaN
2 5  6.0
```

You can also select multiple rows from each group by specifying multiple nth values as a list of ints.

```python
In [203]: business_dates = pd.date_range(start='4/1/2014', end='6/30/2014', freq='B')
In [204]: df = pd.DataFrame(1, index=business_dates, columns=['a', 'b'])

# get the first, 4th, and last date index for each month
In [205]: df.groupby([df.index.year, df.index.month]).nth([0, 3, -1])
Out[205]:
   a  b
2014 4 1 1
    4 1 1
    5 1 1
    5 1 1
    6 1 1
    6 1 1
```
Enumerate group items

To see the order in which each row appears within its group, use the `cumcount` method:

```
In [206]: dfg = pd.DataFrame(list('aaabba'), columns=['A'])
In [207]: dfg
Out[207]:
   A
0  a
1  a
2  a
3  b
4  b
5  a
In [208]: dfg.groupby('A').cumcount()
Out[208]:
   0  0
   1  1
   2  2
   3  0
   4  1
   5  3
dtype: int64
In [209]: dfg.groupby('A').cumcount(ascending=False)
Out[209]:
   0  3
   1  2
   2  1
   3  1
   4  0
   5  0
dtype: int64
```

Enumerate groups

To see the ordering of the groups (as opposed to the order of rows within a group given by `cumcount`) you can use `ngroup()`.

Note that the numbers given to the groups match the order in which the groups would be seen when iterating over the groupby object, not the order they are first observed.

```
In [210]: dfg = pd.DataFrame(list('aaabba'), columns=['A'])
In [211]: dfg
Out[211]:
   A
0  a
1  a
2  a
3  b
4  b
5  a
```
In [212]: dfg.groupby('A').ngroup()
Out[212]:
0 0
1 0
2 0
3 1
4 1
5 0
dtype: int64

In [213]: dfg.groupby('A').ngroup(ascending=False)
Out[213]:
0 1
1 1
2 1
3 0
4 0
5 1
dtype: int64

Plotting

Groupby also works with some plotting methods. For example, suppose we suspect that some features in a DataFrame may differ by group, in this case, the values in column 1 where the group is “B” are 3 higher on average.

In [214]: np.random.seed(1234)
In [215]: df = pd.DataFrame(np.random.randn(50, 2))
In [216]: df['g'] = np.random.choice(['A', 'B'], size=50)
In [217]: df.loc[df['g'] == 'B', 1] += 3

We can easily visualize this with a boxplot:

In [218]: df.groupby('g').boxplot()
The result of calling `boxplot` is a dictionary whose keys are the values of our grouping column `g` (“A” and “B”). The values of the resulting dictionary can be controlled by the `return_type` keyword of `boxplot`. See the visualization documentation for more.

**Warning:** For historical reasons, `df.groupby("g").boxplot()` is not equivalent to `df.boxplot(by="g")`. See here for an explanation.

### Piping function calls

Similar to the functionality provided by `DataFrame` and `Series`, functions that take `GroupBy` objects can be chained together using a `pipe` method to allow for a cleaner, more readable syntax. To read about `.pipe` in general terms, see here.

Combining `.groupby` and `.pipe` is often useful when you need to reuse GroupBy objects.

As an example, imagine having a DataFrame with columns for stores, products, revenue and quantity sold. We’d like to do a groupwise calculation of `prices` (i.e. revenue/quantity) per store and per product. We could do this in a multi-step operation, but expressing it in terms of piping can make the code more readable. First we set the data:

```python
In [219]: n = 1000
In [220]: df = pd.DataFrame({'Store': np.random.choice(['Store_1', 'Store_2'], n),
```
'Product': np.random.choice(['Product_1', 'Product_2'], n),
'Revenue': (np.random.random(n) * 50 + 10).round(2),
'Quantity': np.random.randint(1, 10, size=n))

In [221]: df.head(2)
Out[221]:
<table>
<thead>
<tr>
<th>Store</th>
<th>Product</th>
<th>Revenue</th>
<th>Quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Store_2</td>
<td>Product_1</td>
<td>26.12</td>
<td>1</td>
</tr>
<tr>
<td>Store_2</td>
<td>Product_1</td>
<td>28.86</td>
<td>1</td>
</tr>
</tbody>
</table>

Now, to find prices per store/product, we can simply do:

In [222]: (df.groupby(['Store', 'Product'])
     ....: .pipe(lambda grp: grp.Revenue.sum() / grp.Quantity.sum())
     ....: .unstack().round(2))
Out[222]:
<table>
<thead>
<tr>
<th>Product</th>
<th>Product_1</th>
<th>Product_2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Store</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Store_1</td>
<td>6.82</td>
<td>7.05</td>
</tr>
<tr>
<td>Store_2</td>
<td>6.30</td>
<td>6.64</td>
</tr>
</tbody>
</table>

Piping can also be expressive when you want to deliver a grouped object to some arbitrary function, for example:

In [223]: def mean(groupby):
     ....:     return groupby.mean()
     ....: In [224]: df.groupby(['Store', 'Product']).pipe(mean)
Out[224]:
<table>
<thead>
<tr>
<th>Revenue</th>
<th>Quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Store</td>
<td>Product</td>
</tr>
<tr>
<td>Product_1</td>
<td>34.62</td>
</tr>
<tr>
<td>Store_2</td>
<td>35.48</td>
</tr>
<tr>
<td>Product_1</td>
<td>32.97</td>
</tr>
<tr>
<td>Store_2</td>
<td>34.68</td>
</tr>
</tbody>
</table>

where `mean` takes a GroupBy object and finds the mean of the Revenue and Quantity columns respectively for each Store-Product combination. The `mean` function can be any function that takes in a GroupBy object; the `.pipe` will pass the GroupBy object as a parameter into the function you specify.

### 2.16.11 Examples

#### Regrouping by factor

Regroup columns of a DataFrame according to their sum, and sum the aggregated ones.

In [225]: df = pd.DataFrame({'a': [1, 0, 0], 'b': [0, 1, 0],
     ....:     'c': [1, 0, 0], 'd': [2, 3, 4]})
Out[225]:
<table>
<thead>
<tr>
<th>c</th>
<th>d</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>0</td>
<td>4</td>
</tr>
</tbody>
</table>
Multi-column factorization

By using `ngroup()`, we can extract information about the groups in a way similar to `factorize()` (as described further in the reshaping API) but which applies naturally to multiple columns of mixed type and different sources. This can be useful as an intermediate categorical-like step in processing, when the relationships between the group rows are more important than their content, or as input to an algorithm which only accepts the integer encoding. (For more information about support in pandas for full categorical data, see the Categorical introduction and the API documentation.)

In [227]: df.groupby(df.sum(), axis=1).sum()
Out[227]:
   1 9
   0 2 2
   1 1 3
   2 0 4

In [228]: df = pd.DataFrame({"A": [1, 1, 2, 3, 2], "B": list("aaaba")})
In [229]: df
Out[229]:
   A B
  0 1 a
  1 1 a
  2 2 a
  3 3 b
  4 2 a

In [230]: df.groupby(["A", "B"]).ngroup()
Out[230]:
   0 0
   1 0
   2 1
   3 2
   4 1
dtype: int64

In [231]: df.groupby(["A", [0, 0, 0, 1, 1]]).ngroup()
Out[231]:
   0 0
   1 0
   2 1
   3 3
   4 2
dtype: int64
Groupby by indexer to ‘resample’ data

Resampling produces new hypothetical samples (resamples) from already existing observed data or from a model that generates data. These new samples are similar to the pre-existing samples.

In order to resample to work on indices that are non-datetimelike, the following procedure can be utilized.

In the following examples, \texttt{df.index // 5} returns a binary array which is used to determine what gets selected for the groupby operation.

\textbf{Note:} The below example shows how we can downsample by consolidation of samples into fewer samples. Here by using \texttt{df.index // 5}, we are aggregating the samples in bins. By applying \texttt{std()} function, we aggregate the information contained in many samples into a small subset of values which is their standard deviation thereby reducing the number of samples.

```python
In [232]: df = pd.DataFrame(np.random.randn(10, 2))

In [233]: df
Out[233]:
    0   1
0  0.793893  0.321153
1  0.342250  1.618906
2 -0.975807  1.918201
3 -0.810847 -1.405919
4 -1.977759  0.461659
5  0.730057 -1.316938
6  0.751328  0.528290
7  0.505895 -1.081009
8 -0.257759 -1.701948
9 -1.006349  0.020208

In [234]: df.index // 5
Out[234]: Int64Index([0, 0, 0, 0, 0, 1, 1, 1, 1, 1], dtype='int64')

In [235]: df.groupby(df.index // 5).std()
Out[235]:
    0   1
0  0.823647  1.312912
1  0.760109  0.942941

Returning a Series to propagate names

Group DataFrame columns, compute a set of metrics and return a named Series. The Series name is used as the name for the column index. This is especially useful in conjunction with reshaping operations such as stacking in which the column index name will be used as the name of the inserted column:

```python
In [236]: def compute_metrics(x):
                result = {'b_sum': x['b'].sum(), 'c_mean': x['c'].mean()}
                return pd.Series(result, name='metrics')

In [237]: compute_metrics(x)
```

(continues on next page)
In [238]: result = df.groupby('a').apply(compute_metrics)

In [239]: result
Out[239]:
metrics  b_sum  c_mean
   a
  0  2.0   0.5
  1  2.0   0.5
  2  2.0   0.5

In [240]: result.stack()
Out[240]:
a  metrics
0  b_sum  2.0
   c_mean  0.5
1  b_sum  2.0
   c_mean  0.5
2  b_sum  2.0
   c_mean  0.5
dtype: float64

2.17 Time series / date functionality

pandas contains extensive capabilities and features for working with time series data for all domains. Using the NumPy datetime64 and timedelta64 dtypes, pandas has consolidated a large number of features from other Python libraries like scikits.timeseries as well as created a tremendous amount of new functionality for manipulating time series data.

For example, pandas supports:

Parsing time series information from various sources and formats

In [1]: import datetime
In [2]: dti = pd.to_datetime(['1/1/2018', np.datetime64('2018-01-01'),
                        datetime.datetime(2018, 1, 1))
In [3]: dti
                      dtype='datetime64[ns]', freq=None)

Generate sequences of fixed-frequency dates and time spans

In [4]: dti = pd.date_range('2018-01-01', periods=3, freq='H')
In [5]: dti
Out[5]: DatetimeIndex(['2018-01-01 00:00:00', '2018-01-01 01:00:00',
                      '2018-01-01 02:00:00'],
                      dtype='datetime64[ns]', freq='H')

Manipulating and converting date times with timezone information
In [6]: dti = dti.tz_localize('UTC')

In [7]: dti
Out[7]:
DatetimeIndex(['2018-01-01 00:00:00+00:00', '2018-01-01 01:00:00+00:00',
              '2018-01-01 02:00:00+00:00'],
       dtype='datetime64[ns, UTC]', freq='H')

In [8]: dti.tz_convert('US/Pacific')
Out[8]:
DatetimeIndex(['2017-12-31 16:00:00-08:00', '2017-12-31 17:00:00-08:00',
              '2017-12-31 18:00:00-08:00'],
       dtype='datetime64[ns, US/Pacific]', freq='H')

Resampling or converting a time series to a particular frequency

In [9]: idx = pd.date_range('2018-01-01', periods=5, freq='H')

In [10]: ts = pd.Series(range(len(idx)), index=idx)

In [11]: ts
Out[11]:
2018-01-01 00:00:00    0
2018-01-01 01:00:00    1
2018-01-01 02:00:00    2
2018-01-01 03:00:00    3
2018-01-01 04:00:00    4
Freq: H, dtype: int64

In [12]: ts.resample('2H').mean()
Out[12]:
2018-01-01 00:00:00  0.5
2018-01-01 02:00:00  2.5
2018-01-01 04:00:00  4.0
Freq: 2H, dtype: float64

Performing date and time arithmetic with absolute or relative time increments

In [13]: friday = pd.Timestamp('2018-01-05')

In [14]: friday.day_name()
Out[14]: 'Friday'

# Add 1 day
In [15]: saturday = friday + pd.Timedelta('1 day')

In [16]: saturday.day_name()
Out[16]: 'Saturday'

# Add 1 business day (Friday --> Monday)
In [17]: monday = friday + pd.offsets.BDay()

In [18]: monday.day_name()
Out[18]: 'Monday'

pandas provides a relatively compact and self-contained set of tools for performing the above tasks and more.

2.17. Time series / date functionality
2.17.1 Overview

pandas captures 4 general time related concepts:

1. Date times: A specific date and time with timezone support. Similar to `datetime.datetime` from the standard library.
2. Time deltas: An absolute time duration. Similar to `datetime.timedelta` from the standard library.
3. Time spans: A span of time defined by a point in time and its associated frequency.
4. Date offsets: A relative time duration that respects calendar arithmetic. Similar to `dateutil.relativedelta.relativedelta` from the `dateutil` package.

<table>
<thead>
<tr>
<th>Concept</th>
<th>Scalar Class</th>
<th>Array Class</th>
<th>pandas Data Type</th>
<th>Primary Creation Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date times</td>
<td>Timestamp</td>
<td>DatetimeIndex</td>
<td>datetime64[ns]</td>
<td>to_datetime</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>or datetime64[ns, tz]</td>
<td>date_range</td>
</tr>
<tr>
<td>Time deltas</td>
<td>Timedelta</td>
<td>TimedeltaIndex</td>
<td>timedelta64[ns]</td>
<td>to_timedelta</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>TimedeltaIndex</td>
<td>timedelta_range</td>
</tr>
<tr>
<td>Time spans</td>
<td>Period</td>
<td>PeriodIndex</td>
<td>period[freq]</td>
<td>Period or period_range</td>
</tr>
<tr>
<td>Date offsets</td>
<td>DateOffset</td>
<td>None</td>
<td>None</td>
<td>DateOffset</td>
</tr>
</tbody>
</table>

For time series data, it’s conventional to represent the time component in the index of a `Series` or `DataFrame` so manipulations can be performed with respect to the time element.

```python
In [19]: pd.Series(range(3), index=pd.date_range('2000', freq='D', periods=3))
Out[19]:
2000-01-01 0
2000-01-02 1
2000-01-03 2
Freq: D, dtype: int64
```

However, `Series` and `DataFrame` can directly also support the time component as data itself.

```python
In [20]: pd.Series(pd.date_range('2000', freq='D', periods=3))
Out[20]:
0 2000-01-01
1 2000-01-02
2 2000-01-03
dtype: datetime64[ns]
```

`Series` and `DataFrame` have extended data type support and functionality for `datetime`, `timedelta`, and `Period` data when passed into those constructors. `DateOffset` data however will be stored as object data.

```python
In [21]: pd.Series(pd.period_range('1/1/2011', freq='M', periods=3))
Out[21]:
0 2011-01
1 2011-02
2 2011-03
dtype: period[M]
```

```python
In [22]: pd.Series([pd.DateOffset(1), pd.DateOffset(2)])
Out[22]:
0 <DateOffset>
```

(continues on next page)
Lastly, pandas represents null date times, time deltas, and time spans as NaT which is useful for representing missing or null date like values and behaves similar as np.nan does for float data.

```python
In [24]: pd.Timestamp(pd.NaT)
Out[24]: NaT

In [25]: pd.Timedelta(pd.NaT)
Out[25]: NaT

In [26]: pd.Period(pd.NaT)
Out[26]: NaT

# Equality acts as np.nan would
In [27]: pd.NaT == pd.NaT
Out[27]: False
```

### 2.17.2 Timestamps vs. time spans

Timestamped data is the most basic type of time series data that associates values with points in time. For pandas objects it means using the points in time.

```python
In [28]: pd.Timestamp(datetime.datetime(2012, 5, 1))
Out[28]: Timestamp('2012-05-01 00:00:00')

In [29]: pd.Timestamp('2012-05-01')
Out[29]: Timestamp('2012-05-01 00:00:00')

In [30]: pd.Timestamp(2012, 5, 1)
Out[30]: Timestamp('2012-05-01 00:00:00')
```

However, in many cases it is more natural to associate things like change variables with a time span instead. The span represented by Period can be specified explicitly, or inferred from datetime string format.

For example:

```python
In [31]: pd.Period('2011-01')
Out[31]: Period('2011-01', 'M')

In [32]: pd.Period('2012-05', freq='D')
Out[32]: Period('2012-05-01', 'D')
```

`Timestamp` and `Period` can serve as an index. Lists of `Timestamp` and `Period` are automatically coerced to `DatetimeIndex` and `PeriodIndex` respectively.
pandas allows you to capture both representations and convert between them. Under the hood, pandas represents timestamps using instances of Timestamp and sequences of timestamps using instances of DatetimeIndex. For regular time spans, pandas uses Period objects for scalar values and PeriodIndex for sequences of spans. Better support for irregular intervals with arbitrary start and end points are forth-coming in future releases.

### 2.17.3 Converting to timestamps

To convert a Series or list-like object of date-like objects e.g. strings, epochs, or a mixture, you can use the to_datetime function. When passed a Series, this returns a Series (with the same index), while a list-like is converted to a DatetimeIndex:

```python
In [43]: pd.to_datetime(pd.Series(['Jul 31, 2009', '2010-01-10', None]))
Out[43]:
0   2009-07-31
1 2010-01-10
2       NaT
dtype: datetime64[ns]
```
In [44]: pd.to_datetime(['2005/11/23', '2010.12.31'])
Out[44]: DatetimeIndex(['2005-11-23', '2010-12-31'], dtype='datetime64[ns]',
                     freq=None)

If you use dates which start with the day first (i.e. European style), you can pass the `dayfirst` flag:

In [45]: pd.to_datetime(['04-01-2012 10:00'], dayfirst=True)
Out[45]: DatetimeIndex(['2012-01-04 10:00:00'], dtype='datetime64[ns]', freq=None)

In [46]: pd.to_datetime(['14-01-2012', '01-14-2012'], dayfirst=True)
Out[46]: DatetimeIndex(['2012-01-14', '2012-01-14'], dtype='datetime64[ns]',
                        freq=None)

Warning: You see in the above example that `dayfirst` isn’t strict, so if a date can’t be parsed with the day being first it will be parsed as if `dayfirst` were False.

If you pass a single string to `to_datetime`, it returns a single `Timestamp`. `Timestamp` can also accept string input, but it doesn’t accept string parsing options like `dayfirst` or `format`, so use `to_datetime` if these are required.

In [47]: pd.to_datetime('2010/11/12')
Out[47]: Timestamp('2010-11-12 00:00:00')

In [48]: pd.Timestamp('2010/11/12')
Out[48]: Timestamp('2010-11-12 00:00:00')

You can also use the DatetimeIndex constructor directly:

In [49]: pd.DatetimeIndex(['2018-01-01', '2018-01-03', '2018-01-05'])
Out[49]: DatetimeIndex(['2018-01-01', '2018-01-03', '2018-01-05'], dtype='datetime64[ns]',
                       freq=None)

The string 'infer' can be passed in order to set the frequency of the index as the inferred frequency upon creation:

In [50]: pd.DatetimeIndex(['2018-01-01', '2018-01-03', '2018-01-05'], freq='infer')
Out[50]: DatetimeIndex(['2018-01-01', '2018-01-03', '2018-01-05'], dtype='datetime64[ns]',
                       freq='2D')

Providing a format argument

In addition to the required datetime string, a `format` argument can be passed to ensure specific parsing. This could also potentially speed up the conversion considerably.

In [51]: pd.to_datetime('2010/11/12', format='%Y/%m/%d')
Out[51]: Timestamp('2010-11-12 00:00:00')

In [52]: pd.to_datetime('12-11-2010 00:00', format='%d-%m-%Y %H:%M')
Out[52]: Timestamp('2010-11-12 00:00:00')

For more information on the choices available when specifying the `format` option, see the Python `datetime` documentation.
Assembling datetime from multiple DataFrame columns

You can also pass a DataFrame of integer or string columns to assemble into a Series of Timestamps.

In [53]: df = pd.DataFrame({'year': [2015, 2016],
                        'month': [2, 3],
                        'day': [4, 5],
                        'hour': [2, 3]})

In [54]: pd.to_datetime(df)
Out[54]:
0 2015-02-04 02:00:00
1 2016-03-05 03:00:00
dtype: datetime64[ns]

You can pass only the columns that you need to assemble.

In [55]: pd.to_datetime(df[['year', 'month', 'day']])
Out[55]:
0 2015-02-04
1 2016-03-05
dtype: datetime64[ns]

pd.to_datetime looks for standard designations of the datetime component in the column names, including:

- required: year, month, day
- optional: hour, minute, second, millisecond, microsecond, nanosecond

Invalid data

The default behavior, errors='raise', is to raise when unparsable:

In [2]: pd.to_datetime(['2009/07/31', 'asd'], errors='raise')
ValueError: Unknown string format

Pass errors='ignore' to return the original input when unparsable:

In [56]: pd.to_datetime(['2009/07/31', 'asd'], errors='ignore')
Out[56]: Index(['2009/07/31', 'asd'], dtype='object')

Pass errors='coerce' to convert unparsable data to NaT (not a time):

In [57]: pd.to_datetime(['2009/07/31', 'asd'], errors='coerce')
Out[57]: DatetimeIndex(['2009-07-31', 'NaT'], dtype='datetime64[ns]', freq=None)
Epoch timestamps

pandas supports converting integer or float epoch times to Timestamp and DatetimeIndex. The default unit is nanoseconds, since that is how Timestamp objects are stored internally. However, epochs are often stored in another unit which can be specified. These are computed from the starting point specified by the origin parameter.

```python
In [58]: pd.to_datetime([1349720105, 1349806505, 1349892905, 1349979305, 1350065705], unit='s')
Out[58]: DatetimeIndex(['2012-10-08 18:15:05', '2012-10-09 18:15:05', '2012-10-10 18:15:05', '2012-10-11 18:15:05', '2012-10-12 18:15:05'], dtype='datetime64[ns]', freq=None)
```

```python
In [59]: pd.to_datetime([1349720105100, 1349720105200, 1349720105300, 1349720105400, 1349720105500], unit='ms')
Out[59]: DatetimeIndex(['2012-10-08 18:15:05.100000', '2012-10-08 18:15:05.200000', '2012-10-08 18:15:05.300000', '2012-10-08 18:15:05.400000', '2012-10-08 18:15:05.500000'], dtype='datetime64[ns]', freq=None)
```

**Note:** The unit parameter does not use the same strings as the format parameter that was discussed above. The available units are listed on the documentation for pandas.to_datetime().

Constructing a Timestamp or DatetimeIndex with an epoch timestamp with the tz argument specified will current localize the epoch timestamps to UTC first then convert the result to the specified time zone. However, this behavior is deprecated, and if you have epochs in wall time in another timezone, it is recommended to read the epochs as timezone-naive timestamps and then localize to the appropriate timezone:

```python
In [60]: pd.Timestamp(1262347200000000000).tz_localize('US/Pacific')
Out[60]: Timestamp('2010-01-01 12:00:00-0800', tz='US/Pacific')
```

```python
In [61]: pd.DatetimeIndex([1262347200000000000]).tz_localize('US/Pacific')
Out[61]: DatetimeIndex(['2010-01-01 12:00:00-08:00'], dtype='datetime64[ns, US/Pacific]', freq=None)
```

**Note:** Epoch times will be rounded to the nearest nanosecond.

**Warning:** Conversion of float epoch times can lead to inaccurate and unexpected results. Python floats have about 15 digits precision in decimal. Rounding during conversion from float to high precision Timestamp is unavoidable. The only way to achieve exact precision is to use a fixed-width types (e.g. an int64).

```python
In [62]: pd.to_datetime([1490195805.433, 1490195805.433502912], unit='s')
Out[62]: DatetimeIndex(['2017-03-22 15:16:45.433000088', '2017-03-22 15:16:45.433502913'], dtype='datetime64[ns]', freq=None)
```

```python
In [63]: pd.to_datetime(1490195805433502912, unit='ns')
Out[63]: Timestamp('2017-03-22 15:16:45.433502912')
```
See also:

*Using the origin Parameter*

### From timestamps to epoch

To invert the operation from above, namely, to convert from a `Timestamp` to a ‘unix’ epoch:

```python
In [64]: stamps = pd.date_range('2012-10-08 18:15:05', periods=4, freq='D)
In [65]: stamps
Out[65]: DatetimeIndex(['2012-10-08 18:15:05', '2012-10-09 18:15:05',
                   '2012-10-10 18:15:05', '2012-10-11 18:15:05'],
               dtype='datetime64[ns]', freq='D')
```

We subtract the epoch (midnight at January 1, 1970 UTC) and then floor divide by the “unit” (1 second).

```python
In [66]: (stamps - pd.Timestamp("1970-01-01")) // pd.Timedelta('1s')
Out[66]: Int64Index([1349720105, 1349806505, 1349892905, 1349979305], dtype='int64')
```

### Using the origin Parameter

Using the `origin` parameter, one can specify an alternative starting point for creation of a `DatetimeIndex`. For example, to use 1960-01-01 as the starting date:

```python
In [67]: pd.to_datetime([1, 2, 3], unit='D', origin=pd.Timestamp('1960-01-01'))
Out[67]: DatetimeIndex(['1960-01-02', '1960-01-03', '1960-01-04'], dtype=
                   'datetime64[ns]', freq=None)
```

The default is set at `origin='unix'`, which defaults to 1970-01-01 00:00:00. Commonly called ‘unix epoch’ or POSIX time.

```python
In [68]: pd.to_datetime([1, 2, 3], unit='D')
                   'datetime64[ns]', freq=None)
```

### 2.17.4 Generating ranges of timestamps

To generate an index with timestamps, you can use either the `DatetimeIndex` or `Index` constructor and pass in a list of datetime objects:

```python
In [69]: dates = [datetime.datetime(2012, 5, 1),
           ...:   datetime.datetime(2012, 5, 2),
           ...:   datetime.datetime(2012, 5, 3)]

# Note the frequency information
In [70]: index = pd.DatetimeIndex(dates)

In [71]: index
Out[71]: DatetimeIndex(['2012-05-01', '2012-05-02', '2012-05-03'], dtype=
                   'datetime64[ns]', freq=None)
```

(continues on next page)
In practice this becomes very cumbersome because we often need a very long index with a large number of timestamps. If we need timestamps on a regular frequency, we can use the `date_range()` and `bdate_range()` functions to create a `DatetimeIndex`. The default frequency for `date_range` is a **calendar day** while the default for `bdate_range` is a **business day**:

```python
In [74]: start = datetime.datetime(2011, 1, 1)
In [75]: end = datetime.datetime(2012, 1, 1)
In [76]: index = pd.date_range(start, end)
In [77]: index
dtype='datetime64[ns]', length=366, freq='D')

In [78]: index = pd.bdate_range(start, end)
In [79]: index
dtype='datetime64[ns]', length=260, freq='B')
```

Convenience functions like `date_range` and `bdate_range` can utilize a variety of **frequency aliases**:

```python
In [80]: pd.date_range(start, periods=1000, freq='M')
dtype='datetime64[ns]', length=1000, freq='M')

In [81]: pd.bdate_range(start, periods=250, freq='BQS')
```

(continues on next page)
date_range and bdate_range make it easy to generate a range of dates using various combinations of parameters like start, end, periods, and freq. The start and end dates are strictly inclusive, so dates outside of those specified will not be generated:

```python
In [82]: pd.date_range(start, end, freq='BM')
```
```
Out[82]:
dtype='datetime64[ns]', freq='BM')
```

```python
In [83]: pd.date_range(start, end, freq='W')
```
```
Out[83]:
               '2011-08-14', '2011-08-21', '2011-08-28', '2011-09-04',
               '2011-12-04', '2011-12-11', '2011-12-18', '2011-12-25',
               '2012-01-01'],
dtype='datetime64[ns]', freq='W-SUN')
```

```python
In [84]: pd.bdate_range(end=end, periods=20)
```
```
Out[84]:
DatetimeIndex(['2011-12-05', '2011-12-06', '2011-12-07', '2011-12-08',
               '2011-12-09', '2011-12-10', '2011-12-11', '2011-12-12',
               '2011-12-13', '2011-12-14', '2011-12-15', '2011-12-16',
               '2011-12-17', '2011-12-18', '2011-12-19', '2011-12-20',
               '2011-12-21', '2011-12-22', '2011-12-23', '2011-12-24',
               '2011-12-25', '2011-12-26', '2011-12-27', '2011-12-28',
               '2011-12-29', '2011-12-30'],
dtype='datetime64[ns]', freq='B')
```

```python
In [85]: pd.bdate_range(start=start, periods=20)
```
```
Out[85]:
               '2011-01-27', '2011-01-28'],
dtype='datetime64[ns]', freq='B')
```
New in version 0.23.0.

Specifying `start`, `end`, and `periods` will generate a range of evenly spaced dates from `start` to `end` inclusively, with `periods` number of elements in the resulting `DatetimeIndex`:

```python
In [86]: pd.date_range('2018-01-01', '2018-01-05', periods=5)
Out[86]:
dtype='datetime64[ns]', freq=None)
```

```python
In [87]: pd.date_range('2018-01-01', '2018-01-05', periods=10)
Out[87]:
DatetimeIndex(['2018-01-01 00:00:00', '2018-01-01 10:40:00', '2018-01-01 21:20:00',
               '2018-01-02 08:00:00', '2018-01-02 18:40:00', '2018-01-03 05:20:00',
               '2018-01-03 16:00:00', '2018-01-04 02:40:00', '2018-01-04 13:20:00', '2018-01-05 00:00:00'],
dtype='datetime64[ns]', freq=None)
```

**Custom frequency ranges**

`bdate_range` can also generate a range of custom frequency dates by using the `weekmask` and `holidays` parameters. These parameters will only be used if a custom frequency string is passed.

```python
In [88]: weekmask = 'Mon Wed Fri'
In [89]: holidays = [datetime.datetime(2011, 1, 5), datetime.datetime(2011, 3, 14)]
In [90]: pd.bdate_range(start, end, freq='C', weekmask=weekmask, holidays=holidays)
Out[90]:
               '2011-12-09', '2011-12-12', '2011-12-14', '2011-12-16', '2011-12-19', '2011-12-21', '2011-12-23', '2011-12-26', '2011-12-28', '2011-12-30'],
dtype='datetime64[ns]', length=154, freq='C')
```

```python
In [91]: pd.bdate_range(start, end, freq='CBMS', weekmask=weekmask)
Out[91]:
dtype='datetime64[ns]', freq='CBMS')
```

See also:

- Custom business days
2.17.5 Timestamp limitations

Since pandas represents timestamps in nanosecond resolution, the time span that can be represented using a 64-bit integer is limited to approximately 584 years:

```
In [92]: pd.Timestamp.min
Out[92]: Timestamp('1677-09-21 00:12:43.145225')

In [93]: pd.Timestamp.max
Out[93]: Timestamp('2262-04-11 23:47:16.854775807')
```

See also:

*Representing out-of-bounds spans*

2.17.6 Indexing

One of the main uses for `DatetimeIndex` is as an index for pandas objects. The `DatetimeIndex` class contains many time series related optimizations:

- A large range of dates for various offsets are pre-computed and cached under the hood in order to make generating subsequent date ranges very fast (just have to grab a slice).
- Fast shifting using the `shift` method on pandas objects.
- Unioning of overlapping `DatetimeIndex` objects with the same frequency is very fast (important for fast data alignment).
- Quick access to date fields via properties such as `year`, `month`, etc.
- Regularization functions like `snap` and very fast `asof` logic.

`DatetimeIndex` objects have all the basic functionality of regular `Index` objects, and a smorgasbord of advanced time series specific methods for easy frequency processing.

See also:

*Reindexing methods*

**Note:** While pandas does not force you to have a sorted date index, some of these methods may have unexpected or incorrect behavior if the dates are unsorted.

`DatetimeIndex` can be used like a regular index and offers all of its intelligent functionality like selection, slicing, etc.

```
In [94]: rng = pd.date_range(start, end, freq='BM')

In [95]: ts = pd.Series(np.random.randn(len(rng)), index=rng)

In [96]: ts.index
                    dtype='datetime64[ns]', freq='BM')

In [97]: ts[:5].index
Out[97]:
```

(continues on next page)
Partial string indexing

Dates and strings that parse to timestamps can be passed as indexing parameters:

In [99]: ts['1/31/2011']
Out[99]: 0.11920871129693428

In [100]: ts[datetime.datetime(2011, 12, 25):]
Out[100]:
2011-12-30  0.56702
Freq: BM, dtype: float64

In [101]: ts['10/31/2011':'12/31/2011']
Out[101]:
2011-10-31  0.271860
2011-11-30 -0.424972
2011-12-30  0.567020
Freq: BM, dtype: float64

To provide convenience for accessing longer time series, you can also pass in the year or year and month as strings:

In [102]: ts['2011']
Out[102]:
2011-01-31  0.119209
2011-02-28  -1.044236
2011-03-31  -0.861849
2011-04-29  -2.104569
2011-05-31  -0.494929
2011-06-30   1.071804
2011-07-29   0.721555
2011-08-31  -0.706771
2011-09-30  -1.039575
2011-10-31   0.271860
2011-11-30  -0.424972
2011-12-30   0.567020
Freq: BM, dtype: float64

In [103]: ts['2011-6']
Out[103]:
2011-06-30   1.071804
Freq: BM, dtype: float64

This type of slicing will work on a DataFrame with a DatetimeIndex as well. Since the partial string selection is a form of label slicing, the endpoints will be included. This would include matching times on an included date:
In [104]: dft = pd.DataFrame(np.random.randn(100000, 1), columns=['A'],
                       index=pd.date_range('20130101', periods=100000, freq='T'))

In [105]: dft
Out[105]:
          A
2013-01-01 00:00:00  0.276232
2013-01-01 00:01:00 -1.087401
2013-01-01 00:02:00  0.673690
2013-01-01 00:03:00  0.113648
2013-01-01 00:04:00 -1.478427
...         ...
2013-03-11 10:35:00 -0.747967
2013-03-11 10:36:00 -0.345236
2013-03-11 10:37:00 -0.201754
2013-03-11 10:38:00 -1.509067
2013-03-11 10:39:00 -1.693043
[100000 rows x 1 columns]

In [106]: dft['2013']
Out[106]:
          A
2013-01-01 00:00:00  0.276232
2013-01-01 00:01:00 -1.087401
2013-01-01 00:02:00  0.673690
2013-01-01 00:03:00  0.113648
2013-01-01 00:04:00 -1.478427
...         ...
2013-03-11 10:35:00 -0.747967
2013-03-11 10:36:00 -0.345236
2013-03-11 10:37:00 -0.201754
2013-03-11 10:38:00 -1.509067
2013-03-11 10:39:00 -1.693043
[100000 rows x 1 columns]

This starts on the very first time in the month, and includes the last date and time for the month:

In [107]: dft['2013-1':'2013-2']
Out[107]:
          A
2013-01-01 00:00:00  0.276232
2013-01-01 00:01:00 -1.087401
2013-01-01 00:02:00  0.673690
2013-01-01 00:03:00  0.113648
2013-01-01 00:04:00 -1.478427
...         ...
2013-02-28 23:55:00  0.850929
2013-02-28 23:56:00  0.976712
2013-02-28 23:57:00 -2.693884
2013-02-28 23:58:00 -1.575535
2013-02-28 23:59:00 -1.573517
[84960 rows x 1 columns]
This specifies a stop time **that includes all of the times on the last day**:

```python
In [108]: dft['2013-1':'2013-2-28']
Out[108]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013-01-01 00:00:00</td>
<td>0.276232</td>
</tr>
<tr>
<td>2013-01-01 00:01:00</td>
<td>-1.087401</td>
</tr>
<tr>
<td>2013-01-01 00:02:00</td>
<td>-0.673690</td>
</tr>
<tr>
<td>2013-01-01 00:03:00</td>
<td>0.113648</td>
</tr>
<tr>
<td>2013-01-01 00:04:00</td>
<td>-1.478427</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>2013-02-28 23:55:00</td>
<td>0.850929</td>
</tr>
<tr>
<td>2013-02-28 23:56:00</td>
<td>0.976712</td>
</tr>
<tr>
<td>2013-02-28 23:57:00</td>
<td>-2.693884</td>
</tr>
<tr>
<td>2013-02-28 23:58:00</td>
<td>-1.575535</td>
</tr>
<tr>
<td>2013-02-28 23:59:00</td>
<td>-1.573517</td>
</tr>
</tbody>
</table>

[84960 rows x 1 columns]
```

This specifies an **exact** stop time (and is not the same as the above):

```python
In [109]: dft['2013-1':'2013-2-28 00:00:00']
Out[109]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013-01-01 00:00:00</td>
<td>0.276232</td>
</tr>
<tr>
<td>2013-01-01 00:01:00</td>
<td>-1.087401</td>
</tr>
<tr>
<td>2013-01-01 00:02:00</td>
<td>-0.673690</td>
</tr>
<tr>
<td>2013-01-01 00:03:00</td>
<td>0.113648</td>
</tr>
<tr>
<td>2013-01-01 00:04:00</td>
<td>-1.478427</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>2013-02-27 23:55:00</td>
<td>0.850929</td>
</tr>
<tr>
<td>2013-02-27 23:56:00</td>
<td>0.976712</td>
</tr>
<tr>
<td>2013-02-27 23:57:00</td>
<td>-2.693884</td>
</tr>
<tr>
<td>2013-02-27 23:58:00</td>
<td>-1.575535</td>
</tr>
<tr>
<td>2013-02-27 23:59:00</td>
<td>-1.573517</td>
</tr>
</tbody>
</table>

[83521 rows x 1 columns]
```

We are stopping on the included end-point as it is part of the index:

```python
In [110]: dft['2013-1-15':'2013-1-15 12:30:00']
Out[110]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013-01-15 00:00:00</td>
<td>-0.984810</td>
</tr>
<tr>
<td>2013-01-15 00:01:00</td>
<td>0.941451</td>
</tr>
<tr>
<td>2013-01-15 00:02:00</td>
<td>1.559365</td>
</tr>
<tr>
<td>2013-01-15 00:03:00</td>
<td>1.034374</td>
</tr>
<tr>
<td>2013-01-15 00:04:00</td>
<td>-1.480656</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>2013-01-15 12:26:00</td>
<td>0.371454</td>
</tr>
<tr>
<td>2013-01-15 12:27:00</td>
<td>-0.930806</td>
</tr>
<tr>
<td>2013-01-15 12:28:00</td>
<td>-0.069177</td>
</tr>
<tr>
<td>2013-01-15 12:29:00</td>
<td>0.066510</td>
</tr>
<tr>
<td>2013-01-15 12:30:00</td>
<td>-0.003945</td>
</tr>
</tbody>
</table>

[751 rows x 1 columns]
```

DatetimeIndex partial string indexing also works on a DataFrame with a MultiIndex:

2.17. Time series / date functionality
In [111]: dft2 = pd.DataFrame(np.random.randn(20, 1),
                      columns=['A'],
                      index=pd.MultiIndex.from_product(
                      [pd.date_range('20130101', periods=10, freq='12H'),
                       ['a', 'b']]))

In [112]: dft2

Out[112]:
          A
2013-01-01 00:00:00 a -0.298694
         b  0.823553
2013-01-01 12:00:00 a  0.943285
         b -1.479399
2013-01-02 00:00:00 a -1.643342
         b  2.059802
 ... ... ...
2013-01-04 12:00:00 b  0.069036
2013-01-05 00:00:00 a  0.122297
         b  1.422060
2013-01-05 12:00:00 a  0.370079
         b  1.016331
[20 rows x 1 columns]

In [113]: dft2.loc['2013-01-05']

Out[113]:
          A
2013-01-05 00:00:00 a  0.122297
         b  1.422060
2013-01-05 12:00:00 a  0.370079
         b  1.016331

In [114]: idx = pd.IndexSlice

In [115]: dft2 = dft2.swaplevel(0, 1).sort_index()

In [116]: dft2.loc[idx[:, '2013-01-05'], :]

Out[116]:
          A
a 2013-01-05 00:00:00  0.122297
2013-01-05 12:00:00  0.370079
b 2013-01-05 00:00:00  1.422060
2013-01-05 12:00:00  1.016331

New in version 0.25.0.
Slicing with string indexing also honors UTC offset.

In [117]: df = pd.DataFrame([0], index=pd.DatetimeIndex(['2019-01-01'],
                                                        tz='US/Pacific'))

In [118]: df

Out[118]:
         D
2019-01-01 00:00:00-08:00 D

In [119]: df['2019-01-01 12:00:00+04:00':'2019-01-01 13:00:00+04:00']

Out[119]:
         D
2019-01-01 12:00:00-08:00 D

(continues on next page)
Slice vs. exact match

Changed in version 0.20.0.

The same string used as an indexing parameter can be treated either as a slice or as an exact match depending on the resolution of the index. If the string is less accurate than the index, it will be treated as a slice, otherwise as an exact match.

Consider a Series object with a minute resolution index:

```
In [120]: series_minute = pd.Series([1, 2, 3],
                            pd.DatetimeIndex(['2011-12-31 23:59:00',
                                             '2012-01-01 00:00:00',
                                             '2012-01-01 00:02:00']))

In [121]: series_minute.index.resolution
Out[121]: 'minute'
```

A timestamp string less accurate than a minute gives a Series object.

```
In [122]: series_minute['2011-12-31 23']
Out[122]:
2011-12-31 23:59:00    1
 dtype: int64
```

A timestamp string with minute resolution (or more accurate), gives a scalar instead, i.e. it is not casted to a slice.

```
In [123]: series_minute['2011-12-31 23:59']
Out[123]:
2011-12-31 23:59:00    1
Out[124]:
In [124]: series_minute['2011-12-31 23:59:00']
Out[124]:
2011-12-31 23:59:00    1
```

If index resolution is second, then the minute-accurate timestamp gives a Series.

```
In [125]: series_second = pd.Series([1, 2, 3],
                      pd.DatetimeIndex(['2011-12-31 23:59:59',
                                        '2012-01-01 00:00:00',
                                        '2012-01-01 00:00:01']))

In [126]: series_second.index.resolution
Out[126]: 'second'

In [127]: series_second['2011-12-31 23:59']
Out[127]:
2011-12-31 23:59:59    1
Out[127]:
```

If the timestamp string is treated as a slice, it can be used to index DataFrame with [] as well.

2.17. Time series / date functionality
```python
In [128]: dft_minute = pd.DataFrame({"a": [1, 2, 3], "b": [4, 5, 6]},
       index=series_minute.index)
       
In [129]: dft_minute['2011-12-31 23']
Out[129]:
         a  b
2011-12-31 23:59:00 1 4
```

**Warning:** However, if the string is treated as an exact match, the selection in DataFrame's [] will be column-wise and not row-wise, see *Indexing Basics*. For example `dft_minute['2011-12-31 23:59']` will raise `KeyError` as '2012-12-31 23:59' has the same resolution as the index and there is no column with such name:

To *always* have unambiguous selection, whether the row is treated as a slice or a single selection, use `.loc`.

```python
In [130]: dft_minute.loc['2011-12-31 23:59']
Out[130]:
         a  b
Name: 2011-12-31 23:59:00, dtype: int64
```

Note also that `DatetimeIndex` resolution cannot be less precise than day.

```python
In [131]: series_monthly = pd.Series([1, 2, 3],
       pd.DatetimeIndex(['2011-12', '2012-01', '2012-02']))
       
In [132]: series_monthly.index.resolution
Out[132]: 'day'

In [133]: series_monthly['2011-12'] # returns Series
Out[133]:
2011-12-01 1
dtype: int64
```

**Exact indexing**

As discussed in previous section, indexing a `DatetimeIndex` with a partial string depends on the “accuracy” of the period, in other words how specific the interval is in relation to the resolution of the index. In contrast, indexing with `Timestamp` or `datetime` objects is exact, because the objects have exact meaning. These also follow the semantics of including both endpoints.

These `Timestamp` and `datetime` objects have exact hours, minutes, and seconds, even though they were not explicitly specified (they are 0).

```python
In [134]: dft[datetime.datetime(2013, 1, 1):datetime.datetime(2013, 2, 28)]
Out[134]:
       A
2013-01-01 00:00:00 0.276232
2013-01-01 00:01:00 -1.087401
2013-01-01 00:02:00 -0.673690
2013-01-01 00:03:00 0.113648
```
2013-01-01 00:04:00 -1.478427
... ... 
2013-02-27 23:56:00 1.197749
2013-02-27 23:57:00 0.720521
2013-02-27 23:58:00 -0.072718
2013-02-27 23:59:00 -0.681192
2013-02-28 00:00:00 -0.557501

[83521 rows x 1 columns]

With no defaults.

In [135]: dft[datetime.datetime(2013, 1, 1, 10, 12, 0):
   .....: datetime.datetime(2013, 2, 28, 10, 12, 0)]
   .....:
Out [135]:
   A
2013-01-01 10:12:00 0.565375
2013-01-01 10:13:00 0.068184
2013-01-01 10:14:00 0.788871
2013-01-01 10:15:00 -0.280343
2013-01-01 10:16:00 0.931536
... ... 
2013-02-28 10:08:00 0.148098
2013-02-28 10:09:00 -0.388138
2013-02-28 10:10:00 0.139348
2013-02-28 10:11:00 0.085288
2013-02-28 10:12:00 0.950146

[83521 rows x 1 columns]

Truncating & fancy indexing

A truncate() convenience function is provided that is similar to slicing. Note that truncate assumes a 0 value for any unspecified date component in a DatetimeIndex in contrast to slicing which returns any partially matching dates:

In [136]: rng2 = pd.date_range('2011-01-01', '2012-01-01', freq='W')

In [137]: ts2 = pd.Series(np.random.randn(len(rng2)), index=rng2)

In [138]: ts2.truncate(before='2011-11', after='2011-12')
Out [138]:
   2011-11-06  0.437823
   2011-11-13  -0.293083
   2011-11-20  -0.059881
   2011-11-27   1.252450
Freq: W-SUN, dtype: float64

In [139]: ts2['2011-11':'2011-12']
Out [139]:
   2011-11-06  0.437823
   2011-11-13  -0.293083
   2011-11-20  -0.059881
   2011-11-27   1.252450

(continues on next page)
2011-12-04 0.046611
2011-12-11 0.059478
2011-12-18 -0.286539
2011-12-25 0.841669
Freq: W-SUN, dtype: float64

Even complicated fancy indexing that breaks the DatetimeIndex frequency regularity will result in a DatetimeIndex, although frequency is lost:

```python
In [140]: ts2[[0, 2, 6]].index
Out[140]: DatetimeIndex(['2011-01-02', '2011-01-16', '2011-02-13'], dtype=˓→'datetime64[ns]', freq=None)
```

### 2.17.7 Time/date components

There are several time/date properties that one can access from Timestamp or a collection of timestamps like a DatetimeIndex.

<table>
<thead>
<tr>
<th>Property</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>year</td>
<td>The year of the datetime</td>
</tr>
<tr>
<td>month</td>
<td>The month of the datetime</td>
</tr>
<tr>
<td>day</td>
<td>The days of the datetime</td>
</tr>
<tr>
<td>hour</td>
<td>The hour of the datetime</td>
</tr>
<tr>
<td>minute</td>
<td>The minutes of the datetime</td>
</tr>
<tr>
<td>second</td>
<td>The seconds of the datetime</td>
</tr>
<tr>
<td>microsecond</td>
<td>The microseconds of the datetime</td>
</tr>
<tr>
<td>nanosecond</td>
<td>The nanoseconds of the datetime</td>
</tr>
<tr>
<td>date</td>
<td>Returns datetime.date (does not contain timezone information)</td>
</tr>
<tr>
<td>time</td>
<td>Returns datetime.time (does not contain timezone information)</td>
</tr>
<tr>
<td>timetz</td>
<td>Returns datetime.time as local time with timezone information</td>
</tr>
<tr>
<td>dayofyear</td>
<td>The ordinal day of year</td>
</tr>
<tr>
<td>weekofyear</td>
<td>The week ordinal of the year</td>
</tr>
<tr>
<td>week</td>
<td>The week ordinal of the year</td>
</tr>
<tr>
<td>dayofweek</td>
<td>The number of the day of the week with Monday=0, Sunday=6</td>
</tr>
<tr>
<td>weekday</td>
<td>The number of the day of the week with Monday=0, Sunday=6</td>
</tr>
<tr>
<td>quarter</td>
<td>Quarter of the date: Jan-Mar = 1, Apr-Jun = 2, etc.</td>
</tr>
<tr>
<td>days_in_month</td>
<td>The number of days in the month of the datetime</td>
</tr>
<tr>
<td>is_month_start</td>
<td>Logical indicating if first day of month (defined by frequency)</td>
</tr>
<tr>
<td>is_month_end</td>
<td>Logical indicating if last day of month (defined by frequency)</td>
</tr>
<tr>
<td>is_quarter_start</td>
<td>Logical indicating if first day of quarter (defined by frequency)</td>
</tr>
<tr>
<td>is_quarter_end</td>
<td>Logical indicating if last day of quarter (defined by frequency)</td>
</tr>
<tr>
<td>is_year_start</td>
<td>Logical indicating if first day of year (defined by frequency)</td>
</tr>
<tr>
<td>is_year_end</td>
<td>Logical indicating if last day of year (defined by frequency)</td>
</tr>
<tr>
<td>is_leap_year</td>
<td>Logical indicating if the date belongs to a leap year</td>
</tr>
</tbody>
</table>

Furthermore, if you have a Series with datetimelike values, then you can access these properties via the `.dt` accessor, as detailed in the section on `.dt accessors`.

New in version 1.1.0.

You may obtain the year, week and day components of the ISO year from the ISO 8601 standard:
In [141]: idx = pd.date_range(start='2019-12-29', freq='D', periods=4)

In [142]: idx.isocalendar()
Out[142]:

<table>
<thead>
<tr>
<th>year</th>
<th>week</th>
<th>day</th>
</tr>
</thead>
<tbody>
<tr>
<td>2019</td>
<td>52</td>
<td>7</td>
</tr>
<tr>
<td>2019</td>
<td>52</td>
<td>1</td>
</tr>
<tr>
<td>2019</td>
<td>52</td>
<td>2</td>
</tr>
<tr>
<td>2020</td>
<td>1</td>
<td>3</td>
</tr>
</tbody>
</table>

In [143]: idx.to_series().dt.isocalendar()
Out[143]:

<table>
<thead>
<tr>
<th>year</th>
<th>week</th>
<th>day</th>
</tr>
</thead>
<tbody>
<tr>
<td>2019</td>
<td>52</td>
<td>7</td>
</tr>
<tr>
<td>2019</td>
<td>52</td>
<td>1</td>
</tr>
<tr>
<td>2019</td>
<td>52</td>
<td>2</td>
</tr>
<tr>
<td>2020</td>
<td>1</td>
<td>3</td>
</tr>
</tbody>
</table>

2.17.8 DateOffset objects

In the preceding examples, frequency strings (e.g. 'D') were used to specify a frequency that defined:

• how the date times in DatetimeIndex were spaced when using date_range()

• the frequency of a Period or PeriodIndex

These frequency strings map to a DateOffset object and its subclasses. A DateOffset is similar to a Timedelta that represents a duration of time but follows specific calendar duration rules. For example, a Timedelta day will always increment datetimes by 24 hours, while a DateOffset day will increment datetimes to the same time the next day whether a day represents 23, 24 or 25 hours due to daylight savings time. However, all DateOffset subclasses that are an hour or smaller (Hour, Minute, Second, Milli, Micro, Nano) behave like Timedelta and respect absolute time.

The basic DateOffset acts similar to dateutil.relativedelta (relativedelta documentation) that shifts a date time by the corresponding calendar duration specified. The arithmetic operator (+) or the apply method can be used to perform the shift.

# This particular day contains a day light savings time transition
In [144]: ts = pd.Timestamp('2016-10-30 00:00:00', tz='Europe/Helsinki')

# Respects absolute time
In [145]: ts + pd.Timedelta(days=1)
Out[145]: Timestamp('2016-10-30 23:00:00+0200', tz='Europe/Helsinki')

# Respects calendar time
In [146]: ts + pd.DateOffset(days=1)
Out[146]: Timestamp('2016-10-31 00:00:00+0200', tz='Europe/Helsinki')

In [147]: friday = pd.Timestamp('2018-01-05')

In [148]: friday.day_name()
Out[148]: 'Friday'

# Add 2 business days (Friday --> Tuesday)
In [149]: two_business_days = 2 * pd.offsets.BDay()
Most `DateOffsets` have associated frequencies strings, or offset aliases, that can be passed into `freq` keyword arguments. The available date offsets and associated frequency strings can be found below:

<table>
<thead>
<tr>
<th>Date Offset</th>
<th>Frequency String</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>DateOffset</code></td>
<td>None</td>
<td>Generic offset class, defaults to 1 calendar day</td>
</tr>
<tr>
<td><code>BDay</code> or <code>BusinessDay</code></td>
<td>'B'</td>
<td>business day (weekday)</td>
</tr>
<tr>
<td><code>CDay</code> or <code>CustomBusinessDay</code></td>
<td>'C'</td>
<td>custom business day</td>
</tr>
<tr>
<td><code>Week</code></td>
<td>'W'</td>
<td>one week, optionally anchored on a day of the week</td>
</tr>
<tr>
<td><code>WeekOfMonth</code></td>
<td>'WOM'</td>
<td>the x-th day of the y-th week of each month</td>
</tr>
<tr>
<td><code>LastWeekOfMonth</code></td>
<td>'LWOM'</td>
<td>the x-th day of the last week of each month</td>
</tr>
<tr>
<td><code>MonthEnd</code></td>
<td>'M'</td>
<td>calendar month end</td>
</tr>
<tr>
<td><code>MonthBegin</code></td>
<td>'MS'</td>
<td>calendar month begin</td>
</tr>
<tr>
<td><code>BMonthEnd</code></td>
<td>'BM'</td>
<td>business month end</td>
</tr>
<tr>
<td><code>BMMonthBegin</code></td>
<td>'BMS'</td>
<td>business month begin</td>
</tr>
<tr>
<td><code>CBMonthEnd</code></td>
<td>'CBM'</td>
<td>custom business month end</td>
</tr>
<tr>
<td><code>CBMonthBegin</code></td>
<td>'CBMS'</td>
<td>custom business month begin</td>
</tr>
<tr>
<td><code>SemiMonthEnd</code></td>
<td>'SM'</td>
<td>15th (or other day_of_month) and calendar month end</td>
</tr>
<tr>
<td><code>SemiMonthBegin</code></td>
<td>'SMS'</td>
<td>15th (or other day_of_month) and calendar month begin</td>
</tr>
<tr>
<td><code>QuarterEnd</code></td>
<td>'Q'</td>
<td>calendar quarter end</td>
</tr>
<tr>
<td><code>QuarterBegin</code></td>
<td>'QS'</td>
<td>calendar quarter begin</td>
</tr>
<tr>
<td><code>BQuarterEnd</code></td>
<td>'BQ'</td>
<td>business quarter end</td>
</tr>
<tr>
<td><code>BQuarterBegin</code></td>
<td>'BQS'</td>
<td>business quarter begin</td>
</tr>
<tr>
<td><code>FY5253Quarter</code></td>
<td>'REQ'</td>
<td>retail (aka 52-53 week) quarter</td>
</tr>
<tr>
<td><code>YearEnd</code></td>
<td>'A'</td>
<td>calendar year end</td>
</tr>
<tr>
<td><code>YearBegin</code></td>
<td>'AS' or 'BYS'</td>
<td>calendar year begin</td>
</tr>
<tr>
<td><code>BYearEnd</code></td>
<td>'BA'</td>
<td>business year end</td>
</tr>
<tr>
<td><code>BYearBegin</code></td>
<td>'BAS'</td>
<td>business year begin</td>
</tr>
<tr>
<td><code>FY5253</code></td>
<td>'RE'</td>
<td>retail (aka 52-53 week) year</td>
</tr>
<tr>
<td><code>Easter</code></td>
<td>None</td>
<td>Easter holiday</td>
</tr>
<tr>
<td><code>BusinessHour</code></td>
<td>'BH'</td>
<td>business hour</td>
</tr>
</tbody>
</table>
Table 3 – continued from previous page

<table>
<thead>
<tr>
<th>Date Offset</th>
<th>Frequency String</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>CustomBusinessHour</td>
<td>'CBH'</td>
<td>custom business hour</td>
</tr>
<tr>
<td>Day</td>
<td>'D'</td>
<td>one absolute day</td>
</tr>
<tr>
<td>Hour</td>
<td>'H'</td>
<td>one hour</td>
</tr>
<tr>
<td>Minute</td>
<td>'T' or 'min'</td>
<td>one minute</td>
</tr>
<tr>
<td>Second</td>
<td>'S'</td>
<td>one second</td>
</tr>
<tr>
<td>Milli</td>
<td>'L' or 'ms'</td>
<td>one millisecond</td>
</tr>
<tr>
<td>Micro</td>
<td>'U' or 'us'</td>
<td>one microsecond</td>
</tr>
<tr>
<td>Nano</td>
<td>'N'</td>
<td>one nanosecond</td>
</tr>
</tbody>
</table>

DateOffsets additionally have rollforward() and rollback() methods for moving a date forward or backward respectively to a valid offset date relative to the offset. For example, business offsets will roll dates that land on the weekends (Saturday and Sunday) forward to Monday since business offsets operate on the weekdays.

```
In [153]: ts = pd.Timestamp('2018-01-06 00:00:00')
In [154]: ts.day_name()
Out[154]: 'Saturday'

# BusinessHour's valid offset dates are Monday through Friday
In [155]: offset = pd.offsets.BusinessHour(start='09:00')

# Bring the date to the closest offset date (Monday)
In [156]: offset.rollforward(ts)
Out[156]: Timestamp('2018-01-08 09:00:00')

# Date is brought to the closest offset date first and then the hour is added
In [157]: ts + offset
Out[157]: Timestamp('2018-01-08 10:00:00')
```

These operations preserve time (hour, minute, etc) information by default. To reset time to midnight, use normalize() before or after applying the operation (depending on whether you want the time information included in the operation).

```
In [158]: ts = pd.Timestamp('2014-01-01 09:00')
In [159]: day = pd.offsets.Day()

In [160]: day.apply(ts)
Out[160]: Timestamp('2014-01-02 09:00:00')

In [161]: day.apply(ts).normalize()
Out[161]: Timestamp('2014-01-02 00:00:00')

In [162]: ts = pd.Timestamp('2014-01-01 22:00')
In [163]: hour = pd.offsets.Hour()

In [164]: hour.apply(ts)
Out[164]: Timestamp('2014-01-01 23:00:00')

In [165]: hour.apply(ts).normalize()
Out[165]: Timestamp('2014-01-01 00:00:00')
```

(continues on next page)
Parametric offsets

Some of the offsets can be “parameterized” when created to result in different behaviors. For example, the \texttt{Week} offset for generating weekly data accepts a \texttt{weekday} parameter which results in the generated dates always lying on a particular day of the week:

\begin{verbatim}
In [167]: d = datetime.datetime(2008, 8, 18, 9, 0)
In [168]: d + pd.offsets.Week()
Out[168]: Timestamp('2008-08-25 09:00:00')
In [169]: (d + pd.offsets.Week(weekday=4)).weekday()
Out[169]: 4
In [170]: d - pd.offsets.Week()
Out[170]: Timestamp('2008-08-11 09:00:00')
\end{verbatim}

The normalize option will be effective for addition and subtraction.

\begin{verbatim}
In [173]: d + pd.offsets.Week(normalize=True)
Out[173]: Timestamp('2008-08-25 00:00:00')
In [174]: d - pd.offsets.Week(normalize=True)
Out[174]: Timestamp('2008-08-11 00:00:00')
\end{verbatim}

Another example is parameterizing \texttt{YearEnd} with the specific ending month:

\begin{verbatim}
In [175]: d + pd.offsets.YearEnd()
Out[175]: Timestamp('2008-12-31 09:00:00')
In [176]: d + pd.offsets.YearEnd(month=6)
Out[176]: Timestamp('2009-06-30 09:00:00')
\end{verbatim}

Using offsets with \texttt{Series} / \texttt{DatetimeIndex}

Offsets can be used with either a \texttt{Series} or \texttt{DatetimeIndex} to apply the offset to each element.

\begin{verbatim}
In [177]: rng = pd.date_range('2012-01-01', '2012-01-03')
In [178]: s = pd.Series(rng)
In [179]: rng
Out[179]: DatetimeIndex(['2012-01-01', '2012-01-02', '2012-01-03'], dtype='datetime64[ns]', freq='D')
\end{verbatim}
In [180]: rng + pd.DateOffset(months=2)
Out[180]: DatetimeIndex(['2012-03-01', '2012-03-02', '2012-03-03'], dtype='datetime64[ns]', freq=None)

In [181]: s + pd.DateOffset(months=2)
Out[181]: 
0    2012-03-01
1    2012-03-02
2    2012-03-03
 dtype: datetime64[ns]

In [182]: s - pd.DateOffset(months=2)
Out[182]: 
0    2011-11-01
1    2011-11-02
2    2011-11-03
 dtype: datetime64[ns]

If the offset class maps directly to a Timedelta (Day, Hour, Minute, Second, Micro, Milli, Nano) it can be used exactly like a Timedelta - see the Timedelta section for more examples.

In [183]: s - pd.offsets.Day(2)
Out[183]: 
0    2011-12-30
1    2011-12-31
2    2012-01-01
 dtype: datetime64[ns]

In [184]: td = s - pd.Series(pd.date_range('2011-12-29', '2011-12-31'))

In [185]: td
Out[185]: 
0      3 days
1      3 days
2      3 days
 dtype: timedelta64[ns]

In [186]: td + pd.offsets.Minute(15)
Out[186]: 
0 3 days 00:15:00
1 3 days 00:15:00
2 3 days 00:15:00
 dtype: timedelta64[ns]

Note that some offsets (such as BQuarterEnd) do not have a vectorized implementation. They can still be used but may calculate significantly slower and will show a PerformanceWarning

In [187]: rng + pd.offsets.BQuarterEnd()
Out[187]: DatetimeIndex(['2012-03-30', '2012-03-30', '2012-03-30'], dtype='datetime64[ns]', freq=None)
Custom business days

The `CDay` or `CustomBusinessDay` class provides a parametric `BusinessDay` class which can be used to create customized business day calendars which account for local holidays and local weekend conventions.

As an interesting example, let’s look at Egypt where a Friday-Saturday weekend is observed.

```
In [188]: weekmask_egypt = 'Sun Mon Tue Wed Thu'

# They also observe International Workers' Day so let's
# add that for a couple of years
In [189]: holidays = ['2012-05-01',
                  datetime.datetime(2013, 5, 1),
                  np.datetime64('2014-05-01')]

In [190]: bday_egypt = pd.offsets.CustomBusinessDay(holidays=holidays,
                                               weekmask=weekmask_egypt)

In [191]: dt = datetime.datetime(2013, 4, 30)
In [192]: dt + 2 * bday_egypt
Out[192]: Timestamp('2013-05-05 00:00:00')
```

Let’s map to the weekday names:

```
In [193]: dts = pd.date_range(dt, periods=5, freq=bday_egypt)
In [194]: pd.Series(dts.weekday, dts).map(
                  pd.Series('Mon Tue Wed Thu Fri Sat Sun'.split()))
Out[194]:
2013-04-30 Tue
2013-05-02 Thu
2013-05-05 Sun
2013-05-06 Mon
2013-05-07 Tue
Freq: C, dtype: object
```

Holiday calendars can be used to provide the list of holidays. See the `holiday calendar` section for more information.

```
In [195]: from pandas.tseries.holiday import USFederalHolidayCalendar
In [196]: bday_us = pd.offsets.CustomBusinessDay(calendar=USFederalHolidayCalendar())

# Friday before MLK Day
In [197]: dt = datetime.datetime(2014, 1, 17)

# Tuesday after MLK Day (Monday is skipped because it's a holiday)
In [198]: dt + bday_us
Out[198]: Timestamp('2014-01-21 00:00:00')
```

Monthly offsets that respect a certain holiday calendar can be defined in the usual way.

```
In [199]: bmth_us = pd.offsets.CustomBusinessMonthBegin(  
                  calendar=USFederalHolidayCalendar())
```

(continues on next page)
# Skip new years

In [200]: dt = datetime.datetime(2013, 12, 17)

In [201]: dt + bmth_us

Out[201]: Timestamp('2014-01-02 00:00:00')

# Define date index with custom offset

In [202]: pd.date_range(start='20100101', end='20120101', freq=bmth_us)

Out[202]: DatetimeIndex(['2010-01-04', '2010-02-01', '2010-03-01', '2010-04-01',
   '2010-05-03', '2010-06-01', '2010-07-01', '2010-08-02',
   '2010-09-01', '2010-10-01', '2010-11-01', '2010-12-01',
   '2011-01-03', '2011-02-01', '2011-03-01', '2011-04-01',
   '2011-09-01', '2011-10-03', '2011-11-01', '2011-12-01'],
dtype='datetime64[ns]', freq='CBMS')

Note: The frequency string ‘C’ is used to indicate that a CustomBusinessDay DateOffset is used, it is important to note that since CustomBusinessDay is a parameterised type, instances of CustomBusinessDay may differ and this is not detectable from the ‘C’ frequency string. The user therefore needs to ensure that the ‘C’ frequency string is used consistently within the user’s application.

**Business hour**

The BusinessHour class provides a business hour representation on BusinessDay, allowing to use specific start and end times.

By default, BusinessHour uses 9:00 - 17:00 as business hours. Adding BusinessHour will increment Timestamp by hourly frequency. If target Timestamp is out of business hours, move to the next business hour then increment it. If the result exceeds the business hours end, the remaining hours are added to the next business day.

In [203]: bh = pd.offsets.BusinessHour()

In [204]: bh

Out[204]: <BusinessHour: BH=09:00-17:00>

# 2014-08-01 is Friday

In [205]: pd.Timestamp('2014-08-01 10:00').weekday()

Out[205]: 4

In [206]: pd.Timestamp('2014-08-01 10:00') + bh

Out[206]: Timestamp('2014-08-01 11:00:00')

# Below example is the same as: pd.Timestamp('2014-08-01 09:00') + bh

In [207]: pd.Timestamp('2014-08-01 08:00') + bh

Out[207]: Timestamp('2014-08-01 10:00:00')

# If the results is on the end time, move to the next business day

In [208]: pd.Timestamp('2014-08-01 16:00') + bh

Out[208]: Timestamp('2014-08-04 09:00:00')

# Remainings are added to the next day

(continues on next page)
In [209]: pd.Timestamp('2014-08-01 16:30') + bh
Out[209]: Timestamp('2014-08-04 09:30:00')

# Adding 2 business hours
In [210]: pd.Timestamp('2014-08-01 10:00') + pd.offsets.BusinessHour(2)
Out[210]: Timestamp('2014-08-01 12:00:00')

# Subtracting 3 business hours
In [211]: pd.Timestamp('2014-08-01 10:00') + pd.offsets.BusinessHour(-3)
Out[211]: Timestamp('2014-07-31 15:00:00')

You can also specify start and end time by keywords. The argument must be a str with an hour:minute
representation or a datetime.time instance. Specifying seconds, microseconds and nanoseconds as business hour
results in ValueError.

In [212]: bh = pd.offsets.BusinessHour(start='11:00', end=datetime.time(20, 0))
In [213]: bh
Out[213]: <BusinessHour: BH=11:00-20:00>
In [214]: pd.Timestamp('2014-08-01 13:00') + bh
Out[214]: Timestamp('2014-08-01 14:00:00')
In [215]: pd.Timestamp('2014-08-01 09:00') + bh
Out[215]: Timestamp('2014-08-01 12:00:00')
In [216]: pd.Timestamp('2014-08-01 18:00') + bh
Out[216]: Timestamp('2014-08-01 19:00:00')

Passing start time later than end represents midnight business hour. In this case, business hour exceeds midnight
and overlap to the next day. Valid business hours are distinguished by whether it started from valid BusinessDay.

In [217]: bh = pd.offsets.BusinessHour(start='17:00', end='09:00')
In [218]: bh
Out[218]: <BusinessHour: BH=17:00-09:00>
In [219]: pd.Timestamp('2014-08-01 17:00') + bh
Out[219]: Timestamp('2014-08-01 18:00:00')
In [220]: pd.Timestamp('2014-08-01 23:00') + bh
Out[220]: Timestamp('2014-08-02 00:00:00')

# Although 2014-08-02 is Saturday,
# it is valid because it starts from 08-01 (Friday).
In [221]: pd.Timestamp('2014-08-02 04:00') + bh
Out[221]: Timestamp('2014-08-02 05:00:00')

# Although 2014-08-04 is Monday,
# it is out of business hours because it starts from 08-03 (Sunday).
In [222]: pd.Timestamp('2014-08-04 04:00') + bh
Out[222]: Timestamp('2014-08-04 18:00:00')

Applying BusinessHour.rollforward and rollback to out of business hours results in the next business
hour start or previous day’s end. Different from other offsets, BusinessHour.rollforward may output different
results from apply by definition.
This is because one day’s business hour end is equal to next day’s business hour start. For example, under the default business hours (9:00 - 17:00), there is no gap (0 minutes) between 2014-08-01 17:00 and 2014-08-04 09:00.

```python
# This adjusts a Timestamp to business hour edge
In [223]: pd.offsets.BusinessHour().rollback(pd.Timestamp('2014-08-02 15:00'))
Out[223]: Timestamp('2014-08-01 17:00:00')

In [224]: pd.offsets.BusinessHour().rollforward(pd.Timestamp('2014-08-02 15:00'))
Out[224]: Timestamp('2014-08-04 09:00:00')

# It is the same as BusinessHour().apply(pd.Timestamp('2014-08-01 17:00')).
# And it is the same as BusinessHour().apply(pd.Timestamp('2014-08-04 09:00'))
In [225]: pd.offsets.BusinessHour().apply(pd.Timestamp('2014-08-02 15:00'))
Out[225]: Timestamp('2014-08-04 10:00:00')

# BusinessDay results (for reference)
In [226]: pd.offsets.BusinessHour().rollforward(pd.Timestamp('2014-08-02'))
Out[226]: Timestamp('2014-08-04 09:00:00')

# It is the same as BusinessDay().apply(pd.Timestamp('2014-08-01'))
# The result is the same as rollworward because BusinessDay never overlap.
In [227]: pd.offsets.BusinessHour().apply(pd.Timestamp('2014-08-02'))
Out[227]: Timestamp('2014-08-04 10:00:00')
```

BusinessHour regards Saturday and Sunday as holidays. To use arbitrary holidays, you can use CustomBusinessHour offset, as explained in the following subsection.

**Custom business hour**

The CustomBusinessHour is a mixture of BusinessHour and CustomBusinessDay which allows you to specify arbitrary holidays. CustomBusinessHour works as the same as BusinessHour except that it skips specified custom holidays.

```python
In [228]: from pandas.tseries.holiday import USFederalHolidayCalendar

In [229]: bhour_us = pd.offsets.CustomBusinessHour(calendar=USFederalHolidayCalendar())

# Friday before MLK Day
In [230]: dt = datetime.datetime(2014, 1, 17, 15)

In [231]: dt + bhour_us
Out[231]: Timestamp('2014-01-17 16:00:00')

# Tuesday after MLK Day (Monday is skipped because it's a holiday)
In [232]: dt + bhour_us * 2
Out[232]: Timestamp('2014-01-21 09:00:00')
```

You can use keyword arguments supported by either BusinessHour and CustomBusinessDay.

```python
In [233]: bhour_mon = pd.offsets.CustomBusinessHour(start='10:00',
                      weekmask='Tue Wed Thu Fri')

# Monday is skipped because it's a holiday, business hour starts from 10:00
```

(continues on next page)
Offset aliases

A number of string aliases are given to useful common time series frequencies. We will refer to these aliases as offset aliases.

<table>
<thead>
<tr>
<th>Alias</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>B</td>
<td>business day frequency</td>
</tr>
<tr>
<td>C</td>
<td>custom business day frequency</td>
</tr>
<tr>
<td>D</td>
<td>calendar day frequency</td>
</tr>
<tr>
<td>W</td>
<td>weekly frequency</td>
</tr>
<tr>
<td>M</td>
<td>month end frequency</td>
</tr>
<tr>
<td>SM</td>
<td>semi-month end frequency (15th and end of month)</td>
</tr>
<tr>
<td>BM</td>
<td>business month end frequency</td>
</tr>
<tr>
<td>CBM</td>
<td>custom business month end frequency</td>
</tr>
<tr>
<td>MS</td>
<td>month start frequency</td>
</tr>
<tr>
<td>SMS</td>
<td>semi-month start frequency (1st and 15th)</td>
</tr>
<tr>
<td>BMS</td>
<td>business month start frequency</td>
</tr>
<tr>
<td>CBMS</td>
<td>custom business month start frequency</td>
</tr>
<tr>
<td>Q</td>
<td>quarter end frequency</td>
</tr>
<tr>
<td>BQ</td>
<td>business quarter end frequency</td>
</tr>
<tr>
<td>QS</td>
<td>quarter start frequency</td>
</tr>
<tr>
<td>BQS</td>
<td>business quarter start frequency</td>
</tr>
<tr>
<td>A, Y</td>
<td>year end frequency</td>
</tr>
<tr>
<td>BA, BY</td>
<td>business year end frequency</td>
</tr>
<tr>
<td>AS, YS</td>
<td>year start frequency</td>
</tr>
<tr>
<td>BAS, BYS</td>
<td>business year start frequency</td>
</tr>
<tr>
<td>BH</td>
<td>business hour frequency</td>
</tr>
<tr>
<td>H</td>
<td>hourly frequency</td>
</tr>
<tr>
<td>T, min</td>
<td>minutely frequency</td>
</tr>
<tr>
<td>S</td>
<td>secondly frequency</td>
</tr>
<tr>
<td>L, ms</td>
<td>milliseconds</td>
</tr>
<tr>
<td>U, us</td>
<td>microseconds</td>
</tr>
<tr>
<td>N</td>
<td>nanoseconds</td>
</tr>
</tbody>
</table>

Combining aliases

As we have seen previously, the alias and the offset instance are fungible in most functions:

<table>
<thead>
<tr>
<th>In [235]:</th>
<th>pd.date_range(start, periods=5, freq='B')</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>dtype='datetime64[ns]', freq='B')</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>In [236]:</th>
<th>pd.date_range(start, periods=5, freq=pd.offsets.BDay())</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>dtype='datetime64[ns]', freq='B')</td>
</tr>
</tbody>
</table>
You can combine together day and intraday offsets:

```python
In [237]: pd.date_range(start, periods=10, freq='2h20min')
Out[237]:
DatetimeIndex(['2011-01-01 00:00:00', '2011-01-01 02:20:00',
               '2011-01-01 04:40:00', '2011-01-01 07:00:00',
               '2011-01-01 09:20:00', '2011-01-01 11:40:00',
               '2011-01-01 14:00:00', '2011-01-01 16:20:00',
               '2011-01-01 18:40:00', '2011-01-01 21:00:00'],
            dtype='datetime64[ns]', freq='140T')
```

```python
In [238]: pd.date_range(start, periods=10, freq='1D10U')
Out[238]:
DatetimeIndex(['2011-01-01 00:00:00', '2011-01-02 00:00:00.000010',
               '2011-01-03 00:00:00.000020', '2011-01-04 00:00:00.000030',
               '2011-01-05 00:00:00.000040', '2011-01-06 00:00:00.000050',
               '2011-01-07 00:00:00.000060', '2011-01-08 00:00:00.000070',
               '2011-01-09 00:00:00.000080', '2011-01-10 00:00:00.000090'],
            dtype='datetime64[ns]', freq='86400000010U')
```

### Anchored offsets

For some frequencies you can specify an anchoring suffix:

<table>
<thead>
<tr>
<th>Alias</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>W-SUN</td>
<td>weekly frequency (Sundays). Same as ‘W’</td>
</tr>
<tr>
<td>W-MON</td>
<td>weekly frequency (Mondays)</td>
</tr>
<tr>
<td>W-TUE</td>
<td>weekly frequency (Tuesdays)</td>
</tr>
<tr>
<td>W-WED</td>
<td>weekly frequency (Wednesdays)</td>
</tr>
<tr>
<td>W-THU</td>
<td>weekly frequency (Thursdays)</td>
</tr>
<tr>
<td>W-FRI</td>
<td>weekly frequency (Fridays)</td>
</tr>
<tr>
<td>W-SAT</td>
<td>weekly frequency (Saturdays)</td>
</tr>
<tr>
<td>(B)Q(S)-DEC</td>
<td>quarterly frequency, year ends in December. Same as ‘Q’</td>
</tr>
<tr>
<td>(B)Q(S)-JAN</td>
<td>quarterly frequency, year ends in January</td>
</tr>
<tr>
<td>(B)Q(S)-FEB</td>
<td>quarterly frequency, year ends in February</td>
</tr>
<tr>
<td>(B)Q(S)-MAR</td>
<td>quarterly frequency, year ends in March</td>
</tr>
<tr>
<td>(B)Q(S)-APR</td>
<td>quarterly frequency, year ends in April</td>
</tr>
<tr>
<td>(B)Q(S)-MAY</td>
<td>quarterly frequency, year ends in May</td>
</tr>
<tr>
<td>(B)Q(S)-JUN</td>
<td>quarterly frequency, year ends in June</td>
</tr>
<tr>
<td>(B)Q(S)-JUL</td>
<td>quarterly frequency, year ends in July</td>
</tr>
<tr>
<td>Alias</td>
<td>Description</td>
</tr>
<tr>
<td>------------</td>
<td>--------------------------------------------------</td>
</tr>
<tr>
<td>(B)Q(S)-AUG</td>
<td>quarterly frequency, year ends in August</td>
</tr>
<tr>
<td>(B)Q(S)-SEP</td>
<td>quarterly frequency, year ends in September</td>
</tr>
<tr>
<td>(B)Q(S)-OCT</td>
<td>quarterly frequency, year ends in October</td>
</tr>
<tr>
<td>(B)Q(S)-NOV</td>
<td>quarterly frequency, year ends in November</td>
</tr>
<tr>
<td>(B)A(S)-DEC</td>
<td>annual frequency, anchored end of December. Same as ‘A’</td>
</tr>
<tr>
<td>(B)A(S)-JAN</td>
<td>annual frequency, anchored end of January</td>
</tr>
<tr>
<td>(B)A(S)-FEB</td>
<td>annual frequency, anchored end of February</td>
</tr>
<tr>
<td>(B)A(S)-MAR</td>
<td>annual frequency, anchored end of March</td>
</tr>
<tr>
<td>(B)A(S)-APR</td>
<td>annual frequency, anchored end of April</td>
</tr>
<tr>
<td>(B)A(S)-MAY</td>
<td>annual frequency, anchored end of May</td>
</tr>
<tr>
<td>(B)A(S)-JUN</td>
<td>annual frequency, anchored end of June</td>
</tr>
<tr>
<td>(B)A(S)-JUL</td>
<td>annual frequency, anchored end of July</td>
</tr>
<tr>
<td>(B)A(S)-AUG</td>
<td>annual frequency, anchored end of August</td>
</tr>
<tr>
<td>(B)A(S)-SEP</td>
<td>annual frequency, anchored end of September</td>
</tr>
<tr>
<td>(B)A(S)-OCT</td>
<td>annual frequency, anchored end of October</td>
</tr>
<tr>
<td>(B)A(S)-NOV</td>
<td>annual frequency, anchored end of November</td>
</tr>
</tbody>
</table>

These can be used as arguments to `date_range`, `bdate_range`, constructors for `DatetimeIndex`, as well as various other timeseries-related functions in pandas.

**Anchored offset semantics**

For those offsets that are anchored to the start or end of specific frequency (`MonthEnd`, `MonthBegin`, `WeekEnd`, etc), the following rules apply to rolling forward and backwards.

When \( n \) is not 0, if the given date is not on an anchor point, it snapped to the next(previous) anchor point, and moved \(|n|-1\) additional steps forwards or backwards.

```python
In [239]: pd.Timestamp('2014-01-02') + pd.offsets.MonthBegin(n=1)
Out[239]: Timestamp('2014-02-01 00:00:00')

In [240]: pd.Timestamp('2014-01-02') + pd.offsets.MonthEnd(n=1)
Out[240]: Timestamp('2014-01-31 00:00:00')

In [241]: pd.Timestamp('2014-01-02') - pd.offsets.MonthBegin(n=1)
```

(continues on next page)
Out[241]: Timestamp('2014-01-01 00:00:00')

In [242]: pd.Timestamp('2014-01-02') - pd.offsets.MonthEnd(n=1)
Out[242]: Timestamp('2013-12-31 00:00:00')

In [243]: pd.Timestamp('2014-01-02') + pd.offsets.MonthBegin(n=4)
Out[243]: Timestamp('2014-05-01 00:00:00')

In [244]: pd.Timestamp('2014-01-02') - pd.offsets.MonthBegin(n=4)
Out[244]: Timestamp('2013-10-01 00:00:00')

If the given date is on an anchor point, it is moved $|n|$ points forwards or backwards.

In [245]: pd.Timestamp('2014-01-01') + pd.offsets.MonthBegin(n=1)
Out[245]: Timestamp('2014-02-01 00:00:00')

In [246]: pd.Timestamp('2014-01-31') + pd.offsets.MonthEnd(n=1)
Out[246]: Timestamp('2014-02-28 00:00:00')

In [247]: pd.Timestamp('2014-01-01') - pd.offsets.MonthBegin(n=1)
Out[247]: Timestamp('2013-12-01 00:00:00')

In [248]: pd.Timestamp('2014-01-31') - pd.offsets.MonthEnd(n=1)
Out[248]: Timestamp('2013-12-31 00:00:00')

In [249]: pd.Timestamp('2014-01-01') + pd.offsets.MonthBegin(n=4)
Out[249]: Timestamp('2014-05-01 00:00:00')

In [250]: pd.Timestamp('2014-01-31') - pd.offsets.MonthBegin(n=4)
Out[250]: Timestamp('2013-10-01 00:00:00')

For the case when $n=0$, the date is not moved if on an anchor point, otherwise it is rolled forward to the next anchor point.

In [251]: pd.Timestamp('2014-01-02') + pd.offsets.MonthBegin(n=0)
Out[251]: Timestamp('2014-02-01 00:00:00')

In [252]: pd.Timestamp('2014-01-02') + pd.offsets.MonthEnd(n=0)
Out[252]: Timestamp('2014-01-31 00:00:00')

In [253]: pd.Timestamp('2014-01-01') + pd.offsets.MonthBegin(n=0)
Out[253]: Timestamp('2014-01-01 00:00:00')

In [254]: pd.Timestamp('2014-01-31') + pd.offsets.MonthEnd(n=0)
Out[254]: Timestamp('2014-01-31 00:00:00')
Holidays / holiday calendars

Holidays and calendars provide a simple way to define holiday rules to be used with CustomBusinessDay or in other analysis that requires a predefined set of holidays. The AbstractHolidayCalendar class provides all the necessary methods to return a list of holidays and only rules need to be defined in a specific holiday calendar class. Furthermore, the start_date and end_date class attributes determine over what date range holidays are generated. These should be overwritten on the AbstractHolidayCalendar class to have the range apply to all calendar subclasses. USFederalHolidayCalendar is the only calendar that exists and primarily serves as an example for developing other calendars.

For holidays that occur on fixed dates (e.g., US Memorial Day or July 4th) an observance rule determines when that holiday is observed if it falls on a weekend or some other non-observed day. Defined observance rules are:

<table>
<thead>
<tr>
<th>Rule</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>nearest_workday</td>
<td>move Saturday to Friday and Sunday to Monday</td>
</tr>
<tr>
<td>sunday_to_monday</td>
<td>move Sunday to following Monday</td>
</tr>
<tr>
<td>next_monday_or_tuesday</td>
<td>Saturday to Monday and Sunday/Monday to Tuesday</td>
</tr>
<tr>
<td>previous_friday</td>
<td>move Saturday and Sunday to previous Friday</td>
</tr>
<tr>
<td>next_monday</td>
<td>move Saturday and Sunday to following Monday</td>
</tr>
</tbody>
</table>

An example of how holidays and holiday calendars are defined:

```python
In [255]: from pandas.tseries.holiday import
....:     Holiday, USMemorialDay,
....:     AbstractHolidayCalendar, nearest_workday, MO
....:
In [256]: class ExampleCalendar(AbstractHolidayCalendar):
....:     rules = [
....:     USMemorialDay,
....:     Holiday('July 4th', month=7, day=4, observance=nearest_workday),
....:     Holiday('Columbus Day', month=10, day=1,
....:     offset=pd.DateOffset(weekday=MO(2)))
....:     ]
....:
In [257]: cal = ExampleCalendar()

In [258]: cal.holidays(datetime.datetime(2012, 1, 1), datetime.datetime(2012, 12, 31))
Out[258]: DatetimeIndex(['2012-05-28', '2012-07-04', '2012-10-08'], dtype='datetime64[ns]', freq=None)
```

hint weekday=MO(2) is same as 2 * Week(weekday=2)

Using this calendar, creating an index or doing offset arithmetic skips weekends and holidays (i.e., Memorial Day/July 4th). For example, the below defines a custom business day offset using the ExampleCalendar. Like any other offset, it can be used to create a DatetimeIndex or added to datetime or Timestamp objects.

```python
In [259]: pd.date_range(start='7/1/2012', end='7/10/2012',
....:     freq=pd.offsets.CDay(calendar=cal)).to_pydatetime()
```

(continues on next page)
Ranges are defined by the `start_date` and `end_date` class attributes of `AbstractHolidayCalendar`. The defaults are shown below.

These dates can be overwritten by setting the attributes as datetime/Timestamp/string.

Every calendar class is accessible by name using the `get_calendar` function which returns a holiday class instance. Any imported calendar class will automatically be available by this function. Also, `HolidayCalendarFactory` provides an easy interface to create calendars that are combinations of calendars or calendars with additional rules.
2.17.9 Time series-related instance methods

**Shifting / lagging**

One may want to *shift* or *lag* the values in a time series back and forward in time. The method for this is `shift()`, which is available on all of the pandas objects.

```
In [275]: ts = pd.Series(range(len(rng)), index=rng)
In [276]: ts = ts[:5]
In [277]: ts.shift(1)
Out[277]:
2012-01-01   NaN
2012-01-02   0.0
2012-01-03   1.0
Freq: D, dtype: float64
```

The `shift` method accepts an `freq` argument which can accept a `DateOffset` class or other `timedelta`-like object or also an *offset alias*.

When `freq` is specified, `shift` method changes all the dates in the index rather than changing the alignment of the data and the index:

```
In [278]: ts.shift(5, freq='D')
Out[278]:
2012-01-06    0
2012-01-07    1
2012-01-08    2
Freq: D, dtype: int64

In [279]: ts.shift(5, freq=pd.offsets.BDay())
Out[279]:
2012-01-06    0
2012-01-09    1
2012-01-10    2
dtype: int64

In [280]: ts.shift(5, freq='BM')
Out[280]:
2012-05-31    0
2012-05-31    1
2012-05-31    2
dtype: int64
```

Note that with when `freq` is specified, the leading entry is no longer NaN because the data is not being realigned.
Frequency conversion

The primary function for changing frequencies is the `asfreq()` method. For a `DatetimeIndex`, this is basically just a thin, but convenient wrapper around `reindex()` which generates a `date_range` and calls `reindex`.

```
In [281]: dr = pd.date_range('1/1/2010', periods=3, freq=3 * pd.offsets.BDay())

In [282]: ts = pd.Series(np.random.randn(3), index=dr)

In [283]: ts
Out[283]:
2010-01-01    1.494522
2010-01-06   -0.778425
2010-01-11   -0.253355
Freq: 3B, dtype: float64

In [284]: ts.asfreq(pd.offsets.BDay(), method='pad')
Out[284]:
2010-01-01    1.494522
2010-01-04    1.494522
2010-01-05    1.494522
2010-01-06   -0.778425
2010-01-07   -0.778425
2010-01-08   -0.778425
2010-01-11   -0.253355
Freq: B, dtype: float64
```

`asfreq` provides a further convenience so you can specify an interpolation method for any gaps that may appear after the frequency conversion.

```
In [285]: ts.asfreq(pd.offsets.BDay(), method='pad')
Out[285]:
2010-01-01    1.494522
2010-01-04    1.494522
2010-01-05    1.494522
2010-01-06   -0.778425
2010-01-07   -0.778425
2010-01-08   -0.778425
2010-01-11   -0.253355
Freq: B, dtype: float64
```

Filling forward / backward

Related to `asfreq` and `reindex` is `fillna()`, which is documented in the missing data section.

Converting to Python datetimes

`DatetimeIndex` can be converted to an array of Python native `datetime.datetime` objects using the `to_pydatetime` method.
2.17.10 Resampling

Pandas has a simple, powerful, and efficient functionality for performing resampling operations during frequency conversion (e.g., converting secondly data into 5-minutely data). This is extremely common in, but not limited to, financial applications.

`resample()` is a time-based groupby, followed by a reduction method on each of its groups. See some cookbook examples for some advanced strategies.

The `resample()` method can be used directly from `DataFrameGroupBy` objects, see the `groupby docs`.

Note: `.resample()` is similar to using a `rolling()` operation with a time-based offset, see a discussion here.

### Basics

```python
In [286]: rng = pd.date_range('1/1/2012', periods=100, freq='S')
In [287]: ts = pd.Series(np.random.randint(0, 500, len(rng)), index=rng)
In [288]: ts.resample('5Min').sum()
Out[288]:
2012-01-01  25103
Freq: 5T, dtype: int64
```

The `resample` function is very flexible and allows you to specify many different parameters to control the frequency conversion and resampling operation.

Any function available via `dispatching` is available as a method of the returned object, including `sum`, `mean`, `std`, `sem`, `max`, `min`, `median`, `first`, `last`, `ohlc`:

```python
In [289]: ts.resample('5Min').mean()
Out[289]:
2012-01-01  251.03
Freq: 5T, dtype: float64
In [290]: ts.resample('5Min').ohlc()
Out[290]:
open  high   low  close
2012-01-01  308  460   9  205
In [291]: ts.resample('5Min').max()
Out[291]:
2012-01-01   460
Freq: 5T, dtype: int64
```

For downsampling, `closed` can be set to ‘left’ or ‘right’ to specify which end of the interval is closed:

```python
In [292]: ts.resample('5Min', closed='right').mean()
Out[292]:
2011-12-31  23:55:00 308.000000
2012-01-01  00:00:00  250.454545
Freq: 5T, dtype: float64
In [293]: ts.resample('5Min', closed='left').mean()
```

(continues on next page)
Parameters like `label` are used to manipulate the resulting labels. `label` specifies whether the result is labeled with the beginning or the end of the interval.

```python
In [294]: ts.resample('5Min').mean()  # by default label='left'
Out[294]:
2012-01-01 251.03
Freq: 5T, dtype: float64

In [295]: ts.resample('5Min', label='left').mean()
Out[295]:
2012-01-01 251.03
Freq: 5T, dtype: float64
```

**Warning:** The default values for `label` and `closed` is `left` for all frequency offsets except for ‘M’, ‘A’, ‘Q’, ‘BM’, ‘BA’, ‘BQ’, and ‘W’ which all have a default of ‘right’.

This might unintendedly lead to looking ahead, where the value for a later time is pulled back to a previous time as in the following example with the `BusinessDay` frequency:

```python
In [296]: s = pd.date_range('2000-01-01', '2000-01-05').to_series()
In [297]: s.iloc[2] = pd.NaT
In [298]: s.dt.day_name()
Out[298]:
2000-01-01 Saturday
2000-01-02 Sunday
2000-01-03 NaN
2000-01-04 Tuesday
2000-01-05 Wednesday
Freq: D, dtype: object
```

# default: label='left', closed='left'

```python
In [299]: s.resample('B').last().dt.day_name()
Out[299]:
1999-12-31 Sunday
2000-01-03 NaN
2000-01-04 Tuesday
2000-01-05 Wednesday
Freq: B, dtype: object
```

Notice how the value for Sunday got pulled back to the previous Friday. To get the behavior where the value for Sunday is pushed to Monday, use instead

```python
In [300]: s.resample('B', label='right', closed='right').last().dt.day_name()
Out[300]:
2000-01-03 Sunday
2000-01-04 Tuesday
2000-01-05 Wednesday
Freq: B, dtype: object
```

The `axis` parameter can be set to 0 or 1 and allows you to resample the specified axis for a `DataFrame`.

2.17. Time series / date functionality
kind can be set to ‘timestamp’ or ‘period’ to convert the resulting index to/from timestamp and time span representations. By default resample retains the input representation.

convention can be set to ‘start’ or ‘end’ when resampling period data (detail below). It specifies how low frequency periods are converted to higher frequency periods.

**Upsampling**

For upsampling, you can specify a way to upsample and the limit parameter to interpolate over the gaps that are created:

```
# from secondly to every 250 milliseconds
In [301]: ts[:2].resample('250L').asfreq()
Out[301]:
2012-01-01 00:00:00.000   308.0
2012-01-01 00:00:00.250     NaN
2012-01-01 00:00:00.500     NaN
2012-01-01 00:00:00.750     NaN
2012-01-01 00:00:01.000   204.0
Freq: 250L, dtype: float64
```

```
In [302]: ts[:2].resample('250L').ffill()
Out[302]:
2012-01-01 00:00:00.000   308
2012-01-01 00:00:00.250   308
2012-01-01 00:00:00.500   308
2012-01-01 00:00:00.750   308
2012-01-01 00:00:01.000   204
Freq: 250L, dtype: int64
```

```
In [303]: ts[:2].resample('250L').ffill(limit=2)
Out[303]:
2012-01-01 00:00:00.000   308.0
2012-01-01 00:00:00.250   308.0
2012-01-01 00:00:00.500   308.0
2012-01-01 00:00:00.750     NaN
2012-01-01 00:00:01.000   204.0
Freq: 250L, dtype: float64
```

**Sparse resampling**

Sparse timeseries are the ones where you have a lot fewer points relative to the amount of time you are looking to resample. Naively upsampling a sparse series can potentially generate lots of intermediate values. When you don’t want to use a method to fill these values, e.g. fill_method is None, then intermediate values will be filled with NaN.

Since resample is a time-based groupby, the following is a method to efficiently resample only the groups that are not all NaN.

```
In [304]: rng = pd.date_range('2014-1-1', periods=100, freq='D') + pd.Timedelta('1s')
In [305]: ts = pd.Series(range(100), index=rng)
```

If we want to resample to the full range of the series:
In [306]: ts.resample('3T').sum()
Out[306]:
2014-01-01 00:00:00  0
2014-01-01 00:03:00  0
2014-01-01 00:06:00  0
2014-01-01 00:09:00  0
2014-01-01 00:12:00  0
              ..
2014-04-09 23:48:00  0
2014-04-09 23:51:00  0
2014-04-09 23:54:00  0
2014-04-09 23:57:00  0
2014-04-10 00:00:00  99
Freq: 3T, Length: 47521, dtype: int64

We can instead only resample those groups where we have points as follows:

In [307]: from functools import partial
In [308]: from pandas.tseries.frequencies import to_offset
In [309]: def round(t, freq):
       ....:     freq = to_offset(freq)
       ....:     return pd.Timestamp(t.value // freq.delta.value) * freq.delta.value
       ....:
In [310]: ts.groupby(partial(round, freq='3T')).sum()
Out[310]:
2014-01-01  0
2014-01-02  1
2014-01-03  2
2014-01-04  3
2014-01-05  4
              ..
2014-04-06  95
2014-04-07  96
2014-04-08  97
2014-04-09  98
2014-04-10  99
Length: 100, dtype: int64

Aggregation

Similar to the aggregating API, groupby API, and the window functions API, a Resampler can be selectively resampled.

Resampling a DataFrame, the default will be to act on all columns with the same function.

In [311]: df = pd.DataFrame(np.random.randn(1000, 3),
                   index=pd.date_range('1/1/2012', freq='S', periods=1000),
                   columns=['A', 'B', 'C'])
In [312]: r = df.resample('3T')
In [313]: r.mean()
We can select a specific column or columns using standard getitem.

We can select a specific column or columns using standard getitem.

You can pass a list or dict of functions to do aggregation with, outputting a DataFrame:

On a resampled DataFrame, you can pass a list of functions to apply to each column, which produces an aggregated result with a hierarchical index:
By passing a dict to `aggregate` you can apply a different aggregation to the columns of a `DataFrame`:

```python
In [318]: r.agg({'A': np.sum,
          'B': lambda x: np.std(x, ddof=1)})
```

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012-01-01 00:00:00</td>
<td>-6.088060</td>
<td>1.001294</td>
</tr>
<tr>
<td>2012-01-01 00:03:00</td>
<td>10.243678</td>
<td>1.074597</td>
</tr>
<tr>
<td>2012-01-01 00:06:00</td>
<td>-10.590584</td>
<td>0.987309</td>
</tr>
<tr>
<td>2012-01-01 00:09:00</td>
<td>11.362228</td>
<td>0.944953</td>
</tr>
<tr>
<td>2012-01-01 00:12:00</td>
<td>33.541257</td>
<td>1.095025</td>
</tr>
<tr>
<td>2012-01-01 00:15:00</td>
<td>-8.595393</td>
<td>1.035312</td>
</tr>
</tbody>
</table>

The function names can also be strings. In order for a string to be valid it must be implemented on the resampled object:

```python
In [319]: r.agg({'A': 'sum', 'B': 'std'})
```

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012-01-01 00:00:00</td>
<td>-6.088060</td>
<td>1.001294</td>
</tr>
<tr>
<td>2012-01-01 00:03:00</td>
<td>10.243678</td>
<td>1.074597</td>
</tr>
<tr>
<td>2012-01-01 00:06:00</td>
<td>-10.590584</td>
<td>0.987309</td>
</tr>
<tr>
<td>2012-01-01 00:09:00</td>
<td>11.362228</td>
<td>0.944953</td>
</tr>
<tr>
<td>2012-01-01 00:12:00</td>
<td>33.541257</td>
<td>1.095025</td>
</tr>
<tr>
<td>2012-01-01 00:15:00</td>
<td>-8.595393</td>
<td>1.035312</td>
</tr>
</tbody>
</table>

Furthermore, you can also specify multiple aggregation functions for each column separately.

```python
In [320]: r.agg({'A': ['sum', 'std'], 'B': ['mean', 'std']})
```

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>sum</td>
<td>std</td>
<td>mean</td>
</tr>
<tr>
<td>2012-01-01 00:00:00</td>
<td>-6.088060</td>
<td>1.043263</td>
</tr>
<tr>
<td>2012-01-01 00:03:00</td>
<td>10.243678</td>
<td>1.058534</td>
</tr>
<tr>
<td>2012-01-01 00:06:00</td>
<td>-10.590584</td>
<td>0.949264</td>
</tr>
<tr>
<td>2012-01-01 00:09:00</td>
<td>11.362228</td>
<td>1.028096</td>
</tr>
<tr>
<td>2012-01-01 00:12:00</td>
<td>33.541257</td>
<td>0.884586</td>
</tr>
<tr>
<td>2012-01-01 00:15:00</td>
<td>-8.595393</td>
<td>1.035476</td>
</tr>
</tbody>
</table>

If a `DataFrame` does not have a datetimelike index, but instead you want to resample based on datetimelike column in the frame, it can passed to the `on` keyword.

```python
In [321]: df = pd.DataFrame({'date': pd.date_range('2015-01-01', freq='W', periods=5),
                      'a': np.arange(5),
                      index=pd.MultiIndex.from_arrays([
                          [1, 2, 3, 4, 5],
                          pd.date_range('2015-01-01', freq='W', periods=5)],
                      names=['v', 'd']))
```

```python
In [322]: df
```

<table>
<thead>
<tr>
<th></th>
<th>date a</th>
</tr>
</thead>
<tbody>
<tr>
<td>v d</td>
<td></td>
</tr>
<tr>
<td>1 2015-01-04 2015-01-04</td>
<td>0</td>
</tr>
<tr>
<td>2 2015-01-11 2015-01-11</td>
<td>1</td>
</tr>
<tr>
<td>3 2015-01-18 2015-01-18</td>
<td>2</td>
</tr>
</tbody>
</table>
Similarly, if you instead want to resample by a datetimelike level of MultiIndex, its name or location can be passed to the level keyword.

```python
In [324]: df.resample('M', level='d').sum()
Out[324]:
       a
2015-01-31  6
2015-02-28  4
```

### Iterating through groups

With the Resampler object in hand, iterating through the grouped data is very natural and functions similarly to `itertools.groupby()`:

```python
In [325]: small = pd.Series(
       ..:     range(6),
       ..:     index=pd.to_datetime(["2017-01-01T00:00:00",
       ..:             '2017-01-01T00:30:00",
       ..:             '2017-01-01T00:31:00",
       ..:             '2017-01-01T01:00:00",
       ..:             '2017-01-01T03:00:00",
       ..:             '2017-01-01T03:05:00'])

In [326]: resampled = small.resample('H')

In [327]: for name, group in resampled:
       ..:     print("Group: ", name)
       ..:     print("-" * 27)
       ..:     print(group, end="\n\n")

Group: 2017-01-01 00:00:00
------------------------
2017-01-01 00:00:00 0
2017-01-01 00:30:00 1
2017-01-01 00:31:00 2
dtype: int64

Group: 2017-01-01 01:00:00
------------------------
2017-01-01 01:00:00 3
dtype: int64
```

(continues on next page)
Group: 2017-01-01 02:00:00
---------------------------
Series([], dtype: int64)

Group: 2017-01-01 03:00:00
---------------------------
2017-01-01 03:00:00 4
2017-01-01 03:05:00 5
dtype: int64

See Iterating through groups or Resampler.__iter__ for more.

Use origin or offset to adjust the start of the bins

New in version 1.1.0.

The bins of the grouping are adjusted based on the beginning of the day of the time series starting point. This works well with frequencies that are multiples of a day (like 30D) or that divide a day evenly (like 90s or 1min). This can create inconsistencies with some frequencies that do not meet this criteria. To change this behavior you can specify a fixed Timestamp with the argument origin.

For example:

```python
In [328]: start, end = '2000-10-01 23:30:00', '2000-10-02 00:30:00'

In [329]: middle = '2000-10-02 00:00:00'

In [330]: rng = pd.date_range(start, end, freq='7min')

In [331]: ts = pd.Series(np.arange(len(rng)) * 3, index=rng)

In [332]: ts
Out[332]:
2000-10-01 23:30:00    0
2000-10-01 23:37:00    3
2000-10-01 23:44:00    6
2000-10-01 23:51:00    9
2000-10-01 23:58:00   12
2000-10-02 00:05:00   15
2000-10-02 00:12:00   18
2000-10-02 00:19:00   21
2000-10-02 00:26:00   24
Freq: 7T, dtype: int64
```

Here we can see that, when using origin with its default value ('start_day'), the result after '2000-10-02 00:00:00' are not identical depending on the start of time series:

```python
In [333]: ts.resample('17min', origin='start_day').sum()
Out[333]:
2000-10-01 23:14:00    0
2000-10-01 23:31:00    9
2000-10-01 23:48:00   21
2000-10-02 00:05:00   54
2000-10-02 00:22:00   24
Freq: 17T, dtype: int64
```

(continues on next page)
Here we can see that, when setting origin to 'epoch', the result after 2000-10-02 00:00:00 are identical depending on the start of time series:

If needed you can use a custom timestamp for origin:

If needed you can just adjust the bins with an offset Timedelta that would be added to the default origin. Those two examples are equivalent for this time series:

(continues on next page)
Note the use of 'start' for origin on the last example. In that case, origin will be set to the first value of the timeseries.

2.17.11 Time span representation

Regular intervals of time are represented by Period objects in pandas while sequences of Period objects are collected in a PeriodIndex, which can be created with the convenience function period_range.

Period

A Period represents a span of time (e.g., a day, a month, a quarter, etc). You can specify the span via freq keyword using a frequency alias like below. Because freq represents a span of Period, it cannot be negative like “-3D”.

```
In [341]: pd.Period('2012', freq='A-DEC')
Out[341]: Period('2012', 'A-DEC')

In [342]: pd.Period('2012-1-1', freq='D')
Out[342]: Period('2012-01-01', 'D')

In [343]: pd.Period('2012-1-1 19:00', freq='H')
Out[343]: Period('2012-01-01 19:00', 'H')

In [344]: pd.Period('2012-1-1 19:00', freq='5H')
Out[344]: Period('2012-01-01 19:00', '5H')
```

Adding and subtracting integers from periods shifts the period by its own frequency. Arithmetic is not allowed between Period with different freq (span).

```
In [345]: p = pd.Period('2012', freq='A-DEC')

In [346]: p + 1
Out[346]: Period('2013', 'A-DEC')

In [347]: p - 3
Out[347]: Period('2009', 'A-DEC')

In [348]: p = pd.Period('2012-01', freq='2M')

In [349]: p + 2
Out[349]: Period('2012-05', '2M')

In [350]: p - 1
Out[350]: Period('2011-11', '2M')

In [351]: p == pd.Period('2012-01', freq='3M')
---------------------------------------------------------------------------
IncompatibleFrequency
Traceback (most recent call last)
<ipython-input-351-4b67dc0b596c> in <module>
----> 1 p == pd.Period('2012-01', freq='3M')
```
If `Period` freq is daily or higher (D, H, T, S, L, U, N), offsets and timedelta-like can be added if the result can have the same freq. Otherwise, `ValueError` will be raised.

```python
In [352]: p = pd.Period('2014-07-01 09:00', freq='H')
```

```python
In [353]: p + pd.offsets.Hour(2)
```

```python
Out[353]: Period('2014-07-01 11:00', 'H')
```

```python
In [354]: p + datetime.timedelta(minutes=120)
```

```python
Out[354]: Period('2014-07-01 11:00', 'H')
```

```python
In [355]: p + np.timedelta64(7200, 's')
```

```python
Out[355]: Period('2014-07-01 11:00', 'H')
```

```python
In [1]: p + pd.offsets.Minute(5)
```

Traceback
...

`ValueError: Input has different freq from Period(freq=H)`

If `Period` has other frequencies, only the same offsets can be added. Otherwise, `ValueError` will be raised.

```python
In [356]: p = pd.Period('2014-07', freq='M')
```

```python
In [357]: p + pd.offsets.MonthEnd(3)
```

```python
Out[357]: Period('2014-10', 'M')
```

```python
In [1]: p + pd.offsets.MonthBegin(3)
```

Traceback
...

`ValueError: Input has different freq from Period(freq=M)`

Taking the difference of `Period` instances with the same frequency will return the number of frequency units between them:

```python
```

```python
Out[358]: <10 * YearEnds: month=12>
```

**PeriodIndex and period_range**

Regular sequences of `Period` objects can be collected in a `PeriodIndex`, which can be constructed using the `period_range` convenience function:

```python
In [359]: prng = pd.period_range('1/1/2011', '1/1/2012', freq='M')
```

```python
In [360]: prng
```

```python
          '2012-01', '2012-02', '2012-03', '2012-04', '2012-05', '2012-06',
          '2012-07', '2012-08', '2012-09', '2012-10', '2012-11', '2012-12'],
         dtype='datetime64[ns]', freq='M')
```
The `PeriodIndex` constructor can also be used directly:

```python
In [361]: pd.PeriodIndex(['2011-1', '2011-2', '2011-3'], freq='M')
Out[361]: PeriodIndex(['2011-01', '2011-02', '2011-03'], dtype='period[M]', freq='M')
```

Passing multiplied frequency outputs a sequence of `Period` which has multiplied span.

```python
In [362]: pd.period_range(start='2014-01', freq='3M', periods=4)
```

If `start` or `end` are `Period` objects, they will be used as anchor endpoints for a `PeriodIndex` with frequency matching that of the `PeriodIndex` constructor.

```python
In [363]: pd.period_range(start=pd.Period('2017Q1', freq='Q'),
     ....:   end=pd.Period('2017Q2', freq='Q'), freq='M')
     ....:
Out[363]: PeriodIndex(['2017-03', '2017-04', '2017-05', '2017-06'], dtype='period[M]', freq='M')
```

Just like `DatetimeIndex`, a `PeriodIndex` can also be used to index pandas objects:

```python
In [364]: ps = pd.Series(np.random.randn(len(prng)), prng)
In [365]: ps
Out[365]:
2011-01 -2.916901
2011-02  0.514474
2011-03  1.346470
2011-04  0.816397
2011-05  2.258648
2011-06  0.494789
2011-07  0.301239
2011-08  0.464776
2011-09 -1.393581
2011-10  0.056780
2011-11  0.197035
2011-12  2.261385
2012-01 -0.329583
Freq: M, dtype: float64
```

PeriodIndex supports addition and subtraction with the same rule as `Period`.

```python
In [366]: idx = pd.period_range('2014-07-01 09:00', periods=5, freq='H')
In [367]: idx
Out[367]: PeriodIndex(['2014-07-01 09:00', '2014-07-01 10:00', '2014-07-01 11:00',
     ....:   '2014-07-01 12:00', '2014-07-01 13:00'], dtype='period[H]', freq='H')
In [368]: idx + pd.offsets.Hour(2)
Out[368]:
```

(continues on next page)
PeriodIndex has its own dtype named period, refer to *Period Dtypes*.

**Period dtypes**

PeriodIndex has a custom period dtype. This is a pandas extension dtype similar to the *timezone aware dtype* (datetime64[ns, tz]).

The period dtype holds the freq attribute and is represented with period[freq] like period[D] or period[M], using *frequency strings*.

```python
In [372]: pi = pd.period_range('2016-01-01', periods=3, freq='M')
In [373]: pi
Out[373]: PeriodIndex(['2016-01', '2016-02', '2016-03'], dtype='period[M]', freq='M')
In [374]: pi.dtype
Out[374]: period[M]
```

The period dtype can be used in `.astype(...)`. It allows one to change the freq of a PeriodIndex like `.asfreq()` and convert a DatetimeIndex to PeriodIndex like `to_period()`:

```python
# change monthly freq to daily freq
In [375]: pi.astype('period[D]')
Out[375]: PeriodIndex(['2016-01-31', '2016-02-29', '2016-03-31'], dtype='period[D]', freq='D')

# convert to DatetimeIndex
In [376]: pi.astype('datetime64[ns]')
Out[376]: DatetimeIndex(['2016-01-01', '2016-02-01', '2016-03-01'], dtype='datetime64[ns]', freq='MS')

# convert to PeriodIndex
In [377]: dti = pd.date_range('2011-01-01', freq='M', periods=3)
In [378]: dti
Out[378]: DatetimeIndex(['2011-01-31', '2011-02-28', '2011-03-31'], dtype='datetime64[ns]', freq='M')
In [379]: dti.astype('period[M]')
Out[379]: PeriodIndex(['2011-01', '2011-02', '2011-03'], dtype='period[M]', freq='M')
```
PeriodIndex partial string indexing

PeriodIndex now supports partial string slicing with non-monotonic indexes.

New in version 1.1.0.

You can pass in dates and strings to Series and DataFrame with PeriodIndex, in the same manner as DatetimeIndex. For details, refer to DatetimeIndex Partial String Indexing.

```python
In [380]: ps['2011-01']
Out[380]: -2.9169013294054507

In [381]: ps[datetime.datetime(2011, 12, 25):]
Out[381]:
2011-12 2.261385
2012-01 -0.329583
Freq: M, dtype: float64

In [382]: ps['10/31/2011':'12/31/2011']
Out[382]:
2011-10 0.056780
2011-11 0.197035
2011-12 2.261385
Freq: M, dtype: float64
```

Passing a string representing a lower frequency than PeriodIndex returns partial sliced data.

```python
In [383]: ps['2011']
Out[383]:
2011-01 -2.916901
2011-02  0.514474
2011-03  1.346470
2011-04  0.816397
2011-05  2.258648
2011-06  0.494789
2011-07  0.301239
2011-08  0.464776
2011-09 -1.393581
2011-10  0.056780
2011-11  0.197035
2011-12  2.261385
Freq: M, dtype: float64
```

```python
In [384]: dfp = pd.DataFrame(np.random.randn(600, 1),
                      columns=['A'],
                      index=pd.period_range('2013-01-01 09:00',
                                             periods=600,
                                             freq='T'))

In [385]: dfp
Out[385]:
   A
2013-01-01 09:00 -0.538468
2013-01-01 09:01 -0.365819
2013-01-01 09:02 -0.969051
2013-01-01 09:03 -0.331152
2013-01-01 09:04 -0.245334
```

(continues on next page)
As with `DatetimeIndex`, the endpoints will be included in the result. The example below slices data starting from 10:00 to 11:59.

```python
In [387]: dfp['2013-01-01 10H':'2013-01-01 11H']
Out[387]:
A
2013-01-01 10:00  -0.308975
2013-01-01 10:01  0.542520
2013-01-01 10:02  1.061068
2013-01-01 10:03  0.754005
2013-01-01 10:04  0.352933
...          ...          ...
2013-01-01 11:55  -0.590204
2013-01-01 11:56  1.539990
2013-01-01 11:57  -1.224826
2013-01-01 11:58  0.578798
2013-01-01 11:59  -0.685496
[120 rows x 1 columns]
```
Frequency conversion and resampling with PeriodIndex

The frequency of Period and PeriodIndex can be converted via the asfreq method. Let’s start with the fiscal year 2011, ending in December:

```
In [388]: p = pd.Period('2011', freq='A-DEC')
```

```
In [389]: p
Out[389]: Period('2011', 'A-DEC')
```

We can convert it to a monthly frequency. Using the how parameter, we can specify whether to return the starting or ending month:

```
In [390]: p.asfreq('M', how='start')
Out[390]: Period('2011-01', 'M')
```

```
In [391]: p.asfreq('M', how='end')
Out[391]: Period('2011-12', 'M')
```

The shorthands ‘s’ and ‘e’ are provided for convenience:

```
In [392]: p.asfreq('M', 's')
Out[392]: Period('2011-01', 'M')
```

```
In [393]: p.asfreq('M', 'e')
Out[393]: Period('2011-12', 'M')
```

Converting to a “super-period” (e.g., annual frequency is a super-period of quarterly frequency) automatically returns the super-period that includes the input period:

```
In [394]: p = pd.Period('2011-12', freq='M')

In [395]: p.asfreq('A-NOV')
Out[395]: Period('2012', 'A-NOV')
```

Note that since we converted to an annual frequency that ends the year in November, the monthly period of December 2011 is actually in the 2012 A-NOV period.

Period conversions with anchored frequencies are particularly useful for working with various quarterly data common to economics, business, and other fields. Many organizations define quarters relative to the month in which their fiscal year starts and ends. Thus, first quarter of 2011 could start in 2010 or a few months into 2011. Via anchored frequencies, pandas works for all quarterly frequencies Q-JAN through Q-DEC.

Q-DEC define regular calendar quarters:

```
In [396]: p = pd.Period('2012Q1', freq='Q-DEC')

In [397]: p.asfreq('D', 's')
Out[397]: Period('2012-01-01', 'D')
```

```
In [398]: p.asfreq('D', 'e')
Out[398]: Period('2012-03-31', 'D')
```

Q-MAR defines fiscal year end in March:

```
In [399]: p = pd.Period('2011Q4', freq='Q-MAR')

In [400]: p.asfreq('D', 's')
```
2.17.12 Converting between representations

Timestamped data can be converted to PeriodIndex-ed data using to_period and vice-versa using to_timestamp:

In [402]: rng = pd.date_range('1/1/2012', periods=5, freq='M')
In [403]: ts = pd.Series(np.random.randn(len(rng)), index=rng)
In [404]: ts
Out[404]:
2012-01-31  1.931253
2012-02-29  -0.184594
2012-03-31  0.249656
2012-04-30  -0.978151
2012-05-31  -0.873389
Freq: M, dtype: float64
In [405]: ps = ts.to_period()
In [406]: ps
Out[406]:
2012-01  1.931253
2012-02 -0.184594
2012-03  0.249656
2012-04 -0.978151
2012-05 -0.873389
Freq: M, dtype: float64
In [407]: ps.to_timestamp()
Out[407]:
2012-01-01  1.931253
2012-02-01 -0.184594
2012-03-01  0.249656
2012-04-01 -0.978151
2012-05-01 -0.873389
Freq: MS, dtype: float64
In [408]: ps.to_timestamp('D', how='s')
Out[408]:
2012-01-01  1.931253
2012-02-01 -0.184594
2012-03-01  0.249656
2012-04-01 -0.978151
2012-05-01 -0.873389
Freq: MS, dtype: float64

Remember that ‘s’ and ‘e’ can be used to return the timestamps at the start or end of the period:

In [409]: ps.to_timestamp('D', how='s')
Out[409]:
2012-01-01  1.931253
2012-02-01 -0.184594
2012-03-01  0.249656
2012-04-01 -0.978151
2012-05-01 -0.873389
Freq: MS, dtype: float64

Converting between period and timestamp enables some convenient arithmetic functions to be used. In the following
example, we convert a quarterly frequency with year ending in November to 9am of the end of the month following the quarter end:

In [409]: prng = pd.period_range('1990Q1', '2000Q4', freq='Q-NOV')

In [410]: ts = pd.Series(np.random.randn(len(prng)), prng)

In [411]: ts.index = (prng.asfreq('M', 'e') + 1).asfreq('H', 's') + 9

In [412]: ts.head()
Out[412]:
1990-03-01 09:00 -0.109291
1990-06-01 09:00 -0.637235
1990-09-01 09:00 -1.735925
1990-12-01 09:00 2.096946
1991-03-01 09:00 -1.039926
Freq: H, dtype: float64

2.17.13 Representing out-of-bounds spans

If you have data that is outside of the Timestamp bounds, see Timestamp limitations, then you can use a PeriodIndex and/or Series of Periods to do computations.

In [413]: span = pd.period_range('1215-01-01', '1381-01-01', freq='D')

In [414]: span
Out[414]:
PeriodIndex(['1215-01-01', '1215-01-02', '1215-01-03', '1215-01-04',
 '1215-01-05', '1215-01-06', '1215-01-07', '1215-01-08',
 '1215-01-09', '1215-01-10',
 ..., '1380-12-23', '1380-12-24', '1380-12-25', '1380-12-26',
 '1380-12-27', '1380-12-28', '1380-12-29', '1380-12-30',
 '1380-12-31', '1381-01-01'],
dtype='period[D]', length=60632, freq='D')

To convert from an int64 based YYYYMMDD representation.

In [415]: s = pd.Series([20121231, 20141130, 99991231])

In [416]: s
Out[416]:
0  20121231
1  20141130
2  99991231
dtype: int64

In [417]: def conv(x):
....:     return pd.Period(year=x // 10000, month=x // 100 % 100,
....:     day=x % 100, freq='D')

In [418]: s.apply(conv)
Out[418]:
0  2012-12-31
1  2014-11-30
(continues on next page)
2 9999-12-31
dtype: period[D]

In [419]: s.apply(conv)[2]
Out[419]: Period('9999-12-31', 'D')

These can easily be converted to a `PeriodIndex`:

In [420]: span = pd.PeriodIndex(s.apply(conv))
In [421]: span
Out[421]: PeriodIndex(['2012-12-31', '2014-11-30', '9999-12-31'], dtype='period[D]',
                      freq='D')

2.17.14 Time zone handling

pandas provides rich support for working with timestamps in different time zones using the `pytz` and `dateutil` libraries or class: `datetime.timezone` objects from the standard library.

Working with time zones

By default, pandas objects are time zone unaware:

In [422]: rng = pd.date_range('3/6/2012 00:00', periods=15, freq='D')
In [423]: rng.tz is None
Out[423]: True

To localize these dates to a time zone (assign a particular time zone to a naive date), you can use the `tz_localize` method or the `tz` keyword argument in `date_range()`, `Timestamp`, or `DatetimeIndex`. You can either pass `pytz` or `dateutil` time zone objects or Olson time zone database strings. Olson time zone strings will return `pytz` time zone objects by default. To return `dateutil` time zone objects, append `dateutil/` before the string.

- In `pytz` you can find a list of common (and less common) time zones using `from pytz import common_timezones, all_timezones`.
- `dateutil` uses the OS time zones so there isn’t a fixed list available. For common zones, the names are the same as `pytz`.

In [424]: import dateutil
# pytz
In [425]: rng_pytz = pd.date_range('3/6/2012 00:00', periods=3, freq='D',
                         tz='Europe/London')
In [426]: rng_pytz.tz
Out[426]: <DstTzInfo 'Europe/London' LMT-1 day, 23:59:00 STD>
# dateutil
In [427]: rng_dateutil = pd.date_range('3/6/2012 00:00', periods=3, freq='D')
In [428]: rng_dateutil.tz
Out[428]: tzlocal('Europe/London')

(continues on next page)
In [429]: rng_dateutil.tz
Out[429]: tzfile('/usr/share/zoneinfo/Europe/London')

# dateutil - utc special case
In [430]: rng_utc = pd.date_range('3/6/2012 00:00', periods=3, freq='D',
                         tz=dateutil.tz.tzutc())

In [431]: rng_utc.tz
Out[431]: tzutc()

New in version 0.25.0.

In [432]: rng_utc = pd.date_range('3/6/2012 00:00', periods=3, freq='D',
                         tz=datetime.timezone.utc)

In [433]: rng_utc.tz
Out[433]: datetime.timezone.utc

Note that the UTC time zone is a special case in dateutil and should be constructed explicitly as an instance of dateutil.tz.tzutc. You can also construct other time zones objects explicitly first.

In [434]: import pytz

# pytz
In [435]: tz_pytz = pytz.timezone('Europe/London')

In [436]: rng_pytz = pd.date_range('3/6/2012 00:00', periods=3, freq='D')

In [437]: rng_pytz = rng_pytz.tz_localize(tz_pytz)

In [438]: rng_pytz.tz == tz_pytz
Out[438]: True

To convert a time zone aware pandas object from one time zone to another, you can use the tz_convert method.

In [442]: rng_pytz.tz_convert('US/Eastern')
Out[442]: DatetimeIndex(['2012-03-05 19:00:00-05:00', '2012-03-06 19:00:00-05:00',
                      '2012-03-07 19:00:00-05:00'],
                     dtype='datetime64[ns, US/Eastern]', freq=None)

Note: When using pytz time zones, DatetimeIndex will construct a different time zone object than a Timestamp for the same time zone input. A DatetimeIndex can hold a collection of Timestamp objects.
that may have different UTC offsets and cannot be succinctly represented by one `pytz` time zone instance while one `Timestamp` represents one point in time with a specific UTC offset.

```python
In [443]: dti = pd.date_range('2019-01-01', periods=3, freq='D', tz='US/Pacific')
In [444]: dti.tz
Out[444]: <DstTzInfo 'US/Pacific' LMT-1 day, 16:07:00 STD>
In [445]: ts = pd.Timestamp('2019-01-01', tz='US/Pacific')
In [446]: ts.tz
Out[446]: <DstTzInfo 'US/Pacific' PST-1 day, 16:00:00 STD>
```

**Warning:** Be wary of conversions between libraries. For some time zones, `pytz` and `dateutil` have different definitions of the zone. This is more of a problem for unusual time zones than for 'standard' zones like US/Eastern.

**Warning:** Be aware that a time zone definition across versions of time zone libraries may not be considered equal. This may cause problems when working with stored data that is localized using one version and operated on with a different version. See [here](#) for how to handle such a situation.

**Warning:** For `pytz` time zones, it is incorrect to pass a time zone object directly into the `datetime` constructor (e.g., `datetime.datetime(2011, 1, 1, tz=pytz.timezone('US/Eastern'))`). Instead, the datetime needs to be localized using the `localize` method on the `pytz` time zone object.

**Warning:** If you are using dates beyond 2038-01-18, due to current deficiencies in the underlying libraries caused by the year 2038 problem, daylight saving time (DST) adjustments to timezone aware dates will not be applied. If and when the underlying libraries are fixed, the DST transitions will be applied. It should be noted though, that time zone data for far future time zones are likely to be inaccurate, as they are simple extrapolations of the current set of (regularly revised) rules.

For example, for two dates that are in British Summer Time (and so would normally be GMT+1), both the following asserts evaluate as true:

```python
In [447]: d_2037 = '2037-03-31T010101'
In [448]: d_2038 = '2038-03-31T010101'
In [449]: DST = 'Europe/London'
In [450]: assert pd.Timestamp(d_2037, tz=DST) != pd.Timestamp(d_2037, tz='GMT')
In [451]: assert pd.Timestamp(d_2038, tz=DST) == pd.Timestamp(d_2038, tz='GMT')
```

Under the hood, all timestamps are stored in UTC. Values from a time zone aware `DatetimeIndex` or `Timestamp` will have their fields (day, hour, minute, etc.) localized to the time zone. However, timestamps with the same UTC value are still considered to be equal even if they are in different time zones:
In [452]: rng_eastern = rng_utc.tz_convert('US/Eastern')
In [453]: rng_berlin = rng_utc.tz_convert('Europe/Berlin')
In [454]: rng_eastern[2]
Out[454]: Timestamp('2012-03-07 19:00:00-0500', tz='US/Eastern', freq='D')
In [455]: rng_berlin[2]
Out[455]: Timestamp('2012-03-08 01:00:00+0100', tz='Europe/Berlin', freq='D')
Out[456]: True

Operations between *Series* in different time zones will yield UTC *Series*, aligning the data on the UTC timestamps:

In [457]: ts_utc = pd.Series(range(3), pd.date_range('20130101', periods=3, tz='UTC'))
In [458]: eastern = ts_utc.tz_convert('US/Eastern')
In [459]: berlin = ts_utc.tz_convert('Europe/Berlin')
In [460]: result = eastern + berlin
In [461]: result
Out[461]:
2013-01-01 00:00:00+00:00 0
2013-01-02 00:00:00+00:00 2
2013-01-03 00:00:00+00:00 4
Freq: D, dtype: int64

In [462]: result.index
Out[462]:
DatetimeIndex(['2013-01-01 00:00:00', '2013-01-02 00:00:00', '2013-01-03 00:00:00'],
              dtype='datetime64[ns, UTC]', freq=None)

To remove time zone information, use `tz_localize(None)` or `tz_convert(None)`. `tz_localize(None)` will remove the time zone yielding the local time representation. `tz_convert(None)` will remove the time zone after converting to UTC time.

In [463]: didx = pd.date_range(start='2014-08-01 09:00', freq='H',
                       periods=3, tz='US/Eastern')
......:
......:
In [464]: didx
Out[464]:
DatetimeIndex(['2014-08-01 09:00:00-04:00', '2014-08-01 10:00:00-04:00',
               '2014-08-01 11:00:00-04:00'],
              dtype='datetime64[ns, US/Eastern]', freq='H')
In [465]: didx.tz_localize(None)
Out[465]:
DatetimeIndex(['2014-08-01 09:00:00', '2014-08-01 10:00:00',
               '2014-08-01 11:00:00'],
              dtype='datetime64[ns]', freq=None)
Fold

New in version 1.1.0.

For ambiguous times, pandas supports explicitly specifying the keyword-only fold argument. Due to daylight saving time, one wall clock time can occur twice when shifting from summer to winter time; fold describes whether the datetime-like corresponds to the first (0) or the second time (1) the wall clock hits the ambiguous time. Fold is supported only for constructing from naive `datetime.datetime` (see `datetime` documentation for details) or from `Timestamp` or for constructing from components (see below). Only dateutil timezones are supported (see dateutil documentation for dateutil methods that deal with ambiguous datetimes) as pytz timezones do not support fold (see pytz documentation for details on how pytz deals with ambiguous datetimes). To localize an ambiguous datetime with pytz, please use `Timestamp.tz_localize()`. In general, we recommend to rely on `Timestamp.tz_localize()` when localizing ambiguous datetimes if you need direct control over how they are handled.

Ambiguous times when localizing

tz_localize may not be able to determine the UTC offset of a timestamp because daylight savings time (DST) in a local time zone causes some times to occur twice within one day (“clocks fall back”). The following options are available:

- 'raise': Raises a pytz.AmbiguousTimeError (the default behavior)
- 'infer': Attempt to determine the correct offset base on the monotonicity of the timestamps
- 'NaT': Replaces ambiguous times with NaT
- `bool`: True represents a DST time, False represents non-DST time. An array-like of bool values is supported for a sequence of times.
In [470]: rng_hourly = pd.DatetimeIndex(['11/06/2011 00:00', '11/06/2011 01:00', ......: '11/06/2011 01:00', '11/06/2011 02:00'])

This will fail as there are ambiguous times ('11/06/2011 01:00')

In [2]: rng_hourly.tz_localize('US/Eastern')
AmbiguousTimeError: Cannot infer dst time from Timestamp('2011-11-06 01:00:00'), try using the 'ambiguous' argument

Handle these ambiguous times by specifying the following.

In [471]: rng_hourly.tz_localize('US/Eastern', ambiguous='infer')
Out[471]:
DatetimeIndex(['2011-11-06 00:00:00-04:00', '2011-11-06 01:00:00-04:00', '2011-11-06 01:00:00-05:00', '2011-11-06 02:00:00-05:00'],
dtype='datetime64[ns, US/Eastern]', freq=None)

In [472]: rng_hourly.tz_localize('US/Eastern', ambiguous='NaT')
Out[472]:
DatetimeIndex(['2011-11-06 00:00:00-04:00', 'NaT', 'NaT', '2011-11-06 02:00:00-05:00'],
dtype='datetime64[ns, US/Eastern]', freq=None)

In [473]: rng_hourly.tz_localize('US/Eastern', ambiguous=[True, True, False, False])
Out[473]:
DatetimeIndex(['2011-11-06 00:00:00-04:00', '2011-11-06 01:00:00-04:00', '2011-11-06 01:00:00-05:00', '2011-11-06 02:00:00-05:00'],
dtype='datetime64[ns, US/Eastern]', freq=None)

Nonexistent times when localizing

A DST transition may also shift the local time ahead by 1 hour creating nonexistent local times (“clocks spring forward”). The behavior of localizing a timeseries with nonexistent times can be controlled by the nonexistent argument. The following options are available:

- 'raise': Raises a pytz.NonExistentTimeError (the default behavior)
- 'NaT': Replaces nonexistent times with NaT
- 'shift_forward': Shifts nonexistent times forward to the closest real time
- 'shift_backward': Shifts nonexistent times backward to the closest real time
- timedelta object: Shifts nonexistent times by the timedelta duration

In [474]: dti = pd.date_range(start='2015-03-29 02:30:00', periods=3, freq='H')
# 2:30 is a nonexistent time

Localization of nonexistent times will raise an error by default.

In [2]: dti.tz_localize('Europe/Warsaw')
NonExistentTimeError: 2015-03-29 02:30:00

Transform nonexistent times to NaT or shift the times.
In [475]: dti
Out[475]:
DatetimeIndex(['2015-03-29 02:30:00', '2015-03-29 03:30:00',
              '2015-03-29 04:30:00'],
              dtype='datetime64[ns]', freq='H')

In [476]: dti.tz_localize('Europe/Warsaw', nonexistent='shift_forward')
Out[476]:
DatetimeIndex(['2015-03-29 03:00:00+02:00', '2015-03-29 03:30:00+02:00',
                '2015-03-29 04:30:00+02:00'],
              dtype='datetime64[ns, Europe/Warsaw]', freq=None)

In [477]: dti.tz_localize('Europe/Warsaw', nonexistent='shift_backward')
Out[477]:
DatetimeIndex(['2015-03-29 01:59:59.999999999+01:00',
                '2015-03-29 03:30:00+02:00',
                '2015-03-29 04:30:00+02:00'],
              dtype='datetime64[ns, Europe/Warsaw]', freq=None)

In [478]: dti.tz_localize('Europe/Warsaw', nonexistent=pd.Timedelta(1, unit='H'))
Out[478]:
DatetimeIndex(['2015-03-29 03:30:00+02:00', '2015-03-29 03:30:00+02:00',
                '2015-03-29 04:30:00+02:00'],
              dtype='datetime64[ns, Europe/Warsaw]', freq=None)

In [479]: dti.tz_localize('Europe/Warsaw', nonexistent='NaT')
Out[479]:
DatetimeIndex(['NaT', '2015-03-29 03:30:00+02:00',
                '2015-03-29 04:30:00+02:00'],
              dtype='datetime64[ns, Europe/Warsaw]', freq=None)

Time zone series operations

A Series with time zone naive values is represented with a dtype of datetime64[ns].

In [480]: s_naive = pd.Series(pd.date_range('20130101', periods=3))

In [481]: s_naive
Out[481]:
0  2013-01-01
1  2013-01-02
2  2013-01-03
dtype: datetime64[ns]

A Series with a time zone aware values is represented with a dtype of datetime64[ns, tz] where tz is the time zone

In [482]: s_aware = pd.Series(pd.date_range('20130101', periods=3, tz='US/Eastern'))

In [483]: s_aware
Out[483]:
0  2013-01-01 00:00:00-05:00
1  2013-01-02 00:00:00-05:00
2  2013-01-03 00:00:00-05:00
dtype: datetime64[ns, US/Eastern]

Both of these Series time zone information can be manipulated via the .dt accessor, see the dt accessor section.
For example, to localize and convert a naive stamp to time zone aware.

```
In [484]: s_naive.dt.tz_localize('UTC').dt.tz_convert('US/Eastern')
Out[484]:
0 2012-12-31 19:00:00-05:00
1 2013-01-01 19:00:00-05:00
2 2013-01-02 19:00:00-05:00
dtype: datetime64[ns, US/Eastern]
```

Time zone information can also be manipulated using the `astype` method. This method can localize and convert time zone naive timestamps or convert time zone aware timestamps.

```
# localize and convert a naive time zone
In [485]: s_naive.astype('datetime64[ns, US/Eastern]')
Out[485]:
0 2012-12-31 19:00:00-05:00
1 2013-01-01 19:00:00-05:00
2 2013-01-02 19:00:00-05:00

dtype: datetime64[ns, US/Eastern]

# make an aware tz naive
In [486]: s_aware.astype('datetime64[ns]')
Out[486]:
0 2013-01-01 05:00:00
1 2013-01-02 05:00:00
2 2013-01-03 05:00:00

dtype: datetime64[ns]

# convert to a new time zone
In [487]: s_aware.astype('datetime64[ns, CET]')
Out[487]:
0 2013-01-01 06:00:00+01:00
1 2013-01-02 06:00:00+01:00
2 2013-01-03 06:00:00+01:00

dtype: datetime64[ns, CET]
```

**Note:** Using `Series.to_numpy()` on a `Series` returns a NumPy array of the data. NumPy does not currently support time zones (even though it is *printing* in the local time zone!), therefore an object array of Timestamps is returned for time zone aware data:

```
In [488]: s_naive.to_numpy()
Out[488]:
array([datetime(2013, 1, 1, 0, 0, 0, 0, tzinfo=tzutc()),
       datetime(2013, 1, 2, 0, 0, 0, 0, tzinfo=tzutc()),
       datetime(2013, 1, 3, 0, 0, 0, 0, tzinfo=tzutc())],
      dtype='datetime64[ns]')

In [489]: s_aware.to_numpy()
Out[489]:
array([Timestamp('2013-01-01 00:00:00-0500', tz='US/Eastern', freq='D'),
       Timestamp('2013-01-02 00:00:00-0500', tz='US/Eastern', freq='D'),
       Timestamp('2013-01-03 00:00:00-0500', tz='US/Eastern', freq='D')],
       dtype=object)
```

By converting to an object array of Timestamps, it preserves the time zone information. For example, when converting back to a `Series`:

```
In [490]: pd.Series(s_aware.to_numpy())
Out[490]:
```

(continues on next page)
However, if you want an actual NumPy `datetime64[ns]` array (with the values converted to UTC) instead of an array of objects, you can specify the `dtype` argument:

```python
In [491]: s_aware.to_numpy(dtype='datetime64[ns]')
Out[491]:
array(['2013-01-01T05:00:00.000000000', '2013-01-02T05:00:00.000000000',
       '2013-01-03T05:00:00.000000000'], dtype='datetime64[ns]')
```

## 2.18 Time deltas

Timedeltas are differences in times, expressed in difference units, e.g. days, hours, minutes, seconds. They can be both positive and negative.

`Timedelta` is a subclass of `datetime.timedelta`, and behaves in a similar manner, but allows compatibility with `np.timedelta64` types as well as a host of custom representation, parsing, and attributes.

### 2.18.1 Parsing

You can construct a `Timedelta` scalar through various arguments:

```python
In [1]: import datetime

# strings
In [2]: pd.Timedelta('1 days')
Out[2]: Timedelta('1 days 00:00:00')

In [3]: pd.Timedelta('1 days 00:00:00')
Out[3]: Timedelta('1 days 00:00:00')

In [4]: pd.Timedelta('1 days 2 hours')
Out[4]: Timedelta('1 days 02:00:00')

In [5]: pd.Timedelta('-1 days 2 min 3us')
Out[5]: Timedelta('-2 days +23:57:59.999997')

# like datetime.timedelta
# note: these MUST be specified as keyword arguments
In [6]: pd.Timedelta(days=1, seconds=1)
Out[6]: Timedelta('1 days 00:00:01')

# integers with a unit
In [7]: pd.Timedelta(1, unit='d')
Out[7]: Timedelta('1 days 00:00:00')

# from a datetime.timedelta/np.timedelta64
In [8]: pd.Timedelta(datetime.timedelta(days=1, seconds=1))
Out[8]: Timedelta('1 days 00:00:01')
```
In [9]: pd.Timedelta(np.timedelta64(1, 'ms'))
Out[9]: Timedelta('0 days 00:00:00.001000')

# negative Timedeltas have this string repr
# to be more consistent with datetime.timedelta conventions
In [10]: pd.Timedelta('-1us')
Out[10]: Timedelta('-1 days +23:59:59.999999')

# a NaT
In [11]: pd.Timedelta('nan')
Out[11]: NaT

In [12]: pd.Timedelta('nat')
Out[12]: NaT

# ISO 8601 Duration strings
In [13]: pd.Timedelta('P0DT0H1M0S')
Out[13]: Timedelta('0 days 00:01:00')

In [14]: pd.Timedelta('P0DT0H0M0.000000123S')
Out[14]: Timedelta('0 days 00:00:00.000000123')

New in version 0.23.0: Added constructor for ISO 8601 Duration strings

*DateOffsets* (Day, Hour, Minute, Second, Milli, Micro, Nano) can also be used in construction.

In [15]: pd.Timedelta(pd.offsets.Second(2))
Out[15]: Timedelta('0 days 00:00:02')

Further, operations among the scalars yield another scalar Timedelta.

In [16]: pd.Timedelta(pd.offsets.Day(2)) + pd.Timedelta(pd.offsets.Second(2)) +
   ....: pd.Timedelta('00:00:00.000123')
   ....:
Out[16]: Timedelta('2 days 00:00:02.000123')

to_timedelta

Using the top-level `pd.to_timedelta`, you can convert a scalar, array, list, or Series from a recognized timedelta format/value into a Timedelta type. It will construct Series if the input is a Series, a scalar if the input is scalar-like, otherwise it will output a TimedeltaIndex.

You can parse a single string to a Timedelta:

In [17]: pd.to_timedelta('1 days 06:05:01.00003')
Out[17]: Timedelta('1 days 06:05:01.000030')

In [18]: pd.to_timedelta('15.5us')
Out[18]: Timedelta('0 days 00:00:00.000015500')

or a list/array of strings:

In [19]: pd.to_timedelta(['1 days 06:05:01.00003', '15.5us', 'nan'])
Out[19]: TimedeltaIndex(['1 days 06:05:01.00003', '0 days 00:00:00.000015500', NaT],
   ....dtype='timedelta64[ns]', freq=None)
The `unit` keyword argument specifies the unit of the Timedelta:

```
In [20]: pd.to_timedelta(np.arange(5), unit='s')
Out[20]:
TimedeltaIndex(['0 days 00:00:00', '0 days 00:00:01', '0 days 00:00:02',
               '0 days 00:00:03', '0 days 00:00:04'],
             dtype='timedelta64[ns]', freq=None)
```

```
In [21]: pd.to_timedelta(np.arange(5), unit='d')
Out[21]:
TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'],
              dtype='timedelta64[ns]', freq=None)
```

**Timedelta limitations**

Pandas represents Timedeltas in nanosecond resolution using 64 bit integers. As such, the 64 bit integer limits determine the Timedelta limits.

```
In [22]: pd.Timedelta.min
Out[22]: Timedelta('-106752 days +00:12:43.145224193')
```

```
In [23]: pd.Timedelta.max
Out[23]: Timedelta('106751 days 23:47:16.854775807')
```

### 2.18.2 Operations

You can operate on Series/DataFrames and construct `timedelta64[ns]` Series through subtraction operations on `datetime64[ns]` Series, or Timestamps.

```
In [24]: s = pd.Series(pd.date_range('2012-1-1', periods=3, freq='D'))
```

```
In [25]: td = pd.Series([pd.Timedelta(days=i) for i in range(3)])
```

```
In [26]: df = pd.DataFrame({'A': s, 'B': td})
```

```
In [27]: df
Out[27]:
   A       B
0 2012-01-01 0 days
1 2012-01-02 1 days
2 2012-01-03 2 days
```

```
In [28]: df['C'] = df['A'] + df['B']
```

```
In [29]: df
Out[29]:
   A       B   C
0 2012-01-01 0 days 2012-01-01
1 2012-01-02 1 days 2012-01-03
2 2012-01-03 2 days 2012-01-05
```

```
In [30]: df.dtypes
Out[30]:
A   datetime64[ns]
B  timedelta64[ns]
C   datetime64[ns]
```
```python
dtype: object

In [31]: s - s.max()
Out[31]:
0   -2 days
1   -1 days
2    0 days
dtype: timedelta64[ns]

In [32]: s - datetime.datetime(2011, 1, 1, 3, 5)
Out[32]:
0   364 days 20:55:00
1   365 days 20:55:00
2   366 days 20:55:00
dtype: timedelta64[ns]

In [33]: s + datetime.timedelta(minutes=5)
Out[33]:
0 2012-01-01 00:05:00
1 2012-01-02 00:05:00
2 2012-01-03 00:05:00
dtype: datetime64[ns]

In [34]: s + pd.offsets.Minute(5)
Out[34]:
0 2012-01-01 00:05:00
1 2012-01-02 00:05:00
2 2012-01-03 00:05:00
dtype: datetime64[ns]

In [35]: s + pd.offsets.Minute(5) + pd.offsets.Milli(5)
Out[35]:
0 2012-01-01 00:05:00.005
1 2012-01-02 00:05:00.005
2 2012-01-03 00:05:00.005
dtype: datetime64[ns]
```

Operations with scalars from a timedelta64[ns] series:

```python
In [36]: y = s - s[0]

In [37]: y
Out[37]:
0    0 days
1    1 days
2    2 days
dtype: timedelta64[ns]
```

Series of timedeltas with NaT values are supported:

```python
In [38]: y = s - s.shift()

In [39]: y
Out[39]:
0   NaT
1    1 days
2    1 days
```

(continues on next page)
Elements can be set to \texttt{NaT} using \texttt{np.nan} analogously to datetimes:

\begin{verbatim}
In [40]: y[1] = np.nan

In [41]: y
Out[41]:
0   NaT
1   NaT
2   1 days
dtype: timedelta64[ns]
\end{verbatim}

Operands can also appear in a reversed order (a singular object operated with a Series):

\begin{verbatim}
In [42]: s.max() - s
Out[42]:
0    2 days
1    1 days
2     0 days
dtype: timedelta64[ns]

In [43]: pd.datetime(2011, 1, 1, 3, 5) - s
Out[43]:
0  -365 days +03:05:00
1  -366 days +03:05:00
2  -367 days +03:05:00
dtype: timedelta64[ns]

In [44]: pd.datetime(minutes=5) + s
Out[44]:
0  2012-01-01 00:05:00
1  2012-01-02 00:05:00
2  2012-01-03 00:05:00
dtype: datetime64[ns]
\end{verbatim}

\texttt{min}, \texttt{max} and the corresponding \texttt{idxmin}, \texttt{idxmax} operations are supported on frames:

\begin{verbatim}
In [45]: A = s - pd.Timestamp('20120101') - pd.Timedelta('00:05:05')
In [46]: B = s - pd.Series(pd.date_range('2012-1-2', periods=3, freq='D'))
In [47]: df = pd.DataFrame({'A': A, 'B': B})

In [48]: df
Out[48]:
          A         B
0  -1 days +23:54:55  -1 days
1    0 days 23:54:55  -1 days
2    1 days 23:54:55  -1 days

In [49]: df.min()
Out[49]:
          A         B
A  -1 days +23:54:55  -1 days
B  -1 days +00:00:00  -1 days
dtype: timedelta64[ns]
\end{verbatim}
In [50]: df.min(axis=1)
Out[50]:
0  -1 days
1  -1 days
2  -1 days
dtype: timedelta64[ns]

In [51]: df.idxmin()
Out[51]:
A  0
B  0
dtype: int64

In [52]: df.idxmax()
Out[52]:
A  2
B  0
dtype: int64

min, max, idxmin, idxmax operations are supported on Series as well. A scalar result will be a Timedelta.

In [53]: df.min().max()
Out[53]: Timedelta('-1 days +23:54:55')

In [54]: df.min(axis=1).min()
Out[54]: Timedelta('-1 days +00:00:00')

In [55]: df.min().idxmax()
Out[55]: 'A'

In [56]: df.min(axis=1).idxmin()
Out[56]: 0

You can fillna on timedeltas, passing a timedelta to get a particular value.

In [57]: y.fillna(pd.Timedelta(0))
Out[57]:
0  0 days
1  0 days
2  1 days
dtype: timedelta64[ns]

In [58]: y.fillna(pd.Timedelta(10, unit='s'))
Out[58]:
0  0 days 00:00:10
1  0 days 00:00:10
2  1 days 00:00:00
dtype: timedelta64[ns]

In [59]: y.fillna(pd.Timedelta('-1 days, 00:00:05'))
Out[59]:
0  -1 days +00:00:05
1  -1 days +00:00:05
2  1 days 00:00:00
dtype: timedelta64[ns]

You can also negate, multiply and use abs on Timedeltas:

### 2.18. Time deltas
In [60]: tdl = pd.Timedelta('-1 days 2 hours 3 seconds')

In [61]: tdl
Out[61]: Timedelta('-2 days +21:59:57')

In [62]: -1 * tdl
Out[62]: Timedelta('1 days 02:00:03')

In [63]: - tdl
Out[63]: Timedelta('1 days 02:00:03')

In [64]: abs(tdl)
Out[64]: Timedelta('1 days 02:00:03')

2.18.3 Reductions

Numeric reduction operation for timedelta64[ns] will return Timedelta objects. As usual NaT are skipped during evaluation.

In [65]: y2 = pd.Series(pd.to_timedelta(['-1 days +00:00:05', 'nat',
                                         '-1 days +00:00:05', '1 days']))

In [66]: y2
Out[66]:
0   -1 days +00:00:05
1     NaT
2   -1 days +00:00:05
3    1 days 00:00:00
dtype: timedelta64[ns]

In [67]: y2.mean()
Out[67]: Timedelta('-1 days +16:00:03.333333334')

In [68]: y2.median()
Out[68]: Timedelta('-1 days +00:00:05')

In [69]: y2.quantile(.1)
Out[69]: Timedelta('-1 days +00:00:05')

In [70]: y2.sum()
Out[70]: Timedelta('-1 days +00:00:10')

2.18.4 Frequency conversion

Timedelta Series, TimedeltaIndex, and Timedelta scalars can be converted to other ‘frequencies’ by dividing by another timedelta, or by astyping to a specific timedelta type. These operations yield Series and propagate NaT -> nan. Note that division by the NumPy scalar is true division, while astyping is equivalent of floor division.

In [71]: december = pd.Series(pd.date_range('20121201', periods=4))

In [72]: january = pd.Series(pd.date_range('20130101', periods=4))

In [73]: td = january - december

(continues on next page)
In [74]: td[2] += datetime.timedelta(minutes=5, seconds=3)
In [75]: td[3] = np.nan
In [76]: td
Out[76]:
0 31 days 00:00:00
1 31 days 00:00:00
2 31 days 00:05:03
3 NaT
dtype: timedelta64[ns]

# to days
In [77]: td / np.timedelta64(1, 'D')
Out[77]:
0 31.000000
1 31.000000
2 31.003507
3 NaN
dtype: float64
In [78]: td.astype('timedelta64[D]')
Out[78]:
0 31.0
1 31.0
2 31.0
3 NaN
dtype: float64

# to seconds
In [79]: td / np.timedelta64(1, 's')
Out[79]:
0 2678400.0
1 2678400.0
2 2678703.0
3 NaN
dtype: float64
In [80]: td.astype('timedelta64[s]')
Out[80]:
0 2678400.0
1 2678400.0
2 2678703.0
3 NaN
dtype: float64

# to months (these are constant months)
In [81]: td / np.timedelta64(1, 'M')
Out[81]:
0 1.018501
1 1.018501
2 1.018617
3 NaN
dtype: float64

Dividing or multiplying a timedelta64[ns] Series by an integer or integer Series yields another
timedelta64[ns] dtypes Series.

```python
In [82]: td * -1
Out[82]:
0  -31 days +00:00:00
1  -31 days +00:00:00
2  -32 days +23:54:57
3     NaT
dtype: timedelta64[ns]

In [83]: td * pd.Series([1, 2, 3, 4])
Out[83]:
0   31 days 00:00:00
1   62 days 00:00:00
2   93 days 00:15:09
3        NaT
dtype: timedelta64[ns]
```

Rounded division (floor-division) of a timedelta64[ns] Series by a scalar Timedelta gives a series of integers.

```python
In [84]: td // pd.Timedelta(days=3, hours=4)
Out[84]:
0   9.0
1   9.0
2   9.0
3     NaN
dtype: float64

In [85]: pd.Timedelta(days=3, hours=4) // td
Out[85]:
0   0.0
1   0.0
2   0.0
3     NaN
dtype: float64
```

The mod (%) and divmod operations are defined for Timedelta when operating with another timedelta-like or with a numeric argument.

```python
In [86]: pd.Timedelta(hours=37) % datetime.timedelta(hours=2)
Out[86]: Timedelta('0 days 01:00:00')

# divmod against a timedelta-like returns a pair (int, Timedelta)
In [87]: divmod(datetime.timedelta(hours=2), pd.Timedelta(minutes=11))
Out[87]: (10, Timedelta('0 days 00:10:00'))

# divmod against a numeric returns a pair (Timedelta, Timedelta)
In [88]: divmod(pd.Timedelta(hours=25), 86400000000000)
Out[88]: (Timedelta('0 days 00:00:00.000000001'), Timedelta('0 days 01:00:00'))
```
2.18.5 Attributes

You can access various components of the Timedelta or TimedeltaIndex directly using the attributes `days, seconds, microseconds, nanoseconds`. These are identical to the values returned by `datetime.timedelta`. In that, for example, the `.seconds` attribute represents the number of seconds >= 0 and < 1 day. These are signed according to whether the Timedelta is signed.

These operations can also be directly accessed via the `.dt` property of the Series as well.

**Note:** Note that the attributes are NOT the displayed values of the Timedelta. Use `.components` to retrieve the displayed values.

For a Series:

```python
In [89]: td.dt.days
Out[89]:
0  31.0
1  31.0
2  31.0
3  NaN
dtype: float64

In [90]: td.dt.seconds
Out[90]:
0  0.0
1  0.0
2  303.0
3  NaN
dtype: float64
```

You can access the value of the fields for a scalar Timedelta directly.

```python
In [91]: tds = pd.Timedelta('31 days 5 min 3 sec')

In [92]: tds.days
Out[92]: 31

In [93]: tds.seconds
Out[93]: 303

In [94]: (-tds).seconds
Out[94]: 86097
```

You can use the `.components` property to access a reduced form of the timedelta. This returns a DataFrame indexed similarly to the Series. These are the displayed values of the Timedelta.

```python
In [95]: td.dt.components
Out[95]:
          days   hours   minutes  seconds  milliseconds microseconds nanoseconds
0  31.0000  0.0000    0.0000   0.0000       0.0000         0.0000   0.0000
1  31.0000  0.0000    0.0000   0.0000       0.0000         0.0000   0.0000
2  31.0000  0.0000    5.0000   3.0000       0.0000         0.0000   0.0000
3  NaN    NaN    NaN    NaN        NaN          NaN    NaN

In [96]: td.dt.components.seconds
Out[96]:
```

(continues on next page)
You can convert a Timedelta to an ISO 8601 Duration string with the .isoformat method:

```
In [97]: pd.Timedelta(days=6, minutes=50, seconds=3, milliseonds=10, microseconds=10, nanoseconds=12).isoformat()
....:
Out[97]: 'P6DT0H50M3.010010012S'
```

### 2.18.6 TimedeltaIndex

To generate an index with time delta, you can use either the `TimedeltaIndex` or the `timedelta_range()` constructor.

Using `TimedeltaIndex` you can pass string-like, Timedelta, timedelta, or `np.timedelta64` objects. Passing `np.nan/pd.NaT/nat` will represent missing values.

```
In [98]: pd.TimedeltaIndex(['1 days', '1 days, 00:00:05', np.timedelta64(2, 'D'), datetime.timedelta(days=2, seconds=2)])
....:
Out[98]: TimedeltaIndex(['1 days 00:00:00', '1 days 00:00:05', '2 days 00:00:00', 
'2 days 00:00:02'], dtype='timedelta64[ns]', freq=None)
```

The string ‘infer’ can be passed in order to set the frequency of the index as the inferred frequency upon creation:

```
In [99]: pd.TimedeltaIndex(['0 days', '10 days', '20 days'], freq='infer')
Out[99]: TimedeltaIndex(['0 days', '10 days', '20 days'], dtype='timedelta64[ns]', freq='10D')
```

### Generating ranges of time deltas

Similar to `date_range()`, you can construct regular ranges of a TimedeltaIndex using `timedelta_range()`. The default frequency for `timedelta_range` is calendar day:

```
In [100]: pd.timedelta_range(start='1 days', periods=5)
Out[100]: TimedeltaIndex(['1 days', '2 days', '3 days', '4 days', '5 days'], dtype='timedelta64[ns]', freq='D')
```

Various combinations of `start`, `end`, and `periods` can be used with `timedelta_range`:

```
In [101]: pd.timedelta_range(start='1 days', end='5 days')
Out[101]: TimedeltaIndex(['1 days', '2 days', '3 days', '4 days', '5 days'], dtype='timedelta64[ns]', freq='D')
```

```
In [102]: pd.timedelta_range(end='10 days', periods=4)
Out[102]: TimedeltaIndex(['7 days', '8 days', '9 days', '10 days'], dtype='timedelta64[ns]', freq='D')
```
The `freq` parameter can passed a variety of frequency aliases:

```python
In [103]: pd.timedelta_range(start='1 days', end='2 days', freq='30T')
Out[103]:
TimedeltaIndex(['1 days 00:00:00', '1 days 00:30:00', '1 days 01:00:00',
 '1 days 01:30:00', '1 days 02:00:00', '1 days 02:30:00',
 '1 days 03:00:00', '1 days 03:30:00', '1 days 04:00:00',
 '1 days 04:30:00', '1 days 05:00:00', '1 days 05:30:00',
 '1 days 06:00:00', '1 days 06:30:00', '1 days 07:00:00',
 '1 days 07:30:00', '1 days 08:00:00', '1 days 08:30:00',
 '1 days 09:00:00', '1 days 09:30:00', '1 days 10:00:00',
 '1 days 10:30:00', '1 days 11:00:00', '1 days 11:30:00',
 '1 days 12:00:00', '1 days 12:30:00', '1 days 13:00:00',
 '1 days 13:30:00', '1 days 14:00:00', '1 days 14:30:00',
 '1 days 15:00:00', '1 days 15:30:00', '1 days 16:00:00',
 '1 days 16:30:00', '1 days 17:00:00', '1 days 17:30:00',
 '1 days 18:00:00', '1 days 18:30:00', '1 days 19:00:00',
 '1 days 19:30:00', '1 days 20:00:00', '1 days 20:30:00',
 '1 days 21:00:00', '1 days 21:30:00', '1 days 22:00:00',
 '1 days 22:30:00', '1 days 23:00:00', '1 days 23:30:00',
 '2 days 00:00:00'],
dtype='timedelta64[ns]', freq='30T')
```

```python
In [104]: pd.timedelta_range(start='1 days', periods=5, freq='2D5H')
Out[104]:
TimedeltaIndex(['1 days 00:00:00', '3 days 05:00:00', '5 days 10:00:00',
 '7 days 15:00:00', '9 days 20:00:00'],
dtype='timedelta64[ns]', freq='53H')
```

New in version 0.23.0.

Specifying `start`, `end`, and `periods` will generate a range of evenly spaced timedeltas from `start` to `end` inclusively, with `periods` number of elements in the resulting `TimedeltaIndex`:

```python
In [105]: pd.timedelta_range('0 days', '4 days', periods=5)
Out[105]:
TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'], dtype=timedelta64[ns], freq='D')
```

```python
In [106]: pd.timedelta_range('0 days', '4 days', periods=10)
Out[106]:
TimedeltaIndex(['0 days 00:00:00', '0 days 10:40:00', '0 days 21:20:00',
 '1 days 08:00:00', '1 days 18:40:00', '2 days 05:20:00',
 '2 days 16:00:00', '3 days 02:40:00', '3 days 13:20:00',
 '4 days 00:00:00'],
dtype='timedelta64[ns]', freq='640T')
```

Using the `TimedeltaIndex`

Similarly to other of the datetime-like indices, `DatetimeIndex` and `PeriodIndex`, you can use `TimedeltaIndex` as the index of pandas objects.

```python
In [107]: s = pd.Series(np.arange(100),
       index=pd.timedelta_range('1 days', periods=100, freq='h'))
```

```python
In [108]: s
Out[108]:
(continues on next page)
```

2.18. Time deltas
Selections work similarly, with coercion on string-likes and slices:

```python
In [109]: s['1 day':'2 day']
Out[109]:
1 days 00:00:00    0
1 days 01:00:00    1
1 days 02:00:00    2
1 days 03:00:00    3
1 days 04:00:00    4
   ...
2 days 19:00:00    43
2 days 20:00:00    44
2 days 21:00:00    45
2 days 22:00:00    46
2 days 23:00:00    47
Freq: H, Length: 48, dtype: int64
```

```python
In [110]: s['1 day 01:00:00']
Out[110]: 1
```

```python
In [111]: s[pd.Timedelta('1 day 1h')]
Out[111]: 1
```

Furthermore you can use partial string selection and the range will be inferred:

```python
In [112]: s['1 day':'1 day 5 hours']
Out[112]:
1 days 00:00:00    0
1 days 01:00:00    1
1 days 02:00:00    2
1 days 03:00:00    3
1 days 04:00:00    4
1 days 05:00:00    5
Freq: H, dtype: int64
```
Operations

Finally, the combination of TimedeltaIndex with DatetimeIndex allow certain combination operations that are NaT preserving:

```python
In [113]: tdi = pd.TimedeltaIndex(['1 days', pd.NaT, '2 days'])

In [114]: tdi.to_list()
Out[114]: [Timedelta('1 days 00:00:00'), NaT, Timedelta('2 days 00:00:00')]

In [115]: dti = pd.date_range('20130101', periods=3)

In [116]: dti.to_list()
Out[116]: [Timestamp('2013-01-01 00:00:00', freq='D'),
          Timestamp('2013-01-02 00:00:00', freq='D'),
          Timestamp('2013-01-03 00:00:00', freq='D')]

In [117]: (dti + tdi).to_list()
Out[117]: [Timestamp('2013-01-02 00:00:00'), NaT, Timestamp('2013-01-05 00:00:00')]

In [118]: (dti - tdi).to_list()
Out[118]: [Timestamp('2012-12-31 00:00:00'), NaT, Timestamp('2013-01-01 00:00:00')]
```

Conversions

Similarly to frequency conversion on a Series above, you can convert these indices to yield another Index.

```python
In [119]: tdi / np.timedelta64(1, 's')
Out[119]: Float64Index([86400.0, nan, 172800.0], dtype='float64')

In [120]: tdi.astype('timedelta64[s]')
Out[120]: Float64Index([86400.0, nan, 172800.0], dtype='float64')
```

Scalars type ops work as well. These can potentially return a different type of index.

```python
In [121]: tdi + pd.Timestamp('20130101')
Out[121]: DatetimeIndex(['2013-01-02', 'NaT', '2013-01-03'], dtype='datetime64[ns]',
                      freq=None)

# subtraction of a date and a timedelta -> datelike
# note that trying to subtract a date from a Timedelta will raise an exception
In [122]: (pd.Timestamp('20130101') - tdi).to_list()
Out[122]: [Timestamp('2012-12-31 00:00:00'), NaT, Timestamp('2012-12-30 00:00:00')]

# timedelta + timedelta -> timedelta
In [123]: tdi + pd.Timedelta('10 days')
Out[123]: TimedeltaIndex(['11 days', NaT, '12 days'], dtype='timedelta64[ns]',
                       freq=None)

# division can result in a Timedelta if the divisor is an integer
In [124]: tdi / 2
Out[124]: TimedeltaIndex(['0 days 12:00:00', NaT, '1 days 00:00:00'], dtype=
                         'timedelta64[ns]', freq=None)
```

(continues on next page)
2.18.7 Resampling

Similar to timeseries resampling, we can resample with a TimedeltaIndex.

```python
In [126]: s.resample('D').mean()
Out[126]:
1 days   11.5
2 days   35.5
3 days   59.5
4 days   83.5
5 days   97.5
Freq: D, dtype: float64
```

2.19 Styling

This document is written as a Jupyter Notebook, and can be viewed or downloaded here.

You can apply conditional formatting, the visual styling of a DataFrame depending on the data within, by using the DataFrame.style property. This is a property that returns a Styler object, which has useful methods for formatting and displaying DataFrames.

The styling is accomplished using CSS. You write “style functions” that take scalars, DataFrames or Series, and return like-indexed DataFrames or Series with CSS "attribute: value" pairs for the values. These functions can be incrementally passed to the Styler which collects the styles before rendering.

2.19.1 Building styles

Pass your style functions into one of the following methods:

- `Styler.applymap`: elementwise
- `Styler.apply`: column-/row-/table-wise

Both of those methods take a function (and some other keyword arguments) and applies your function to the DataFrame in a certain way. `Styler.applymap` works through the DataFrame elementwise. `Styler.apply` passes each column or row into your DataFrame one-at-a-time or the entire table at once, depending on the axis keyword argument. For columnwise use `axis=0`, rowwise use `axis=1`, and for the entire table at once use `axis=None`.

For `Styler.applymap` your function should take a scalar and return a single string with the CSS attribute-value pair.

For `Styler.apply` your function should take a Series or DataFrame (depending on the axis parameter), and return a Series or DataFrame with an identical shape where each value is a string with a CSS attribute-value pair.

Let’s see some examples.

```python
[2]:
import pandas as pd
import numpy as np
```

(continues on next page)
np.random.seed(24)
df = pd.DataFrame({'A': np.linspace(1, 10, 10)})
df = pd.concat([df, pd.DataFrame(np.random.randn(10, 4), columns=list('BCDE'))], axis=1)
df.iloc[3, 3] = np.nan
df.iloc[0, 2] = np.nan

Here’s a boring example of rendering a DataFrame, without any (visible) styles:

```python
[3]: df.style
[3]: <pandas.io.formats.style.Styler at 0x7fed91667c10>
```

Note: The DataFrame.style attribute is a property that returns a Styler object. Styler has a _repr_html_ method defined on it so they are rendered automatically. If you want the actual HTML back for further processing or for writing to file call the .render() method which returns a string.

The above output looks very similar to the standard DataFrame HTML representation. But we’ve done some work behind the scenes to attach CSS classes to each cell. We can view these by calling the .render method.

```python
[4]: df.style.highlight_null().render().split('n')[:10]
```

The row0_col12 is the identifier for that particular cell. We’ve also prepended each row/column identifier with a UUID unique to each DataFrame so that the style from one doesn’t collide with the styling from another within the same notebook or page (you can set the uuid if you’d like to tie together the styling of two DataFrames).

When writing style functions, you take care of producing the CSS attribute / value pairs you want. Pandas matches those up with the CSS classes that identify each cell.

Let’s write a simple style function that will color negative numbers red and positive numbers black.

```python
[5]: def color_negative_red(val):
    
    Takes a scalar and returns a string with the css property 'color: red' for negative strings, black otherwise.
    
```

color = 'red' if val < 0 else 'black'
return 'color: $s' % color

In this case, the cell’s style depends only on its own value. That means we should use the Styler.applymap method which works elementwise.

s = df.style.applymap(color_negative_red)
s

Notice the similarity with the standard df.applymap, which operates on DataFrames elementwise. We want you to be able to reuse your existing knowledge of how to interact with DataFrames.

Notice also that our function returned a string containing the CSS attribute and value, separated by a colon just like in a <style> tag. This will be a common theme.

Finally, the input shapes matched. Styler.applymap calls the function on each scalar input, and the function returns a scalar output.

Now suppose you wanted to highlight the maximum value in each column. We can’t use .applymap anymore since that operated elementwise. Instead, we’ll turn to .apply which operates columnwise (or rowwise using the axis keyword). Later on we’ll see that something like highlight_max is already defined on Styler so you wouldn’t need to write this yourself.

highlight_max(s):
   highlight the maximum in a Series yellow.
   is_max = s == s.max()
   return ['background-color: yellow' if v else '' for v in is_max]

df.style.apply(highlight_max)

In this case the input is a Series, one column at a time. Notice that the output shape of highlight_max matches the input shape, an array with len(s) items.

We encourage you to use method chains to build up a style piecewise, before finally rendering at the end of the chain.

df.style.applymap(color_negative_red).apply(highlight_max)

Above we used Styler.apply to pass in each column one at a time.

Debugging Tip: If you’re having trouble writing your style function, try just passing it into DataFrame.apply. Internally, Styler.apply uses DataFrame.apply so the result should be the same.

What if you wanted to highlight just the maximum value in the entire table? Use .apply(function, axis=None) to indicate that your function wants the entire table, not one column or row at a time. Let’s try that next.

We’ll rewrite our highlight_max to handle either Series (from .apply(axis=0 or 1)) or DataFrames (from .apply(axis=None)). We’ll also allow the color to be adjustable, to demonstrate that .apply, and .applymap pass along keyword arguments.
When using `Styler.apply(func, axis=None)`, the function must return a DataFrame with the same index and column labels.

```python
[11]: df.style.apply(highlight_max, color='darkorange', axis=None)
[11]: <pandas.io.formats.style.Styler at 0x7fed6b61dc70>
```

### Building Styles Summary

Style functions should return strings with one or more CSS attribute: value delimited by semicolons. Use

- `Styler.applymap(func)` for elementwise styles
- `Styler.apply(func, axis=0)` for columnwise styles
- `Styler.apply(func, axis=1)` for rowwise styles
- `Styler.apply(func, axis=None)` for tablewise styles

And crucially the input and output shapes of `func` must match. If `x` is the input then `func(x).shape == x.shape`.

#### 2.19.2 Finer control: slicing

Both `Styler.apply` and `Styler.applymap` accept a subset keyword. This allows you to apply styles to specific rows or columns, without having to code that logic into your `style` function.

The value passed to `subset` behaves similar to slicing a DataFrame.

- A scalar is treated as a column label
- A list (or series or numpy array)
- A tuple is treated as `(row_indexer, column_indexer)`

Consider using `pd.IndexSlice` to construct the tuple for the last one.

```python
[12]: df.style.apply(highlight_max, subset=['B', 'C', 'D'])
[12]: <pandas.io.formats.style.Styler at 0x7fed91667ca0>
```

For row and column slicing, any valid indexer to `.loc` will work.

```python
[13]: df.style.applymap(color_negative_red, subset=pd.IndexSlice[2:5, ['B', 'D']])
```
Only label-based slicing is supported right now, not positional.

If your style function uses a `subset` or `axis` keyword argument, consider wrapping your function in a `functools.partial`, partialing out that keyword.

```python
my_func2 = functools.partial(my_func, subset=42)
```

### 2.19.3 Finer Control: Display Values

We distinguish the display value from the actual value in `Styler`. To control the display value, the text is printed in each cell, use `Styler.format`. Cells can be formatted according to a format spec string or a callable that takes a single value and returns a string.

```python
df.style.format("{:.2%}")
```

Use a dictionary to format specific columns.

```python
df.style.format({ 'B': "{:0<4.0f}\n", 'D': ':+.2f' })
```

Or pass in a callable (or dictionary of callables) for more flexible handling.

```python
df.style.format({ "B": lambda x: "±{:2f}".format(abs(x)) })
```

You can format the text displayed for missing values by `na_rep`.

```python
df.style.format("{:.2%}", na_rep="-")
```

These formatting techniques can be used in combination with styling.

```python
df.style.highlight_max().format(None, na_rep="-")
```

### 2.19.4 Built-in styles

Finally, we expect certain styling functions to be common enough that we’ve included a few “built-in” to the `Styler`, so you don’t have to write them yourself.

```python
df.style.highlight_null(null_color='red')
```

You can create “heatmaps” with the `background_gradient` method. These require matplotlib, and we’ll use Seaborn to get a nice colormap.
```python
[20]: import seaborn as sns

    cm = sns.light_palette("green", as_cmap=True)

    s = df.style.background_gradient(cmap=cm)

    s
```

Styler.background_gradient takes the keyword arguments low and high. Roughly speaking these extend the range of your data by low and high percent so that when we convert the colors, the colormap's entire range isn't used. This is useful so that you can actually read the text still.

```python
[21]: # Uses the full color range
    df.loc[:4].style.background_gradient(cmap='viridis')

[21]: <pandas.io.formats.style.Styler at 0x7fed6b62bbb0>

[22]: # Compress the color range
    {df.loc[:4]
     .style
     .background_gradient(cmap='viridis', low=.5, high=0)
     .highlight_null('red')}

[22]: <pandas.io.formats.style.Styler at 0x7fed68c862e0>

There's also .highlight_min and .highlight_max.

```python
[23]: df.style.highlight_max(axis=0)

[23]: <pandas.io.formats.style.Styler at 0x7fed68c86700>

Use Styler.set_properties when the style doesn’t actually depend on the values.

```python
[24]: df.style.set_properties(**{'background-color': 'black',
     'color': 'lawngreen',
     'border-color': 'white'})

[24]: <pandas.io.formats.style.Styler at 0x7fed68ca51c0>

Bar charts

You can include “bar charts” in your DataFrame.

```python
[25]: df.style.bar(subset=['A', 'B'], color='#d65f5f')

[25]: <pandas.io.formats.style.Styler at 0x7fed6b686610>

New in version 0.20.0 is the ability to customize further the bar chart: You can now have the df.style.bar be centered on zero or midpoint value (in addition to the already existing way of having the min value at the left side of the cell), and you can pass a list of [color_negative, color_positive].

Here's how you can change the above with the new align='mid' option:

```python
[26]: df.style.bar(subset=['A', 'B'], align='mid', color=['#d65f5f', '#5fba7d'])

[26]: <pandas.io.formats.style.Styler at 0x7fed68c86d60>

The following example aims to give a highlight of the behavior of the new align options:
import pandas as pd
from IPython.display import HTML

# Test series
test1 = pd.Series([-100, -60, -30, -20], name='All Negative')
test2 = pd.Series([10, 20, 50, 100], name='All Positive')
test3 = pd.Series([-10, -5, 0, 90], name='Both Pos and Neg')

head = ""
<head>
<thead>
<th>Align</th>
<th>All Negative</th>
<th>All Positive</th>
<th>Both Neg and Pos</th>
</thead>
</tbody>
"

aligns = ['left', 'zero', 'mid']
for align in aligns:
    row = "<tr><th>{}</th>".format(align)
    for series in [test1, test2, test3]:
        s = series.copy()
        s.name = ''
        row += "<td>{}</td>".format(s.to_frame().style.bar(align=align,
            color=['#d65f5f', '#5fba7d', '
            width=100].render())

    #testn['width']
    row += '</tr>'
    head += row

head += ""
</tbody>
</table>"

HTML(head)

2.19.5 Sharing styles

Say you have a lovely style built up for a DataFrame, and now you want to apply the same style to a second DataFrame. Export the style with df1.style.export, and import it on the second DataFrame with df1.style.set

```
df2 = -df
style1 = df.style.applymap(color_negative_red)
style1
```

```
<
pandas.io.formats.style.Styler at 0x7fed68c86580>
```

```
style2 = df2.style
style2.use(style1.export())
style2
```
Notice that you’re able to share the styles even though they’re data aware. The styles are re-evaluated on the new DataFrame they’ve been used upon.

### 2.19.6 Other Options

You’ve seen a few methods for data-driven styling. Styler also provides a few other options for styles that don’t depend on the data.

- precision
- captions
- table-wide styles
- missing values representation
- hiding the index or columns

Each of these can be specified in two ways:

- A keyword argument to Styler.__init__
- A call to one of the .set_ or .hide_ methods, e.g. .set_caption or .hide_columns

The best method to use depends on the context. Use the Styler constructor when building many styled DataFrames that should all share the same properties. For interactive use, the .set_ and .hide_ methods are more convenient.

#### Precision

You can control the precision of floats using pandas’ regular `display.precision` option.

```python
[30]: with pd.option_context('display.precision', 2):
    html = (df.style
             .applymap(color_negative_red)
             .apply(highlight_max))
html
```

Or through a set_precision method.

```python
[31]: df.style\n    .applymap(color_negative_red)\n    .apply(highlight_max)\n    .set_precision(2)
```

Setting the precision only affects the printed number; the full-precision values are always passed to your style functions. You can always use `df.round(2).style` if you’d prefer to round from the start.
pandas: powerful Python data analysis toolkit, Release 1.1.1

Captions
Regular table captions can be added in a few ways.
[32]: df.style.set_caption('Colormaps, with a caption.')\
.background_gradient(cmap=cm)
[32]: <pandas.io.formats.style.Styler at 0x7fed68ca5f70>

Table styles
The next option you have are “table styles”. These are styles that apply to the table as a whole, but don’t look at the
data. Certain sytlings, including pseudo-selectors like :hover can only be used this way.
[33]: from IPython.display import HTML
def hover(hover_color="#ffff99"):
return dict(selector="tr:hover",
props=[("background-color", "%s" % hover_color)])
styles = [
hover(),
dict(selector="th", props=[("font-size", "150%"),
("text-align", "center")]),
dict(selector="caption", props=[("caption-side", "bottom")])
]
html = (df.style.set_table_styles(styles)
.set_caption("Hover to highlight."))
html
[33]: <pandas.io.formats.style.Styler at 0x7fed68ca50d0>

table_styles should be a list of dictionaries. Each dictionary should have the selector and props keys.
The value for selector should be a valid CSS selector. Recall that all the styles are already attached to an id,
unique to each Styler. This selector is in addition to that id. The value for props should be a list of tuples of
('attribute', 'value').
table_styles are extremely flexible, but not as fun to type out by hand. We hope to collect some useful ones
either in pandas, or preferable in a new package that builds on top the tools here.
Missing values
You can control the default missing values representation for the entire table through set_na_rep method.
[34]: (df.style
.set_na_rep("FAIL")
.format(None, na_rep="PASS", subset=["D"])
.highlight_null("yellow"))
[34]: <pandas.io.formats.style.Styler at 0x7fed68c4e0a0>

824

Chapter 2. User Guide


Hiding the Index or Columns

The index can be hidden from rendering by calling `Styler.hide_index`. Columns can be hidden from rendering by calling `Styler.hide_columns` and passing in the name of a column, or a slice of columns.

```python
[35]: df.style.hide_index()
[35]: <pandas.io.formats.style.Styler at 0x7fed68c4e400>
[36]: df.style.hide_columns(['C','D'])
[36]: <pandas.io.formats.style.Styler at 0x7fed68c4ef40>
```

CSS classes

Certain CSS classes are attached to cells.

- Index and Column names include `index_name` and `level<k>` where `k` is its level in a MultiIndex
- Index label cells include
  - `row_heading`
  - `row<n>` where `n` is the numeric position of the row
  - `level<k>` where `k` is the level in a MultiIndex
- Column label cells include
  - `col_heading`
  - `col<n>` where `n` is the numeric position of the column
  - `level<k>` where `k` is the level in a MultiIndex
- Blank cells include `blank`
- Data cells include `data`

Limitations

- `DataFrame` only (use `Series.to_frame().style`)
- The index and columns must be unique
- No large repr, and performance isn’t great; this is intended for summary DataFrames
- You can only style the `values`, not the index or columns
- You can only apply styles, you can’t insert new HTML entities

Some of these will be addressed in the future.
Terms

- **Style function**: a function that's passed into `Styler.apply` or `Styler.applymap` and returns values like 'css attribute: value'
- **Built-in style functions**: style functions that are methods on `Styler`
- **Table style**: a dictionary with the two keys `selector` and `props`. `selector` is the CSS selector that `props` will apply to. `props` is a list of `(attribute, value)` tuples. A list of table styles passed into `Styler`.

### 2.19.7 Fun stuff

Here are a few interesting examples.

`Styler` interacts pretty well with widgets. If you're viewing this online instead of running the notebook yourself, you're missing out on interactively adjusting the color palette.

```python
from IPython.html import widgets

@widgets.interact
def f(h_neg=(0, 359, 1), h_pos=(0, 359), s=(0., 99.9), l=(0., 99.9)):
    return df.style.background_gradient(
        cmap=sns.palettes.diverging_palette(h_neg=h_neg, h_pos=h_pos, s=s, l=l, as_cmap=True)
    )

< pandas.io.formats.style.Styler at 0x7fed68ca5c70 >
```

```python
def magnify():
    return [dict(selector="th",
                props=[("font-size", "4pt")]),
            dict(selector="td",
                 props=[('padding', "0em 0em")]),
            dict(selector="th:hover",
                 props=[("font-size", "12pt")]),
            dict(selector="tr:hover td:hover",
                 props=[("max-width", '200px'),
                        ('font-size', '12pt')])
]
```

```python
np.random.seed(25)
cmap = cmap=sns.diverging_palette(5, 250, as_cmap=True)
bigdf = pd.DataFrame(np.random.randn(20, 25)).cumsum()

bigdf.style.background_gradient(cmap, axis=1)
    .set_properties(**{'max-width': '80px', 'font-size': '1pt'})
    .set_caption("Hover to magnify")
    .set_precision(2)
    .set_table_styles(magnify())

< pandas.io.formats.style.Styler at 0x7fed68d50460 >
```
2.19.8 Export to Excel

*New in version 0.20.0*

Experimental: This is a new feature and still under development. We’ll be adding features and possibly making breaking changes in future releases. We’d love to hear your feedback.

Some support is available for exporting styled DataFrames to Excel worksheets using the OpenPyXL or XlsxWriter engines. CSS2.2 properties handled include:

- background-color
- border-style, border-width, border-color and their {top, right, bottom, left variants}
- color
- font-family
- font-style
- font-weight
- text-align
- text-decoration
- vertical-align
- white-space: nowrap

- Only CSS2 named colors and hex colors of the form #rgb or #rrggbb are currently supported.
- The following pseudo CSS properties are also available to set excel specific style properties:
  - number-format

```
[40]: df.style.\n    applymap(color_negative_red).\n    apply(highlight_max).\n    to_excel('styled.xlsx', engine='openpyxl')
```

A screenshot of the output:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>1</td>
<td>1.329212</td>
<td>-0.31628</td>
<td>-0.99081</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>2</td>
<td>-1.070816</td>
<td>-1.438713</td>
<td>0.564417</td>
<td>0.295722</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td>3</td>
<td>-1.626404</td>
<td>0.219565</td>
<td>0.678805</td>
<td>1.889273</td>
</tr>
<tr>
<td>5</td>
<td>3</td>
<td>4</td>
<td>0.961538</td>
<td>0.104011</td>
<td>-0.481165</td>
<td>0.850229</td>
</tr>
<tr>
<td>6</td>
<td>4</td>
<td>5</td>
<td>1.453425</td>
<td>1.057737</td>
<td>0.165562</td>
<td>0.515018</td>
</tr>
<tr>
<td>7</td>
<td>5</td>
<td>6</td>
<td>-1.336936</td>
<td>0.562861</td>
<td>1.392855</td>
<td>-0.063328</td>
</tr>
<tr>
<td>8</td>
<td>6</td>
<td>7</td>
<td>0.121668</td>
<td>1.207603</td>
<td>-0.00204</td>
<td>1.627796</td>
</tr>
<tr>
<td>9</td>
<td>7</td>
<td>8</td>
<td>0.354493</td>
<td>1.037528</td>
<td>-0.385684</td>
<td>0.519818</td>
</tr>
<tr>
<td>10</td>
<td>8</td>
<td>9</td>
<td>1.686583</td>
<td>-1.325963</td>
<td>1.428984</td>
<td>-2.089354</td>
</tr>
<tr>
<td>11</td>
<td>9</td>
<td>10</td>
<td>-0.12982</td>
<td>0.631523</td>
<td>-0.586538</td>
<td>0.29072</td>
</tr>
</tbody>
</table>
2.19.9 Extensibility

The core of pandas is, and will remain, its “high-performance, easy-to-use data structures”. With that in mind, we hope that DataFrame.style accomplishes two goals

- Provide an API that is pleasing to use interactively and is “good enough” for many tasks
- Provide the foundations for dedicated libraries to build on

If you build a great library on top of this, let us know and we’ll link to it.

Subclassing

If the default template doesn’t quite suit your needs, you can subclass Styler and extend or override the template. We’ll show an example of extending the default template to insert a custom header before each table.

```python
from jinja2 import Environment, ChoiceLoader, FileSystemLoader
from IPython.display import HTML
from pandas.io.formats.style import Styler

# We'll use the following template:

with open("templates/myhtml.tpl") as f:
    print(f.read())

{% extends "html.tpl" %}
{% block table %}
<h1>{{ table_title|default("My Table") }}</h1>
{{ super() }}
{% endblock table %}
```

Now that we’ve created a template, we need to set up a subclass of Styler that knows about it.

```python
class MyStyler(Styler):
    env = Environment(
        loader=ChoiceLoader(
            [FileSystemLoader("templates"), # contains ours
             Styler.loader, # the default
            ])
    )
    template = env.get_template("myhtml.tpl")
```

Notice that we include the original loader in our environment’s loader. That’s because we extend the original template, so the Jinja environment needs to be able to find it.

Now we can use that custom styler. It’s __init__ takes a DataFrame.

```python
MyStyler(df)
```

Our custom template accepts a table_title keyword. We can provide the value in the .render method.

```python
HTML(MyStyler(df).render(table_title="Extending Example"))
```

For convenience, we provide the Styler.from_custom_template method that does the same as the custom subclass.
Here's the template structure:

```python
with open("templates/template_structure.html") as f:
    structure = f.read()
HTML(structure)
```

See the template in the GitHub repo for more details.

## 2.20 Options and settings

### 2.20.1 Overview

pandas has an options system that lets you customize some aspects of its behaviour, display-related options being those the user is most likely to adjust.

Options have a full “dotted-style”, case-insensitive name (e.g. `display.max_rows`). You can get/set options directly as attributes of the top-level `options` attribute:

```python
In [1]: import pandas as pd
In [2]: pd.options.display.max_rows
Out[2]: 15
In [3]: pd.options.display.max_rows = 999
In [4]: pd.options.display.max_rows
Out[4]: 999
```

The API is composed of 5 relevant functions, available directly from the `pandas` namespace:

- `get_option()` / `set_option()` - get/set the value of a single option.
- `reset_option()` - reset one or more options to their default value.
- `describe_option()` - print the descriptions of one or more options.
- `option_context()` - execute a codeblock with a set of options that revert to prior settings after execution.

**Note:** Developers can check out `pandas/core/config.py` for more information.

All of the functions above accept a regexp pattern (`re.search` style) as an argument, and so passing in a substring will work - as long as it is unambiguous:

```python
In [5]: pd.get_option("display.max_rows")
Out[5]: 999
In [6]: pd.set_option("display.max_rows", 101)
In [7]: pd.get_option("display.max_rows")
```

(continues on next page)
The following will not work because it matches multiple option names, e.g. \texttt{display.max_colwidth}, \texttt{display.max_rows}, \texttt{display.max_columns}:

```python
In [10]: try:
    ...
    ...:    pd.get_option("column")
    ...
    ...:    except KeyError as e:
    ...
    ...:    print(e)
    ...
    ...
'Pattern matched multiple keys'
```

Note: Using this form of shorthand may cause your code to break if new options with similar names are added in future versions.

You can get a list of available options and their descriptions with \texttt{describe_option}. When called with no argument \texttt{describe_option} will print out the descriptions for all available options.

### 2.20.2 Getting and setting options

As described above, \texttt{get_option()} and \texttt{set_option()} are available from the pandas namespace. To change an option, call \texttt{set_option('option_regex', new_value)}.

```python
In [11]: pd.get_option('mode.sim_interactive')
Out[11]: False

In [12]: pd.set_option('mode.sim_interactive', True)

In [13]: pd.get_option('mode.sim_interactive')
Out[13]: True
```

Note: The option ‘mode.sim_interactive’ is mostly used for debugging purposes.

All options also have a default value, and you can use \texttt{reset_option} to do just that:

```python
In [14]: pd.get_option("display.max_rows")
Out[14]: 60

In [15]: pd.set_option("display.max_rows", 999)

In [16]: pd.get_option("display.max_rows")
Out[16]: 999

In [17]: pd.reset_option("display.max_rows")

In [18]: pd.get_option("display.max_rows")
Out[18]: 60
```

It’s also possible to reset multiple options at once (using a regex):
option_context context manager has been exposed through the top-level API, allowing you to execute code with given option values. Option values are restored automatically when you exit the with block:

```python
In [20]: with pd.option_context("display.max_rows", 10, "display.max_columns", 5):
    ....:     print(pd.get_option("display.max_rows"))
    ....:     print(pd.get_option("display.max_columns"))
    ....:
60
0
```

2.20.3 Setting startup options in Python/IPython environment

Using startup scripts for the Python/IPython environment to import pandas and set options makes working with pandas more efficient. To do this, create a .py or .ipy script in the startup directory of the desired profile. An example where the startup folder is in a default ipython profile can be found at:

```
$IPYTHONDIR/profile_default/startup
```

More information can be found in the ipython documentation. An example startup script for pandas is displayed below:

```python
import pandas as pd
pd.set_option('display.max_rows', 999)
pd.set_option('precision', 5)
```

2.20.4 Frequently used options

The following is a walk-through of the more frequently used display options.

display.max_rows and display.max_columns sets the maximum number of rows and columns displayed when a frame is pretty-printed. Truncated lines are replaced by an ellipsis.
In [26]: pd.set_option('max_rows', 5)

In [27]: df
Out[27]:
   0    1
0  0.469112 -0.282863
1 -1.509059 -1.135632
..   ...     ...
5 -0.494929  1.071804
6  0.721555 -0.706771

[7 rows x 2 columns]

In [28]: pd.reset_option('max_rows')

Once the display.max_rows is exceeded, the display.min_rows options determines how many rows are shown in the truncated repr.

In [29]: pd.set_option('max_rows', 8)

In [30]: pd.set_option('min_rows', 4)

# below max_rows -> all rows shown
In [31]: df = pd.DataFrame(np.random.randn(7, 2))

In [32]: df
Out[32]:
   0    1
0 -1.039575  0.271860
1 -0.424972  0.567020
2  0.276232 -1.087401
3 -0.673690  0.113648
4 -1.478427  0.524988
5  0.404705  0.577046
6 -1.715002 -1.039268

# above max_rows -> only min_rows (4) rows shown
In [33]: df = pd.DataFrame(np.random.randn(9, 2))

In [34]: df
Out[34]:
   0    1
0 -1.039575  0.271860
1 -0.424972  0.567020
2  0.276232 -1.087401
3 -0.673690  0.113648
4 -1.478427  0.524988
5  0.404705  0.577046
6 -1.715002 -1.039268
7 -0.370647 -1.157892
8 -1.344312  0.844885
..   ...     ...
[9 rows x 2 columns]

In [35]: pd.reset_option('max_rows')

In [36]: pd.reset_option('min_rows')

display.expand_frame_repr allows for the representation of dataframes to stretch across pages, wrapped over the full column vs row-wise.
```python
In [37]: df = pd.DataFrame(np.random.randn(5, 10))

In [38]: pd.set_option('expand_frame_repr', True)

In [39]: df

Out[39]:
  0   1   2   3   4   5   6   7
→ 8  9
 0 -0.006154 -0.923061 0.895717 0.805244 -1.206412 2.565646 1.431256 1.340309 -1.
    170299 -0.226169
 1  0.410835  0.813850 0.132003 -0.827317 -0.076467 -1.187678 1.130127 -1.436737 -1.
    413681  1.607920
 2  1.024180  0.569605 0.875906 -2.211372 0.974466 -2.006747 1.130127 -1.436737 -1.
    545952 -1.219217
 3 -1.226825  0.769804 -1.281247 -0.727707 -0.121306 -0.097883 0.695775 0.341734 0.
    959726 -1.110336
 4 -0.619976  0.149748 -0.732339 0.687738 0.176444 0.403310 -0.154951 0.301624 -2.
    179861 -1.369849

In [40]: pd.set_option('expand_frame_repr', False)

In [41]: df

Out[41]:
  0   1   2   3   4   5   6   7
→ 8  9
 0 -0.006154 -0.923061 0.895717 0.805244 -1.206412 2.565646 1.431256 1.340309 -1.
    170299 -0.226169
 1  0.410835  0.813850 0.132003 -0.827317 -0.076467 -1.187678 1.130127 -1.436737 -1.
    413681  1.607920
 2  1.024180  0.569605 0.875906 -2.211372 0.974466 -2.006747 1.130127 -1.436737 -1.
    545952 -1.219217
 3 -1.226825  0.769804 -1.281247 -0.727707 -0.121306 -0.097883 0.695775 0.341734 0.
    959726 -1.110336
 4 -0.619976  0.149748 -0.732339 0.687738 0.176444 0.403310 -0.154951 0.301624 -2.
    179861 -1.369849

In [42]: pd.reset_option('expand_frame_repr')
```

display.large_repr lets you select whether to display dataframes that exceed max_columns or max_rows as a truncated frame, or as a summary.

```python
In [43]: df = pd.DataFrame(np.random.randn(10, 10))

In [44]: pd.set_option('max_rows', 5)

In [45]: pd.set_option('large_repr', 'truncate')

In [46]: df

Out[46]:
  0   1   2   3   4   5   6   7
→ 8  9
 0 -0.954208 1.462696 -1.743161 -0.826591 -0.345352 1.314232 0.690579 0.995761 2.
    396780 0.014871
 1  3.357427 -0.317441 -1.236269 0.896171 -0.487602 -2.006747 0.380396 0.
    804844 0.432390
 2 ... ... ... ... ... ... ... ... ... ...
    ... ...
(continues on next page)```
display.max_colwidth sets the maximum width of columns. Cells of this length or longer will be truncated with an ellipsis.

```
In [51]: df = pd.DataFrame(np.array([['foo', 'bar', 'bim', 'uncomfortably long string

   ....:  ', 'horse', 'cow', 'banana', 'apple']]),

   ....:             ['horse', 'cow', 'banana', 'apple'])))

In [52]: pd.set_option('max_colwidth', 40)

In [53]: df
Out[53]:
      0   1   2                              3
0 foo bar bim uncomfortably long string
1 horse cow banana apple

In [54]: pd.set_option('max_colwidth', 6)

In [55]: df
Out[55]:
      0   1   2   3
0 foo bar bim un...
1 horse cow ba... apple
```
display.max_info_columns sets a threshold for when by-column info will be given.

```
In [56]: pd.reset_option('max_colwidth')
```

```
In [57]: df = pd.DataFrame(np.random.randn(10, 10))
In [58]: pd.set_option('max_info_columns', 11)
In [59]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 10 columns):
     # Column  Non-Null Count Dtype
        --- ------ -------------- -----   
0 0 0 10 non-null  float64
1 1 1 10 non-null  float64
2 2 10 non-null  float64
3 3 10 non-null  float64
4 4 10 non-null  float64
5 5 10 non-null  float64
6 6 10 non-null  float64
7 7 10 non-null  float64
8 8 10 non-null  float64
9 9 10 non-null  float64
dtypes: float64(10)
memory usage: 928.0 bytes
```

```
In [60]: pd.set_option('max_info_columns', 5)
In [61]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Columns: 10 entries, 0 to 9
dtypes: float64(10)
memory usage: 928.0 bytes
```

```
In [62]: pd.reset_option('max_info_columns')
```

display.max_info_rows: df.info() will usually show null-counts for each column. For large frames this
can be quite slow. max_info_rows and max_info_cols limit this null check only to frames with smaller
dimensions then specified. Note that you can specify the option df.info(null_counts=True) to override on
showing a particular frame.

```
In [63]: df = pd.DataFrame(np.random.choice([0, 1, np.nan], size=(10, 10)))
In [64]: df
```

```
  0  1  2  3  4  5  6  7  8  9
0 0.0 NaN 1.0 NaN NaN 0.0 NaN 1.0
1 1.0 NaN 1.0 1.0 NaN 0.0 0.0 NaN
2 0.0 NaN 1.0 0.0 NaN NaN NaN 0.0
3 NaN NaN NaN 0.0 1.0 1.0 NaN 1.0
4 0.0 NaN NaN NaN 0.0 NaN NaN 1.0
5 0.0 1.0 1.0 NaN 0.0 NaN 1.0 0.0
6 1.0 1.0 1.0 NaN 1.0 NaN 1.0 NaN
```

(continues on next page)
7  0.0  0.0  1.0  0.0  1.0  0.0  1.0  0.0  NaN
8  NaN  NaN  NaN  0.0  NaN  NaN  NaN  NaN  1.0  NaN
9  0.0  NaN  0.0  NaN  NaN  0.0  NaN  1.0  1.0  0.0

In [65]: pd.set_option('max_info_rows', 11)

In [66]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 10 columns):
# Column Non-Null Count Dtype
--- ------ -------------- ----- 
0 0 8 non-null float64
1 1 3 non-null float64
2 2 7 non-null float64
3 3 6 non-null float64
4 4 7 non-null float64
5 5 6 non-null float64
6 6 2 non-null float64
7 7 6 non-null float64
8 8 6 non-null float64
9 9 6 non-null float64
dtypes: float64(10)
memory usage: 928.0 bytes

In [67]: pd.set_option('max_info_rows', 5)

In [68]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 10 columns):
# Column Dtype
--- ------ ----- 
0 0 float64
1 1 float64
2 2 float64
3 3 float64
4 4 float64
5 5 float64
6 6 float64
7 7 float64
8 8 float64
9 9 float64
dtypes: float64(10)
memory usage: 928.0 bytes

In [69]: pd.reset_option('max_info_rows')

display.precision sets the output display precision in terms of decimal places. This is only a suggestion.

In [70]: df = pd.DataFrame(np.random.randn(5, 5))

In [71]: pd.set_option('precision', 7)

In [72]: df
Out[72]:
  0  1  2  3  4
(continues on next page)
In [73]: pd.set_option('precision', 4)

In [74]: df

Out[74]:

<p>| | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>-1.1506</td>
<td>-0.7983</td>
<td>-0.5577</td>
<td>0.3814</td>
<td>1.3371</td>
</tr>
<tr>
<td>1</td>
<td>-1.5311</td>
<td>1.3315</td>
<td>-0.5713</td>
<td>-0.0267</td>
<td>-1.0857</td>
</tr>
<tr>
<td>2</td>
<td>-1.1147</td>
<td>-0.0582</td>
<td>-0.4868</td>
<td>1.6851</td>
<td>0.1126</td>
</tr>
<tr>
<td>3</td>
<td>-1.4953</td>
<td>0.8984</td>
<td>-0.1482</td>
<td>-1.5961</td>
<td>0.1597</td>
</tr>
<tr>
<td>4</td>
<td>0.2621</td>
<td>0.0362</td>
<td>0.1847</td>
<td>-0.2551</td>
<td>-0.2710</td>
</tr>
</tbody>
</table>

`display.chop_threshold` sets at what level pandas rounds to zero when it displays a Series of DataFrame. This setting does not change the precision at which the number is stored.

In [75]: df = pd.DataFrame(np.random.randn(6, 6))

In [76]: pd.set_option('chop_threshold', 0)

In [77]: df

Out[77]:

<p>| | | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1.2884</td>
<td>0.2946</td>
<td>-1.1658</td>
<td>0.8470</td>
<td>-0.6856</td>
<td>0.6091</td>
</tr>
<tr>
<td>1</td>
<td>-0.3040</td>
<td>0.6256</td>
<td>-0.0593</td>
<td>0.2497</td>
<td>1.1039</td>
<td>-1.0875</td>
</tr>
<tr>
<td>2</td>
<td>1.9980</td>
<td>-0.2445</td>
<td>0.1362</td>
<td>0.8863</td>
<td>-1.3507</td>
<td>-0.8863</td>
</tr>
<tr>
<td>3</td>
<td>-1.0133</td>
<td>1.9209</td>
<td>-0.3882</td>
<td>-2.3144</td>
<td>0.6655</td>
<td>0.4026</td>
</tr>
<tr>
<td>4</td>
<td>0.3996</td>
<td>-1.7660</td>
<td>0.8504</td>
<td>0.3881</td>
<td>0.9923</td>
<td>0.7441</td>
</tr>
<tr>
<td>5</td>
<td>-0.7398</td>
<td>-1.0549</td>
<td>-0.1796</td>
<td>0.6396</td>
<td>1.5850</td>
<td>1.9067</td>
</tr>
</tbody>
</table>

In [78]: pd.set_option('chop_threshold', .5)

In [79]: df

Out[79]:

<p>| | | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1.2884</td>
<td>0.0000</td>
<td>-1.1658</td>
<td>0.8470</td>
<td>-0.6856</td>
<td>0.6091</td>
</tr>
<tr>
<td>1</td>
<td>0.0000</td>
<td>0.6256</td>
<td>0.0000</td>
<td>0.0000</td>
<td>1.1039</td>
<td>-1.0875</td>
</tr>
<tr>
<td>2</td>
<td>1.9980</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.8863</td>
<td>-1.3507</td>
<td>-0.8863</td>
</tr>
<tr>
<td>3</td>
<td>-1.0133</td>
<td>1.9209</td>
<td>0.0000</td>
<td>-2.3144</td>
<td>0.6655</td>
<td>0.0000</td>
</tr>
<tr>
<td>4</td>
<td>0.0000</td>
<td>-1.7660</td>
<td>0.8504</td>
<td>0.0000</td>
<td>0.9923</td>
<td>0.7441</td>
</tr>
<tr>
<td>5</td>
<td>-0.7398</td>
<td>-1.0549</td>
<td>0.0000</td>
<td>0.6396</td>
<td>1.5850</td>
<td>1.9067</td>
</tr>
</tbody>
</table>

In [80]: pd.reset_option('chop_threshold')

display.colheader_justify controls the justification of the headers. The options are ‘right’, and ‘left’.

In [81]: df = pd.DataFrame(np.array([np.random.randn(6),
                                np.random.randint(1, 9, 6) * .1,
                                np.zeros(6)]).T,
                           columns=['A', 'B', 'C'], dtype='float')

(continues on next page)
In [82]: pd.set_option('colheader_justify', 'right')

In [83]: df
Out[83]:
   A     B     C
0  0.1040  0.1  0.0
1  0.1741  0.5  0.0
2 -0.4395  0.4  0.0
3 -0.7413  0.8  0.0
4 -0.0797  0.4  0.0
5 -0.9229  0.3  0.0

In [84]: pd.set_option('colheader_justify', 'left')

In [85]: df
Out[85]:
   A     B     C
0  0.1040  0.1  0.0
1  0.1741  0.5  0.0
2 -0.4395  0.4  0.0
3 -0.7413  0.8  0.0
4 -0.0797  0.4  0.0
5 -0.9229  0.3  0.0

In [86]: pd.reset_option('colheader_justify')

### 2.20.5 Available options

<table>
<thead>
<tr>
<th>Option</th>
<th>Default</th>
<th>Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>display.chop_threshold</td>
<td>None</td>
<td>If set to a float value, all float values smaller than the given threshold will be displayed as exactly 0.</td>
</tr>
<tr>
<td>display.colheader_justify</td>
<td>right</td>
<td>Controls the justification of column headers. used by DataFrameFormatter.</td>
</tr>
<tr>
<td>display.column_space</td>
<td>12</td>
<td>No description available.</td>
</tr>
<tr>
<td>display.date_dayfirst</td>
<td>False</td>
<td>When True, prints and parses dates with the day first, eg 20/01/2005</td>
</tr>
<tr>
<td>display.date_yearfirst</td>
<td>False</td>
<td>When True, prints and parses dates with the year first, eg 2005/01/20</td>
</tr>
<tr>
<td>display.encoding</td>
<td>UTF-8</td>
<td>Defaults to the detected encoding of the console. Specifies the encoding to be used.</td>
</tr>
<tr>
<td>display.expand_frame_repr</td>
<td>True</td>
<td>Whether to print out the full DataFrame repr for wide DataFrames across multiple lines.</td>
</tr>
<tr>
<td>display.float_format</td>
<td>None</td>
<td>The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See core.format.EngFormatter for an example.</td>
</tr>
<tr>
<td>display.large_repr</td>
<td>truncate</td>
<td>For DataFrames exceeding max_rows/max_cols, the repr (and HTML repr) can be truncated.</td>
</tr>
<tr>
<td>display.latex.escape</td>
<td>True</td>
<td>Escapes special characters in DataFrames, when using the to_latex method.</td>
</tr>
<tr>
<td>display.latex.longtable</td>
<td>False</td>
<td>Specifies if the to_latex method of a DataFrame uses the longtable format.</td>
</tr>
<tr>
<td>display.latex.multicolumn</td>
<td>True</td>
<td>Combines columns when using a MultiIndex.</td>
</tr>
<tr>
<td>display.latex.multicolumn_format</td>
<td>T'</td>
<td>Alignment of multicolumn labels.</td>
</tr>
<tr>
<td>display.latex.multirow</td>
<td>False</td>
<td>Combines rows when using a MultiIndex. Centered instead of top-aligned, separate a MultiIndex as a DataFrame.</td>
</tr>
<tr>
<td>display.max_columns</td>
<td>0 or 20</td>
<td>max_rows and max_columns are used in <strong>repr</strong>() methods to decide if to_str() call is needed.</td>
</tr>
<tr>
<td>display.max_colwidth</td>
<td>50</td>
<td>The maximum width in characters of a column in the repr of a pandas data structure.</td>
</tr>
<tr>
<td>display.max_info_columns</td>
<td>100</td>
<td>max_info_columns is used in DataFrame.info method to decide if per column information is shown.</td>
</tr>
<tr>
<td>display.max_info_rows</td>
<td>1690785</td>
<td>df.info()() will usually show null-counts for each column. For large frames this can be slow.</td>
</tr>
<tr>
<td>display.max_rows</td>
<td>60</td>
<td>This sets the maximum number of rows pandas should output when printing output.</td>
</tr>
<tr>
<td>display.min_rows</td>
<td>10</td>
<td>The numbers of rows to show in a truncated repr (when max_rows is exceeded)</td>
</tr>
<tr>
<td>display.max_seq_items</td>
<td>100</td>
<td>When pretty-printing a long sequence, no more then max_seq_items will be printed.</td>
</tr>
</tbody>
</table>
2.20.6 Number formatting

pandas also allows you to set how numbers are displayed in the console. This option is not set through the `set_options` API.

Use the `set_eng_float_format` function to alter the floating-point formatting of pandas objects to produce a particular format.

For instance:

```python
In [87]: import numpy as np

In [88]: pd.set_eng_float_format(accuracy=3, use_eng_prefix=True)

In [89]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [90]: s / 1.e3
Out[90]:
   a    303.638u
   b   -721.084u
   c   -622.696u
   d    648.250u
   e   -1.945m
dtype: float64

In [91]: s / 1.e6
Out[91]:
   a    303.638n
```

(continues on next page)
To round floats on a case-by-case basis, you can also use `round()` and `round()`.

### 2.20.7 Unicode formatting

**Warning:** Enabling this option will affect the performance for printing of DataFrame and Series (about 2 times slower). Use only when it is actually required.

Some East Asian countries use Unicode characters whose width corresponds to two Latin characters. If a DataFrame or Series contains these characters, the default output mode may not align them properly.

**Note:** Screen captures are attached for each output to show the actual results.

```python
In [92]: df = pd.DataFrame({'': ['UK', ''], '': ['Alice', '']})

In [93]: df
Out[93]:
     0  UK  Alice
     1

In [94]: pd.set_option('display.unicode.east_asian_width', True)

In [95]: df
Out[95]:
     0  UK  Alice
     1

>>> df = pd.DataFrame({u'国籍': ['UK', '日本'], u'名前': ['Alice', 'しのぶ']})

>>> df
    名前  国籍
     0  Alice    UK
     1  しのぶ   日本
```

Enabling `display.unicode.east_asian_width` allows pandas to check each character’s “East Asian Width” property. These characters can be aligned properly by setting this option to `True`. However, this will result in longer render times than the standard `len` function.

```python
In [94]: pd.set_option('display.unicode.east_asian_width', True)

In [95]: df
Out[95]:
     0  UK  Alice
     1

>>> pd.set_option('display.unicode.east_asian_width', True)

>>> df
    名前  国籍
     0  Alice    UK
     1  しのぶ   日本
```

In addition, Unicode characters whose width is “Ambiguous” can either be 1 or 2 characters wide depending on the terminal setting or encoding. The option `display.unicode.ambiguous_as_wide` can be used to handle the ambiguity.
By default, an “Ambiguous” character’s width, such as “¡¡” (inverted exclamation) in the example below, is taken to be 1.

```python
In [96]: df = pd.DataFrame({'a': ['xxx', '¡¡'], 'b': ['yyy', '¡¡']})

In [97]: df
Out[97]:
   a  b
0  xxx  yyy
1  ¡¡  ¡¡

Enabling `display.unicode.ambiguous_as_wide` makes pandas interpret these characters’ widths to be 2. (Note that this option will only be effective when `display.unicode.east_asian_width` is enabled.)

However, setting this option incorrectly for your terminal will cause these characters to be aligned incorrectly:

```python
In [98]: pd.set_option('display.unicode.ambiguous_as_wide', True)

In [99]: df
Out[99]:
   a  b
0  xxx  yyy
1  ¡¡  ¡¡

Enabling `display.unicode.ambiguous_as_wide` makes pandas interpret these characters’ widths to be 2. (Note that this option will only be effective when `display.unicode.east_asian_width` is enabled.)

However, setting this option incorrectly for your terminal will cause these characters to be aligned incorrectly:

```python
In [98]: pd.set_option('display.unicode.ambiguous_as_wide', True)

In [99]: df
Out[99]:
   a  b
0  xxx  yyy
1  ¡¡  ¡¡
```

### 2.2.0.8 Table schema display

`DataFrame` and `Series` will publish a Table Schema representation by default. False by default, this can be enabled globally with the `display.html.table_schema` option:

```python
In [100]: pd.set_option('display.html.table_schema', True)
```

Only 'display.max_rows' are serialized and published.

### 2.2.1 Enhancing performance

In this part of the tutorial, we will investigate how to speed up certain functions operating on pandas `DataFrames` using three different techniques: Cython, Numba and `pandas.eval()`. We will see a speed improvement of ~200 when we use Cython and Numba on a test function operating row-wise on the `DataFrame`. Using `pandas.eval()` we will speed up a sum by an order of ~2.

**Note:** In addition to following the steps in this tutorial, users interested in enhancing performance are highly encouraged to install the recommended dependencies for pandas. These dependencies are often not installed by default, but
2.21.1 Cython (writing C extensions for pandas)

For many use cases writing pandas in pure Python and NumPy is sufficient. In some computationally heavy applications however, it can be possible to achieve sizable speed-ups by offloading work to cython.

This tutorial assumes you have refactored as much as possible in Python, for example by trying to remove for-loops and making use of NumPy vectorization. It’s always worth optimising in Python first.

This tutorial walks through a “typical” process of cythonizing a slow computation. We use an example from the Cython documentation but in the context of pandas. Our final cythonized solution is around 100 times faster than the pure Python solution.

**Pure Python**

We have a DataFrame to which we want to apply a function row-wise.

```
In [1]: df = pd.DataFrame({'a': np.random.randn(1000),
                        'b': np.random.randn(1000),
                        'N': np.random.randint(100, 1000, (1000)),
                        'x': 'x'})
```
```
In [2]: df
Out [2]:
<table>
<thead>
<tr>
<th>a</th>
<th>b</th>
<th>N</th>
<th>x</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.469112</td>
<td>-0.218470</td>
<td>585</td>
<td>x</td>
</tr>
<tr>
<td>-0.282863</td>
<td>-0.061645</td>
<td>841</td>
<td>x</td>
</tr>
<tr>
<td>-1.509059</td>
<td>-0.723780</td>
<td>251</td>
<td>x</td>
</tr>
<tr>
<td>-1.135632</td>
<td>0.551225</td>
<td>972</td>
<td>x</td>
</tr>
<tr>
<td>1.212112</td>
<td>-0.497767</td>
<td>181</td>
<td>x</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>-1.512743</td>
<td>0.874737</td>
<td>374</td>
<td>x</td>
</tr>
<tr>
<td>0.933735</td>
<td>1.120790</td>
<td>246</td>
<td>x</td>
</tr>
<tr>
<td>-0.308013</td>
<td>0.198768</td>
<td>157</td>
<td>x</td>
</tr>
<tr>
<td>-0.079915</td>
<td>1.757555</td>
<td>977</td>
<td>x</td>
</tr>
<tr>
<td>-1.010589</td>
<td>-1.115680</td>
<td>770</td>
<td>x</td>
</tr>
<tr>
<td>[1000 rows x 4 columns]</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
```

Here’s the function in pure Python:

```
In [3]: def f(x):
    ...:     return x * (x - 1)
    ...

In [4]: def integrate_f(a, b, N):
    ...:     s = 0
    ...:     dx = (b - a) / N
    ...:     for i in range(N):
    ...:         s += f(a + i * dx)
    ...:     return s * dx
    ...
```

We achieve our result by using apply (row-wise):

```
In [5]: df.apply(f, axis=1)
Out [5]:
<table>
<thead>
<tr>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.469112</td>
<td>-0.218470</td>
<td>585</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>-0.282863</td>
<td>-0.061645</td>
<td>841</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>-1.509059</td>
<td>-0.723780</td>
<td>251</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>-1.135632</td>
<td>0.551225</td>
<td>972</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>1.212112</td>
<td>-0.497767</td>
<td>181</td>
<td>x</td>
<td></td>
</tr>
</tbody>
</table>
```

```
But clearly this isn’t fast enough for us. Let’s take a look and see where the time is spent during this operation (limited to the most time consuming four calls) using the prun ipython magic function:

```
In [5]: %prun -l 4 df.apply(lambda x: integrate_f(x['a'], x['b'], x['N']), axis=1) #
   --noqa E999  
622826 function calls (622805 primitive calls) in 0.538 seconds
Ordered by: internal time
list reduced from 215 to 4 due to restriction <4>
ncalls  tottime percall  cumtime percall filename:lineno(function)
1000  0.301  0.000  0.449  0.000 <ipython-input-4-c2a74e076cf0>:1(integrate_f)
552423  0.149  0.000  0.149  0.000 <ipython-input-3-c138bdd570e3>:1(f)
3000  0.010  0.000  0.058  0.000 series.py:868(__getitem__)  
3000  0.007  0.000  0.042  0.000 series.py:974(__get_value)
```

By far the majority of time is spend inside either `integrate_f` or `f`, hence we’ll concentrate our efforts cythonizing these two functions.

### Plain Cython

First we’re going to need to import the Cython magic function to ipython:

```
In [6]: %load_ext Cython
```

Now, let’s simply copy our functions over to Cython as is (the suffix is here to distinguish between function versions):

```
In [7]: %cython
   ...: def f_plain(x):
   ...:     return x * (x - 1)
   ...: def integrate_f_plain(a, b, N):
   ...:     s = 0
   ...:     dx = (b - a) / N
   ...:     for i in range(N):
   ...:         s += f_plain(a + i * dx)
   ...:     return s * dx
   ...
```

**Note:** If you’re having trouble pasting the above into your ipython, you may need to be using bleeding edge ipython for paste to play well with cell magics.

```
In [4]: %timeit df.apply(lambda x: integrate_f_plain(x['a'], x['b'], x['N']), axis=1)  
10 loops, best of 3: 85.5 ms per loop
```

Already this has shaved a third off, not too bad for a simple copy and paste.
Adding type

We get another huge improvement simply by providing type information:

```python
In [8]: %%cython
    ...: cdef double f_typed(double x) except? -2:
    ...:     return x * (x - 1)
    ...: cpdef double integrate_f_typed(double a, double b, int N):
    ...:     cdef int i
    ...:     cdef double s, dx
    ...:     s = 0
    ...:     dx = (b - a) / N
    ...:     for i in range(N):
    ...:         s += f_typed(a + i * dx)
    ...:     return s * dx
    ...
```

```python
In [4]: %timeit df.apply(lambda x: integrate_f_typed(x['a'], x['b'], x['N']), axis=1)
10 loops, best of 3: 20.3 ms per loop
```

Now, we’re talking! It’s now over ten times faster than the original python implementation, and we haven’t really modified the code. Let’s have another look at what’s eating up time:

```python
In [9]: %prun -l 4 df.apply(lambda x: integrate_f_typed(x['a'], x['b'], x['N']),
                        axis=1)
70392 function calls (70371 primitive calls) in 0.067 seconds
Ordered by: internal time
List reduced from 209 to 4 due to restriction <4>
ncalls tottime percall cumtime percall filename:lineno(function)
3000 0.008 0.000 0.047 0.000 series.py:868(__getitem__)
3000 0.006 0.000 0.034 0.000 series.py:974(_get_value)
3000 0.005 0.000 0.009 0.000 base.py:4970(_maybe_cast_indexer)
3000 0.004 0.000 0.017 0.000 base.py:2845(get_loc)
```

Using ndarray

It’s calling series... a lot! It’s creating a Series from each row, and get-ting from both the index and the series (three times for each row). Function calls are expensive in Python, so maybe we could minimize these by cythonizing the apply part.

Note: We are now passing ndarrays into the Cython function, fortunately Cython plays very nicely with NumPy.

```python
In [10]: %cython
    ...: cimport numpy as np
    ...: import numpy as np
    ...: cdef double f_typed(double x) except? -2:
    ...:     return x * (x - 1)
    ...: cpdef double integrate_f_typed(double a, double b, int N):
    ...:     cdef int i
    ...:     cdef double s, dx
    ...:     s = 0
    ...:     dx = (b - a) / N
    ...
```
The implementation is simple, it creates an array of zeros and loops over the rows, applying our `integrate_f_typed`, and putting this in the zeros array.

**Warning:** You can not pass a `Series` directly as a `ndarray` typed parameter to a Cython function. Instead pass the actual `ndarray` using the `Series.to_numpy()`. The reason is that the Cython definition is specific to an `ndarray` and not the passed `Series`.

So, do not do this:

```python
apply_integrate_f(df['a'], df['b'], df['N'])
```

But rather, use `Series.to_numpy()` to get the underlying `ndarray`:

```python
apply_integrate_f(df['a'].to_numpy(),
                 df['b'].to_numpy(),
                 df['N'].to_numpy())
```

**Note:** Loops like this would be extremely slow in Python, but in Cython looping over NumPy arrays is fast.

```python
In [4]: %timeit apply_integrate_f(df['a'].to_numpy(),
                           df['b'].to_numpy(),
                           df['N'].to_numpy())
1000 loops, best of 3: 1.25 ms per loop
```

We’ve gotten another big improvement. Let’s check again where the time is spent:

```python
In [11]: %prun -l 4 apply_integrate_f(df['a'].to_numpy(),
                         df['b'].to_numpy(),
                         df['N'].to_numpy())
```

Ordered by: internal time
List reduced from 59 to 4 due to restriction <4>

```plaintext
calls  tottime  percall  cumtime  percall filename:lineno(function)
1  0.002    0.002   0.002    0.002 {built-in method _cython_magic_
 ed103d42466619df78732dedcacaee5.apply_integrate_f}
```

(continues on next page)
As one might expect, the majority of the time is now spent in `apply_integrate_f`, so if we wanted to make anymore efficiencies we must continue to concentrate our efforts here.

**More advanced techniques**

There is still hope for improvement. Here’s an example of using some more advanced Cython techniques:

```cython
In [12]: %cython
.....: cimport cython
.....: cimport numpy as np
.....: import numpy as np
.....: cdef double f_typed(double x) except? -2:
.....:     return x * (x - 1)
.....: cpdef double integrate_f_typed(double a, double b, int N):
.....:     cdef int i
.....:     cdef double s, dx
.....:     s = 0
.....:     dx = (b - a) / N
.....:     for i in range(N):
.....:         s += f_typed(a + i * dx)
.....:     return s * dx
.....: @cython.boundscheck(False)
.....: @cython.wraparound(False)
.....: cpdef np.ndarray[double] apply_integrate_f_wrap(np.ndarray[double] col_a,
.....:                                              np.ndarray[double] col_b,
.....:                                              np.ndarray[int] col_N):
.....:     cdef int i, n = len(col_N)
.....:     assert len(col_a) == len(col_b) == n
.....:     cdef np.ndarray[double] res = np.empty(n)
.....:     for i in range(n):
.....:         res[i] = integrate_f_typed(col_a[i], col_b[i], col_N[i])
.....:     return res

In [4]: %timeit apply_integrate_f_wrap(df['a'].to_numpy(),
.....:                                         df['b'].to_numpy(),
.....:                                         df['N'].to_numpy())
1000 loops, best of 3: 987 us per loop
```

Even faster, with the caveat that a bug in our Cython code (an off-by-one error, for example) might cause a segfault because memory access isn’t checked. For more about `boundscheck` and `wraparound`, see the Cython docs on compiler directives.
2.21.2 Using Numba

A recent alternative to statically compiling Cython code, is to use a *dynamic jit-compiler*, Numba.

Numba gives you the power to speed up your applications with high performance functions written directly in Python. With a few annotations, array-oriented and math-heavy Python code can be just-in-time compiled to native machine instructions, similar in performance to C, C++ and Fortran, without having to switch languages or Python interpreters.

Numba works by generating optimized machine code using the LLVM compiler infrastructure at import time, runtime, or statically (using the included pycc tool). Numba supports compilation of Python to run on either CPU or GPU hardware, and is designed to integrate with the Python scientific software stack.

**Note:** You will need to install Numba. This is easy with conda, by using: `conda install numba`, see *installing using miniconda*.

**Note:** As of Numba version 0.20, pandas objects cannot be passed directly to Numba-compiled functions. Instead, one must pass the NumPy array underlying the pandas object to the Numba-compiled function as demonstrated below.

### Jit

We demonstrate how to use Numba to just-in-time compile our code. We simply take the plain Python code from above and annotate with the `@jit` decorator.

```python
import numba

@numba.jit
def f_plain(x):
    return x * (x - 1)

@numba.jit
def integrate_f_numba(a, b, N):
    s = 0
    dx = (b - a) / N
    for i in range(N):
        s += f_plain(a + i * dx)
    return s * dx

@numba.jit
def apply_integrate_f_numba(col_a, col_b, col_N):
    n = len(col_N)
    result = np.empty(n, dtype='float64')
    assert len(col_a) == len(col_b) == n
    for i in range(n):
        result[i] = integrate_f_numba(col_a[i], col_b[i], col_N[i])
    return result

def compute_numba(df):
    result = apply_integrate_f_numba(df['a'].to_numpy(),
                                      df['b'].to_numpy(),
                                      (continues on next page)
```

2.21. Enhancing performance
Note that we directly pass NumPy arrays to the Numba function. compute_numba is just a wrapper that provides a nicer interface by passing/returning pandas objects.

```python
In [4]: %timeit compute_numba(df)
1000 loops, best of 3: 798 us per loop
```

In this example, using Numba was faster than Cython.

Vectorize

Numba can also be used to write vectorized functions that do not require the user to explicitly loop over the observations of a vector; a vectorized function will be applied to each row automatically. Consider the following toy example of doubling each observation:

```python
import numba

def double_every_value_nonumba(x):
    return x * 2

@numba.vectorize
def double_every_value_withnumba(x):
    return x * 2

# Custom function without numba
In [5]: %timeit df['col1_doubled'] = df['a'].apply(double_every_value_nonumba)  # noqa E501
1000 loops, best of 3: 797 us per loop

# Standard implementation (faster than a custom function)
In [6]: %timeit df['col1_doubled'] = df['a'] * 2
1000 loops, best of 3: 233 us per loop

# Custom function with numba
In [7]: %timeit df['col1_doubled'] = double_every_value_withnumba(df['a'].to_numpy())
1000 loops, best of 3: 145 us per loop
```

Caveats

Note: Numba will execute on any function, but can only accelerate certain classes of functions.

Numba is best at accelerating functions that apply numerical functions to NumPy arrays. When passed a function that only uses operations it knows how to accelerate, it will execute in nopython mode.

If Numba is passed a function that includes something it doesn’t know how to work with – a category that currently includes sets, lists, dictionaries, or string functions – it will revert to object mode. In object mode, Numba will execute but your code will not speed up significantly. If you would prefer that Numba throw an error if it cannot
compile a function in a way that speeds up your code, pass Numba the argument nopython=True (e.g. @numba.jit(nopython=True)). For more on troubleshooting Numba modes, see the Numba troubleshooting page.

Read more in the Numba docs.

### 2.21.3 Expression evaluation via `eval()`

The top-level function `pandas.eval()` implements expression evaluation of `Series` and `DataFrame` objects.

**Note:** To benefit from using `eval()` you need to install `numexpr`. See the recommended dependencies section for more details.

The point of using `eval()` for expression evaluation rather than plain Python is two-fold: 1) large `DataFrame` objects are evaluated more efficiently and 2) large arithmetic and boolean expressions are evaluated all at once by the underlying engine (by default `numexpr` is used for evaluation).

**Note:** You should not use `eval()` for simple expressions or for expressions involving small DataFrames. In fact, `eval()` is many orders of magnitude slower for smaller expressions/objects than plain ol’ Python. A good rule of thumb is to only use `eval()` when you have a `DataFrame` with more than 10,000 rows.

`eval()` supports all arithmetic expressions supported by the engine in addition to some extensions available only in pandas.

**Note:** The larger the frame and the larger the expression the more speedup you will see from using `eval()`.

#### Supported syntax

These operations are supported by `pandas.eval()`:

- Arithmetic operations except for the left shift (<<) and right shift (>>) operators, e.g., `df + 2 * pi / s ** 4 % 42 - the_golden_ratio`
- Comparison operations, including chained comparisons, e.g., `2 < df < df2`
- Boolean operations, e.g., `df < df2 and df3 < df4 or not df_bool`
- List and tuple literals, e.g., `[1, 2] or (1, 2)`
- Attribute access, e.g., `df.a`
- Subscript expressions, e.g., `df[0]`
- Simple variable evaluation, e.g., `pd.eval('df')` (this is not very useful)
- Math functions: `sin`, `cos`, `exp`, `log`, `expm1`, `log1p`, `sqrt`, `sinh`, `cosh`, `tanh`, `arcsin`, `arccos`, `arctan`, `arccosh`, `arcsinh`, `arctanh`, `abs`, `arctan2` and `log10`.

This Python syntax is **not** allowed:

- Expressions
  - Function calls other than math functions.
  - `is/is not` operations
  - `if` expressions
pandas: powerful Python data analysis toolkit, Release 1.1.1

- lambda expressions
- list/set/dict comprehensions
- Literal dict and set expressions
- yield expressions
- Generator expressions
- Boolean expressions consisting of only scalar values

**Statements**
- Neither simple nor compound statements are allowed. This includes things like `for`, `while`, and `if`.

**eval() examples**

pandas.eval() works well with expressions containing large arrays.

First let’s create a few decent-sized arrays to play with:

```python
In [13]: nrows, ncols = 20000, 100
In [14]: df1, df2, df3, df4 = [pd.DataFrame(np.random.randn(nrows, ncols)) for _ in → range(4)]
```

Now let’s compare adding them together using plain ol’ Python versus `eval()`:

```python
In [15]: %timeit df1 + df2 + df3 + df4
   37.4 ms +- 7.92 ms per loop (mean +- std. dev. of 7 runs, 10 loops each)

In [16]: %timeit pd.eval('df1 + df2 + df3 + df4')
   20.2 ms +- 2.49 ms per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

Now let’s do the same thing but with comparisons:

```python
In [17]: %timeit (df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)
   20.8 ms +- 575 us per loop (mean +- std. dev. of 7 runs, 10 loops each)

In [18]: %timeit pd.eval('(df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)')
   28 ms +- 4.52 ms per loop (mean +- std. dev. of 7 runs, 10 loops each)
```

`eval()` also works with unaligned pandas objects:

```python
In [19]: s = pd.Series(np.random.randn(50))
In [20]: %timeit df1 + df2 + df3 + df4 + s
   54.6 ms +- 1.92 ms per loop (mean +- std. dev. of 7 runs, 10 loops each)

In [21]: %timeit pd.eval('df1 + df2 + df3 + df4 + s')
   19.1 ms +- 1.53 ms per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

**Note:** Operations such as

```python
1 and 2  # would parse to 1 & 2, but should evaluate to 2
3 or 4   # would parse to 3 | 4, but should evaluate to 3
~1       # this is okay, but slower when using eval
```
should be performed in Python. An exception will be raised if you try to perform any boolean/bitwise operations with scalar operands that are not of type `bool` or `np.bool_`. Again, you should perform these kinds of operations in plain Python.

The `DataFrame.eval` method

In addition to the top level `pandas.eval()` function you can also evaluate an expression in the “context” of a `DataFrame`.

```python
In [22]: df = pd.DataFrame(np.random.randn(5, 2), columns=['a', 'b'])
In [23]: df.eval('a + b')
Out[23]:
   0  -0.246747
   1   0.867786
   2  -1.626063
   3  -1.134978
   4  -1.027798
   dtype: float64
```

Any expression that is a valid `pandas.eval()` expression is also a valid `DataFrame.eval()` expression, with the added benefit that you don’t have to prefix the name of the `DataFrame` to the column(s) you’re interested in evaluating.

In addition, you can perform assignment of columns within an expression. This allows for formulaic evaluation. The assignment target can be a new column name or an existing column name, and it must be a valid Python identifier.

The `inplace` keyword determines whether this assignment will performed on the original `DataFrame` or return a copy with the new column.

```python
In [24]: df = pd.DataFrame(dict(a=range(5), b=range(5, 10)))
In [25]: df.eval('c = a + b', inplace=True)
In [26]: df.eval('d = a + b + c', inplace=True)
In [27]: df.eval('a = 1', inplace=True)
In [28]: df
Out[28]:
a  b  c  d
0 1  5   5 10
1 2  6   7 14
2 3  7   9 18
3 4  8  11 22
4 5  9  13 26
```

When `inplace` is set to `False`, the default, a copy of the `DataFrame` with the new or modified columns is returned and the original frame is unchanged.

```
In [29]: df
Out[29]:
a  b  c  d
0 1  5   5 10
1 2  6   7 14
2 3  7   9 18
```

(continues on next page)
In [30]: df.eval('e = a - c', inplace=False)
Out[30]:
     a  b  c  d  e
0  1  5  5 10 -4
1  1  6  7 14 -6
2  1  7  9 18 -8
3  1  8 11 22 -10
4  1  9 13 26 -12

In [31]: df
Out[31]:
     a  b  c  d
0  1  5  5 10
1  1  6  7 14
2  1  7  9 18
3  1  8 11 22
4  1  9 13 26

As a convenience, multiple assignments can be performed by using a multi-line string.

In [32]: df.eval(""
       ....: c = a + b
       ....: d = a + b + c
       ....: a = 1""", inplace=False)

Out[32]:
     a  b  c  d
0  1  5  6 12
1  1  6  7 14
2  1  7  8 16
3  1  8  9 18
4  1  9 10 20

The equivalent in standard Python would be

In [33]: df = pd.DataFrame(dict(a=range(5), b=range(5, 10)))
In [34]: df['c'] = df['a'] + df['b']
In [35]: df['d'] = df['a'] + df['b'] + df['c']
In [36]: df['a'] = 1
In [37]: df
Out[37]:
     a  b  c  d
0  1  5  5 10
1  1  6  7 14
2  1  7  9 18
3  1  8 11 22
4  1  9 13 26

The query method has a inplace keyword which determines whether the query modifies the original frame.
In [38]: df = pd.DataFrame(dict(a=range(5), b=range(5, 10)))

In [39]: df.query('a > 2')
Out[39]:
   a  b
0  3  3
1  4  4

In [40]: df.query('a > 2', inplace=True)

In [41]: df
Out[41]:
   a  b
0  3  3
1  4  4

Local variables

You must explicitly reference any local variable that you want to use in an expression by placing the @ character in front of the name. For example,

In [42]: df = pd.DataFrame(np.random.randn(5, 2), columns=list('ab'))

In [43]: newcol = np.random.randn(len(df))

In [44]: df.eval('b + @newcol')
Out[44]:
   0 -0.173926
   1  2.493083
   2 -0.881831
   3 -0.691045
   4  1.334703

In [45]: df.query('b < @newcol')
Out[45]:
   a  b
   0 0.863987 -0.115998
   2 -2.621419 -1.297879

If you don’t prefix the local variable with @, pandas will raise an exception telling you the variable is undefined.

When using DataFrame.eval() and DataFrame.query(), this allows you to have a local variable and a DataFrame column with the same name in an expression.

In [46]: a = np.random.randn()

In [47]: df.query('@a < a')
Out[47]:
   a  b
   0 0.863987 -0.115998

In [48]: df.loc[a < df['a']] # same as the previous expression
Out[48]:
   a  b
   0 0.863987 -0.115998

2.21. Enhancing performance
With `pandas.eval()` you cannot use the @ prefix at all, because it isn’t defined in that context. `pandas` will let you know this if you try to use @ in a top-level call to `pandas.eval()`. For example,

```python
In [49]: a, b = 1, 2
In [50]: pd.eval('@a + b')
Traceback (most recent call last):
  File "/opt/conda/envs/pandas/lib/python3.8/site-packages/IPython/core/�→interactiveshell.py", line 3417, in run_code
    exec(code_obj, self.user_global_ns, self.user_ns)
  File "<ipython-input-50-af17947a194f>", line 1, in <module>
    pd.eval('@a + b')
  File "/pandas-release/pandas/pandas/core/computation/eval.py", line 330, in eval
    _check_for_locals(expr, level, parser)
  File "/pandas-release/pandas/pandas/core/computation/eval.py", line 158, in _check_→for_locals
    raise SyntaxError(msg)
  File "<string>", line unknown
SyntaxError: The '@' prefix is not allowed in top-level eval calls. please refer to your variables by name without the '@' prefix.
```

In this case, you should simply refer to the variables like you would in standard Python.

```python
In [51]: pd.eval('a + b')
Out[51]: 3
```

**pandas.eval() parsers**

There are two different parsers and two different engines you can use as the backend.

The default 'pandas' parser allows a more intuitive syntax for expressing query-like operations (comparisons, conjunctions and disjunctions). In particular, the precedence of the & and | operators is made equal to the precedence of the corresponding boolean operations and and or.

For example, the above conjunction can be written without parentheses. Alternatively, you can use the 'python' parser to enforce strict Python semantics.

```python
In [52]: expr = '(df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)'
In [53]: x = pd.eval(expr, parser='python')
In [54]: expr_no_parens = 'df1 > 0 & df2 > 0 & df3 > 0 & df4 > 0'
In [55]: y = pd.eval(expr_no_parens, parser='pandas')
In [56]: np.all(x == y)
Out[56]: True
```

The same expression can be “anded” together with the word and as well:

```python
In [57]: expr = '(df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)'
```
In [58]: x = pd.eval(expr, parser='python')

In [59]: expr_with_ands = 'df1 > 0 and df2 > 0 and df3 > 0 and df4 > 0'

In [60]: y = pd.eval(expr_with_ands, parser='pandas')

In [61]: np.all(x == y)
Out[61]: True

The `and` and `or` operators here have the same precedence that they would in vanilla Python.

**pandas.eval() backends**

There’s also the option to make `eval()` operate identical to plain ol’ Python.

---

**Note:** Using the `python` engine is generally *not* useful, except for testing other evaluation engines against it. You will achieve no performance benefits using `eval()` with `engine='python'` and in fact may incur a performance hit.

---

You can see this by using `pandas.eval()` with the `python` engine. It is a bit slower (not by much) than evaluating the same expression in Python.

In [62]: %timeit df1 + df2 + df3 + df4
   36.1 ms +- 2.76 ms per loop (mean +- std. dev. of 7 runs, 10 loops each)

In [63]: %timeit pd.eval('df1 + df2 + df3 + df4', engine='python')
   36 ms +- 3 ms per loop (mean +- std. dev. of 7 runs, 10 loops each)

---

**pandas.eval() performance**

`eval()` is intended to speed up certain kinds of operations. In particular, those operations involving complex expressions with large `DataFrame/Series` objects should see a significant performance benefit. Here is a plot showing the running time of `pandas.eval()` as function of the size of the frame involved in the computation. The two lines are two different engines.
Note: Operations with smallish objects (around 15k-20k rows) are faster using plain Python:

This plot was created using a DataFrame with 3 columns each containing floating point values generated using `numpy.random.randn()`.
Technical minutia regarding expression evaluation

Expressions that would result in an object dtype or involve datetime operations (because of NaT) must be evaluated in Python space. The main reason for this behavior is to maintain backwards compatibility with versions of NumPy < 1.7. In those versions of NumPy a call to `ndarray.astype(str)` will truncate any strings that are more than 60 characters in length. Second, we can’t pass object arrays to `numexpr` thus string comparisons must be evaluated in Python space.

The upshot is that this only applies to object-dtype expressions. So, if you have an expression—for example

```python
In [64]: df = pd.DataFrame({'strings': np.repeat(list('cba'), 3),
                        'nums': np.repeat(range(3), 3)})

In [65]: df
Out[65]:
     strings  nums
0      c     0
1      c     0
2      c     0
3      b     1
4      b     1
5      b     1
6      a     2
7      a     2
8      a     2

In [66]: df.query('strings == "a" and nums == 1')
Out[66]:
Empty DataFrame
Columns: [strings, nums]
Index: []
```

the numeric part of the comparison (`nums == 1`) will be evaluated by `numexpr`.

In general, `DataFrame.query()`/`pandas.eval()` will evaluate the subexpressions that can be evaluated by `numexpr` and those that must be evaluated in Python space transparently to the user. This is done by inferring the result type of an expression from its arguments and operators.

### 2.22 Scaling to large datasets

Pandas provides data structures for in-memory analytics, which makes using pandas to analyze datasets that are larger than memory datasets somewhat tricky. Even datasets that are a sizable fraction of memory become unwieldy, as some pandas operations need to make intermediate copies.

This document provides a few recommendations for scaling your analysis to larger datasets. It’s a complement to Enhancing performance, which focuses on speeding up analysis for datasets that fit in memory.

But first, it’s worth considering not using pandas. Pandas isn’t the right tool for all situations. If you’re working with very large datasets and a tool like PostgreSQL fits your needs, then you should probably be using that. Assuming you want or need the expressiveness and power of pandas, let’s carry on.

```python
In [1]: import pandas as pd
In [2]: import numpy as np

```
2.22.1 Load less data

Suppose our raw dataset on disk has many columns:

```
  id_0   name_0   x_0   y_0   id_1   name_1   x_1   y_1
  ⤩     ⤩     ⤩     ⤩     ⤩     ⤩     ⤩     ⤩
  timestamp
  2000-01-01 00:00:00 1015 Michael -0.399453 0.095427 994 Frank -0.176842 ...
  ⤩     ⤩     ⤩     ⤩     ⤩     ⤩     ⤩     ⤩
  2000-01-01 00:01:00 969 Patricia 0.650773 -0.874275 1003 Laura 0.459153 ...
  ⤩     ⤩     ⤩     ⤩     ⤩     ⤩     ⤩     ⤩
  2000-01-01 00:02:00 1016 Victor -0.721465 -0.584710 1046 Michael 0.524994 ...
 pastoral: powerful Python data analysis toolkit, Release 1.1.1
  ⤩     ⤩     ⤩     ⤩     ⤩     ⤩     ⤩     ⤩
 ... ...
  2000-12-30 23:56:00 999 Tim 0.162578 0.512817 1041 Kevin -0.403352 ...
  ⤩     ⤩     ⤩     ⤩     ⤩     ⤩     ⤩     ⤩
  2000-12-30 23:57:00 970 Wendy 0.855949 -0.648988 1011 Jerry -0.569235 ...
  ⤩     ⤩     ⤩     ⤩     ⤩     ⤩     ⤩     ⤩
  2000-12-30 23:58:00 1065 Edith 0.232211 -0.454540 971 Tim 0.335176 ...
  ⤩     ⤩     ⤩     ⤩     ⤩     ⤩     ⤩     ⤩
  2000-12-31 00:00:00 999 Alice -0.222079 -0.919274 1022 Dan 0.031345 ...
  ⤩     ⤩     ⤩     ⤩     ⤩     ⤩     ⤩     ⤩
[525601 rows x 40 columns]
```

To load the columns we want, we have two options. Option 1 loads in all the data and then filters to what we need.

```
In [3]: columns = ['id_0', 'name_0', 'x_0', 'y_0']

In [4]: pd.read_parquet("timeseries_wide.parquet")[columns]
Out[4]:
  id_0  name_0  x_0  y_0  ...
  ⤩  ⤩  ⤩  ⤩  ⤩
  timestamp
  2000-01-01 00:00:00 1015 Michael -0.399453 0.095427 ...
  ⤩  ⤩  ⤩  ⤩  ⤩
  2000-01-01 00:01:00 969 Patricia 0.650773 -0.874275 ...
  ⤩  ⤩  ⤩  ⤩  ⤩
  2000-01-01 00:02:00 1016 Victor -0.721465 -0.584710 ...
  ⤩  ⤩  ⤩  ⤩  ⤩
 ... ...
  2000-12-30 23:56:00 999 Tim 0.162578 0.512817 ...
  ⤩  ⤩  ⤩  ⤩  ⤩
  2000-12-30 23:57:00 970 Wendy 0.855949 -0.648988 ...
  ⤩  ⤩  ⤩  ⤩  ⤩
  2000-12-30 23:58:00 1065 Edith 0.232211 -0.454540 ...
  ⤩  ⤩  ⤩  ⤩  ⤩
  2000-12-31 00:00:00 999 Alice -0.222079 -0.919274 ...
  ⤩  ⤩  ⤩  ⤩  ⤩
[525601 rows x 4 columns]
```

Option 2 only loads the columns we request.

```
In [5]: pd.read_parquet("timeseries_wide.parquet", columns=columns)
Out[5]:
(continues on next page)
```

858 Chapter 2. User Guide
If we were to measure the memory usage of the two calls, we’d see that specifying `columns` uses about 1/10th the memory in this case.

With `pandas.read_csv()`, you can specify `usecols` to limit the columns read into memory. Not all file formats that can be read by pandas provide an option to read a subset of columns.

### 2.2.2 Use efficient datatypes

The default pandas data types are not the most memory efficient. This is especially true for text data columns with relatively few unique values (commonly referred to as “low-cardinality” data). By using more efficient data types, you can store larger datasets in memory.

```
In [6]: ts = pd.read_parquet("timeseries.parquet")
```

```
In [7]: ts
Out[7]:
```

```
<table>
<thead>
<tr>
<th>id</th>
<th>name</th>
<th>x</th>
<th>y</th>
</tr>
</thead>
<tbody>
<tr>
<td>1029</td>
<td>Michael</td>
<td>0.278837</td>
<td>0.247932</td>
</tr>
<tr>
<td>1010</td>
<td>Patricia</td>
<td>0.077144</td>
<td>0.490260</td>
</tr>
<tr>
<td>1001</td>
<td>Victor</td>
<td>0.214525</td>
<td>0.258635</td>
</tr>
<tr>
<td>1018</td>
<td>Alice</td>
<td>-0.646866</td>
<td>0.822104</td>
</tr>
<tr>
<td>991</td>
<td>Dan</td>
<td>0.902389</td>
<td>0.466665</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>992</td>
<td>Sarah</td>
<td>0.721155</td>
<td>0.944118</td>
</tr>
<tr>
<td>1007</td>
<td>Ursula</td>
<td>0.409277</td>
<td>0.133227</td>
</tr>
<tr>
<td>1009</td>
<td>Hannah</td>
<td>-0.452802</td>
<td>0.184318</td>
</tr>
<tr>
<td>978</td>
<td>Kevin</td>
<td>-0.904728</td>
<td>-0.179146</td>
</tr>
<tr>
<td>973</td>
<td>Ingrid</td>
<td>-0.370763</td>
<td>-0.794667</td>
</tr>
</tbody>
</table>
```

Now, let’s inspect the data types and memory usage to see where we should focus our attention.

```
In [8]: ts.dtypes
Out[8]:
```

```
<table>
<thead>
<tr>
<th>id</th>
<th>name</th>
<th>x</th>
<th>y</th>
</tr>
</thead>
<tbody>
<tr>
<td>int64</td>
<td>object</td>
<td>float64</td>
<td></td>
</tr>
</tbody>
</table>
```

(continues on next page)
In the dataset, the column named `name` is taking up much more memory than any other. It has just a few unique values, so it's a good candidate for converting to a `Categorical`. With a Categorical, we store each unique name once and use space-efficient integers to know which specific name is used in each row.

```
In [10]: ts2 = ts.copy()
In [11]: ts2['name'] = ts2['name'].astype('category')
In [12]: ts2.memory_usage(deep=True)
```

We can go a bit further and downcast the numeric columns to their smallest types using `pandas.to_numeric()`.

```
In [13]: ts2['id'] = pd.to_numeric(ts2['id'], downcast='unsigned')
In [14]: ts2[['x', 'y']] = ts2[['x', 'y']].apply(pd.to_numeric, downcast='float')
```

```
In [16]: ts2.memory_usage(deep=True)
```

```
In [17]: reduction = (ts2.memory_usage(deep=True).sum() / ts.memory_usage(deep=True).sum())
```
In all, we’ve reduced the in-memory footprint of this dataset to 1/5 of its original size.

See *Categorical data* for more on *Categorical* and *dtypes* for an overview of all of pandas’ dtypes.

### 2.22.3 Use chunking

Some workloads can be achieved with chunking: splitting a large problem like “convert this directory of CSVs to parquet” into a bunch of small problems (“convert this individual CSV file into a Parquet file. Now repeat that for each file in this directory.”). As long as each chunk fits in memory, you can work with datasets that are much larger than memory.

**Note:** Chunking works well when the operation you’re performing requires zero or minimal coordination between chunks. For more complicated workflows, you’re better off using another library.

Suppose we have an even larger “logical dataset” on disk that’s a directory of parquet files. Each file in the directory represents a different year of the entire dataset.

Now we’ll implement an out-of-core *value_counts*. The peak memory usage of this workflow is the single largest chunk, plus a small series storing the unique value counts up to this point. As long as each individual file fits in memory, this will work for arbitrary-sized datasets.
Some readers, like `pandas.read_csv()`, offer parameters to control the chunksize when reading a single file. Manually chunking is an OK option for workflows that don’t require too sophisticated of operations. Some operations, like `groupby`, are much harder to do chunkwise. In these cases, you may be better switching to a different library that implements these out-of-core algorithms for you.

### 2.22.4 Use other libraries

Pandas is just one library offering a DataFrame API. Because of its popularity, pandas’ API has become something of a standard that other libraries implement. The pandas documentation maintains a list of libraries implementing a DataFrame API in our ecosystem page.

For example, Dask, a parallel computing library, has `dask.dataframe`, a pandas-like API for working with larger than memory datasets in parallel. Dask can use multiple threads or processes on a single machine, or a cluster of machines to process data in parallel.

We’ll import `dask.dataframe` and notice that the API feels similar to pandas. We can use Dask’s `read_parquet` function, but provide a globstring of files to read in.

```python
In [20]: import dask.dataframe as dd

In [21]: ddf = dd.read_parquet("data/timeseries/ts*.parquet", engine="pyarrow")
In [22]: ddf
```

Inspecting the `ddf` object, we see a few things:

- There are familiar attributes like `.columns` and `.dtypes`
- There are familiar methods like `.groupby`, `.sum`, etc.
- There are new attributes like `.npartitions` and `.divisions`

The partitions and divisions are how Dask parallelizes computation. A Dask DataFrame is made up of many Pandas DataFrames. A single method call on a Dask DataFrame ends up making many pandas method calls, and Dask knows how to coordinate everything to get the result.
One major difference: the `dask.dataframe` API is lazy. If you look at the repr above, you’ll notice that the values aren’t actually printed out; just the column names and dtypes. That’s because Dask hasn’t actually read the data yet. Rather than executing immediately, doing operations build up a task graph.

Each of these calls is instant because the result isn’t being computed yet. We’re just building up a list of computation to do when someone needs the result. Dask knows that the return type of a `pandas.Series.value_counts` is a pandas Series with a certain dtype and a certain name. So the Dask version returns a Dask Series with the same dtype and the same name.

To get the actual result you can call `.compute()`.
In [29]: %time ddf['name'].value_counts().compute()
CPU times: user 2.48 s, sys: 131 ms, total: 2.61 s
Wall time: 2.11 s
Out[29]:
Laura 230906
Ingrid 230838
Kevin 230698
Dan 230621
Frank 230595
...  
Ray 229603
Xavier 229553
Charlie 229303
Bob 229211
Yvonne 228766
Name: name, Length: 26, dtype: int64

At that point, you get back the same thing you’d get with pandas, in this case a concrete pandas Series with the count of each name.

Calling \texttt{.compute} causes the full task graph to be executed. This includes reading the data, selecting the columns, and doing the \texttt{value_counts}. The execution is done in parallel where possible, and Dask tries to keep the overall memory footprint small. You can work with datasets that are much larger than memory, as long as each partition (a regular pandas DataFrame) fits in memory.

By default, \texttt{dask.dataframe} operations use a threadpool to do operations in parallel. We can also connect to a cluster to distribute the work on many machines. In this case we’ll connect to a local “cluster” made up of several processes on this single machine.

```python
>>> from dask.distributed import Client, LocalCluster

>>> cluster = LocalCluster()
>>> client = Client(cluster)
>>> client
<Client: 'tcp://127.0.0.1:53349' processes=4 threads=8, memory=17.18 GB>
```

Once this \texttt{client} is created, all of Dask’s computation will take place on the cluster (which is just processes in this case).

Dask implements the most used parts of the pandas API. For example, we can do a familiar groupby aggregation.

In [30]: %time ddf.groupby('name')[['x', 'y']].mean().compute().head()
CPU times: user 3.06 s, sys: 728 ms, total: 3.79 s
Wall time: 2.94 s
Out[30]:
          x          y
name
Alice  0.000086  -0.001170
Bob    -0.000843  -0.000799
Charlie  0.00564  -0.000038
Dan     0.00584   0.000818
Edith  -0.00116  -0.000044

The grouping and aggregation is done out-of-core and in parallel.

When Dask knows the divisions of a dataset, certain optimizations are possible. When reading parquet datasets written by dask, the divisions will be known automatically. In this case, since we created the parquet files manually, we need to supply the divisions manually.
In [31]: N = 12

In [32]: starts = [f'20{i:02d}-01-01' for i in range(N)]

In [33]: ends = [f'20{i:02d}-12-13' for i in range(N)]

In [34]: divisions = tuple(pd.to_datetime(starts)) + (pd.Timestamp(ends[-1]),)

In [35]: ddf.divisions = divisions

In [36]: ddf
Out[36]:
Dask DataFrame Structure:

    id  name   x        y
2000-01-01  int64  object  float64  float64
2001-01-01  ...  ...  ...  ...  ...
...  ...  ...  ...  ...
2011-01-01  ...  ...  ...  ...
2011-12-13  ...  ...  ...  ...

Dask Name: read-parquet, 12 tasks

Now we can do things like fast random access with .loc.

In [37]: ddf[['2002-01-01 12:01':'2002-01-01 12:05']].compute()
Out[37]:

    id  name   x        y
timestamp
2002-01-01 12:01:00  983   Laura  0.243985  -0.079392
2002-01-01 12:02:00  1001  Laura  -0.523119  -0.226026
2002-01-01 12:03:00  1059  Oliver  0.612886   0.405680
2002-01-01 12:04:00  993   Kevin  0.451977   0.332947
2002-01-01 12:05:00  1014  Yvonne -0.948681   0.361748

Dask knows to just look in the 3rd partition for selecting values in 2002. It doesn’t need to look at any other data.

Many workflows involve a large amount of data and processing it in a way that reduces the size to something that fits in memory. In this case, we’ll resample to daily frequency and take the mean. Once we’ve taken the mean, we know the results will fit in memory, so we can safely call compute without running out of memory. At that point it’s just a regular pandas object.

In [38]: ddf[['x', 'y']].resample("1D").mean().cumsum().compute().plot()
Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe278bfc7f0>
These Dask examples have all be done using multiple processes on a single machine. Dask can be deployed on a cluster to scale up to even larger datasets.

You see more dask examples at https://examples.dask.org.

## 2.23 Sparse data structures

Pandas provides data structures for efficiently storing sparse data. These are not necessarily sparse in the typical “mostly 0”. Rather, you can view these objects as being “compressed” where any data matching a specific value (NaN / missing value, though any value can be chosen, including 0) is omitted. The compressed values are not actually stored in the array.

```
In [1]: arr = np.random.randn(10)
In [2]: arr[2:-2] = np.nan
In [3]: ts = pd.Series(pd.arrays.SparseArray(arr))
In [4]: ts
Out[4]:
0   0.469112
1  -0.282863
2    NaN
(continues on next page)```
Notice the dtype, `Sparse[float64, nan]`. The `nan` means that elements in the array that are `nan` aren’t actually stored, only the non-`nan` elements are. Those non-`nan` elements have a `float64` dtype.

The sparse objects exist for memory efficiency reasons. Suppose you had a large, mostly NA DataFrame:

```
In [5]: df = pd.DataFrame(np.random.randn(10000, 4))
In [6]: df.iloc[:9998] = np.nan
In [7]: sdf = df.astype(pd.SparseDtype("float", np.nan))
In [8]: sdf.head()
Out[8]:
     0  1   2    3
0   NaN NaN  NaN  NaN
1   NaN NaN  NaN  NaN
2   NaN NaN  NaN  NaN
3   NaN NaN  NaN  NaN
4   NaN NaN  NaN  NaN

In [9]: sdf.dtypes
Out[9]:
    0    Sparse[float64, nan]
    1    Sparse[float64, nan]
    2    Sparse[float64, nan]
    3    Sparse[float64, nan]
dtype: object

In [10]: sdf.sparse.density
Out[10]: 0.0002
```

As you can see, the density (% of values that have not been “compressed”) is extremely low. This sparse object takes up much less memory on disk (pickled) and in the Python interpreter.

```
In [11]: 'dense: {:0.2f} bytes'.format(df.memory_usage().sum() / 1e3)
Out[11]: 'dense: 320.13 bytes'
In [12]: 'sparse: {:0.2f} bytes'.format(sdf.memory_usage().sum() / 1e3)
Out[12]: 'sparse: 0.22 bytes'
```

Functionally, their behavior should be nearly identical to their dense counterparts.
2.23.1 SparseArray

`arrays.SparseArray` is a `ExtensionArray` for storing an array of sparse values (see `dtypes` for more on extension arrays). It is a 1-dimensional ndarry-like object storing only values distinct from the `fill_value`:

```
In [13]: arr = np.random.randn(10)
In [14]: arr[2:5] = np.nan
In [15]: arr[7:8] = np.nan
In [16]: sparr = pd.arrays.SparseArray(arr)
In [17]: sparr
Out[17]:
[-1.9556635297215477, -1.6588664275960427, nan, nan, nan, 1.1589328886422277, 0.
-14529711373305043, nan, 0.6060271905134522, 1.3342113401317768]
Fill: nan
IntIndex
Indices: array([0, 1, 5, 6, 8, 9], dtype=int32)
```

A sparse array can be converted to a regular (dense) ndarray with `numpy.asarray()`

```
In [18]: np.asarray(sparr)
Out[18]:
array([-1.9557, -1.6589, nan, nan, nan, 1.1589, 0.1453,
       nan, 0.606 , 1.3342])
```

2.23.2 SparseDtype

The `SparseArray.dtype` property stores two pieces of information

1. The dtype of the non-sparse values
2. The scalar fill value

```
In [19]: sparr.dtype
Out[19]: Sparse[float64, nan]
```

A `SparseDtype` may be constructed by passing each of these

```
In [20]: pd.SparseDtype(np.dtype('datetime64[ns]'))
Out[20]: Sparse[datetime64[ns], NaT]
```

The default fill value for a given NumPy dtype is the “missing” value for that dtype, though it may be overridden.

```
In [21]: pd.SparseDtype(np.dtype('datetime64[ns]'),
      ....:   fill_value=pd.Timestamp('2017-01-01'))
      ....:
Out[21]: Sparse[datetime64[ns], Timestamp('2017-01-01 00:00:00')]}
```

Finally, the string alias `Sparse[dtype]` may be used to specify a sparse dtype in many places

```
In [22]: pd.array([[1, 0, 0, 2], dtype='Sparse[int]')
Out[22]:
[1, 0, 0, 2]
```
2.23.3 Sparse accessor

New in version 0.24.0.

Pandas provides a .sparse accessor, similar to .str for string data, .cat for categorical data, and .dt for datetime-like data. This namespace provides attributes and methods that are specific to sparse data.

```python
In [23]: s = pd.Series([0, 0, 1, 2], dtype="Sparse[int"]")

In [24]: s.sparse.density
Out[24]: 0.5

In [25]: s.sparse.fill_value
Out[25]: 0
```

This accessor is available only on data with SparseDtype, and on the Series class itself for creating a Series with sparse data from a scipy COO matrix with.

New in version 0.25.0.

A .sparse accessor has been added for DataFrame as well. See Sparse accessor for more.

2.23.4 Sparse calculation

You can apply NumPy ufuncs to SparseArray and get a SparseArray as a result.

```python
In [26]: arr = pd.arrays.SparseArray([1., np.nan, np.nan, -2., np.nan])

In [27]: np.abs(arr)
Out[27]: [1.0, nan, nan, 2.0, nan]
Fill: nan
IntIndex
Indices: array([0, 3], dtype=int32)
```

The ufunc is also applied to fill_value. This is needed to get the correct dense result.

```python
In [28]: arr = pd.arrays.SparseArray([1., -1, -1, -2., -1], fill_value=-1)

In [29]: np.abs(arr)
Out[29]: [1.0, 1, 1, 2.0, 1]
Fill: 1
IntIndex
Indices: array([0, 3], dtype=int32)

In [30]: np.abs(arr).to_dense()
Out[30]: array([1., 1., 1., 2., 1.])
```
2.23.5 Migrating

Note: SparseSeries and SparseDataFrame were removed in pandas 1.0.0. This migration guide is present to aid in migrating from previous versions.

In older versions of pandas, the SparseSeries and SparseDataFrame classes (documented below) were the preferred way to work with sparse data. With the advent of extension arrays, these subclasses are no longer needed. Their purpose is better served by using a regular Series or DataFrame with sparse values instead.

Note: There’s no performance or memory penalty to using a Series or DataFrame with sparse values, rather than a SparseSeries or SparseDataFrame.

This section provides some guidance on migrating your code to the new style. As a reminder, you can use the python warnings module to control warnings. But we recommend modifying your code, rather than ignoring the warning.

Construction

From an array-like, use the regular Series or DataFrame constructors with SparseArray values.

# Previous way
>>> pd.SparseDataFrame({"A": [0, 1]})

# New way
In [31]: pd.DataFrame({"A": pd.arrays.SparseArray([0, 1])})
Out[31]:
   A
0  0
1  1

From a SciPy sparse matrix, use DataFrame.sparse.from_spmatrix().

# Previous way
>>> from scipy import sparse
>>> mat = sparse.eye(3)
>>> df = pd.SparseDataFrame(mat, columns=['A', 'B', 'C'])

# New way
In [32]: from scipy import sparse
In [33]: mat = sparse.eye(3)
In [34]: df = pd.DataFrame.sparse.from_spmatrix(mat, columns=['A', 'B', 'C'])
In [35]: df.dtypes
Out[35]:
   A  Sparse[bool, 0]
   B  Sparse[bool, 0]
   C  Sparse[bool, 0]
dtype: object

Conversion

From sparse to dense, use the .sparse accessors
In [36]: df.sparse.to_dense()
Out[36]:
   A  B  C
0  1.0 0.0 0.0
1  0.0 1.0 0.0
2  0.0 0.0 1.0

In [37]: df.sparse.to_coo()
Out[37]:
<3x3 sparse matrix of type '<class 'numpy.float64'>'
    with 3 stored elements in COOrdinate format>

From dense to sparse, use `DataFrame.astype()` with a `SparseDtype`.

In [38]: dense = pd.DataFrame({'A': [1, 0, 0, 1]})
In [39]: dtype = pd.SparseDtype(int, fill_value=0)
In [40]: dense.astype(dtype)
Out[40]:
     A
0   1
1   0
2   0
3   1

Sparse Properties

Sparse-specific properties, like `density`, are available on the `.sparse` accessor.

In [41]: df.sparse.density
Out[41]: 0.3333333333333333

General differences

In a `SparseDataFrame`, all columns were sparse. A `DataFrame` can have a mixture of sparse and dense columns. As a consequence, assigning new columns to a `DataFrame` with sparse values will not automatically convert the input to be sparse.

```python
# Previous Way
>>> df = pd.SparseDataFrame({'A': [0, 1]})
>>> df['B'] = [0, 0]  # implicitly becomes Sparse
>>> df['B'].dtype
Sparse[int64, nan]
```

Instead, you’ll need to ensure that the values being assigned are sparse

```python
In [42]: df = pd.DataFrame({'A': pd.arrays.SparseArray([0, 1])})
In [43]: df['B'] = [0, 0]  # remains dense
In [44]: df['B'].dtype
Out[44]: dtype('int64')
In [45]: df['B'] = pd.arrays.SparseArray([0, 0])
In [46]: df['B'].dtype
Out[46]: Sparse[int64, 0]
```
The `SparseDataFrame.default_kind` and `SparseDataFrame.default_fill_value` attributes have no replacement.

### 2.23.6 Interaction with scipy.sparse

Use `DataFrame.sparse.from_spmatrix()` to create a DataFrame with sparse values from a sparse matrix. New in version 0.25.0.

```python
In [47]: from scipy.sparse import csr_matrix
In [48]: arr = np.random.random(size=(1000, 5))
In [49]: arr[arr < .9] = 0
In [50]: sp_arr = csr_matrix(arr)
In [51]: sp_arr
Out[51]:
<1000x5 sparse matrix of type '<class 'numpy.float64'>'
with 517 stored elements in Compressed Sparse Row format>
In [52]: sdf = pd.DataFrame.sparse.from_spmatrix(sp_arr)
In [53]: sdf.head()
Out[53]:
    0 1 2 3 4
0  0.956380 0.0 0.0 0.000000 0.0
1  0.000000 0.0 0.0 0.000000 0.0
2  0.000000 0.0 0.0 0.000000 0.0
3  0.000000 0.0 0.0 0.000000 0.0
4  0.999552 0.0 0.0 0.956153 0.0
In [54]: sdf.dtypes
Out[54]:
0 Sparse[float64, 0]
1 Sparse[float64, 0]
2 Sparse[float64, 0]
3 Sparse[float64, 0]
4 Sparse[float64, 0]
dtype: object
```

All sparse formats are supported, but matrices that are not in COOrdinate format will be converted, copying data as needed. To convert back to sparse SciPy matrix in COO format, you can use the `DataFrame.sparse.to_coo()` method:

```python
In [55]: sdf.sparse.to_coo()
Out[55]:
<1000x5 sparse matrix of type '<class 'numpy.float64'>'
with 517 stored elements in COOrdinate format>
```

`Series.sparse.to_coo` is implemented for transforming a Series with sparse values indexed by a `MultiIndex` to a `scipy.sparse.coo_matrix`.

The method requires a `MultiIndex` with two or more levels.
In [56]: s = pd.Series([3.0, np.nan, 1.0, 3.0, np.nan, np.nan])

In [57]: s.index = pd.MultiIndex.from_tuples([(1, 2, 'a', 0),
   ....:  (1, 2, 'a', 1),
   ....:  (1, 1, 'b', 0),
   ....:  (1, 1, 'b', 1),
   ....:  (2, 1, 'b', 0),
   ....:  (2, 1, 'b', 1)],
   ....:  names=['A', 'B', 'C', 'D'])

In [58]: s
Out[58]:
          A B C D
1  2  a  0  3.0
    1  NaN
1  b  0  1.0
    1  3.0
2  1  b  0  NaN
    1  NaN
dtype: float64

In [59]: ss = s.astype('Sparse')

In [60]: ss
Out[60]:
          A B C D
1  2  a  0  3.0
    1  NaN
1  b  0  1.0
    1  3.0
2  1  b  0  NaN
    1  NaN
dtype: Sparse[float64, nan]

In the example below, we transform the Series to a sparse representation of a 2-d array by specifying that the first and second MultiIndex levels define labels for the rows and the third and fourth levels define labels for the columns. We also specify that the column and row labels should be sorted in the final sparse representation.

In [61]: A, rows, columns = ss.sparse.to_coo(row_levels=['A', 'B'],
   ....:  column_levels=['C', 'D'],
   ....:  sort_labels=True)

In [62]: A
Out[62]:
<3x4 sparse matrix of type '<class 'numpy.float64'>'
    with 3 stored elements in COOrdinate format>

In [63]: A.todense()
Out[63]:
matrix([[0., 0., 1., 3.],
        [3., 0., 0., 0.],
        [0., 0., 0., 0.]])

In [64]: rows
Out[64]: [(1, 1), (1, 2), (2, 1)]
Specifying different row and column labels (and not sorting them) yields a different sparse matrix:

```
In [66]: A, rows, columns = ss.sparse.to_coo(row_levels=['A', 'B', 'C'],
                   column_levels=['D'],
                   sort_labels=False)
```

```
In [67]: A
Out[67]:
<3x2 sparse matrix of type '<class 'numpy.float64'>'
    with 3 stored elements in COOrdinate format>
```

```
In [68]: A.todense()
Out[68]:
matrix([[3., 0.],
        [1., 3.],
        [0., 0.]])
```

```
In [69]: rows
Out[69]: [(1, 2, 'a'), (1, 1, 'b'), (2, 1, 'b')]
```

```
In [70]: columns
Out[70]: [0, 1]
```

A convenience method `Series.sparse.from_coo()` is implemented for creating a `Series` with sparse values from a `scipy.sparse.coo_matrix`.

```
In [71]: from scipy import sparse

In [72]: A = sparse.coo_matrix(((3.0, 1.0, 2.0), ([1, 0, 0], [0, 2, 3])),
                           shape=(3, 4))
```

```
In [73]: A
Out[73]:
<3x4 sparse matrix of type '<class 'numpy.float64'>'
    with 3 stored elements in COOrdinate format>
```

```
In [74]: A.todense()
Out[74]:
matrix([[3., 0., 1., 2.],
        [0., 0., 0., 0.]],
        [0., 0., 0., 0.]])
```

The default behaviour (with `dense_index=False`) simply returns a `Series` containing only the non-null entries.

```
In [75]: ss = pd.Series.sparse.from_coo(A)
```

```
In [76]: ss
Out[76]:
0  2  1.0
3  2.0
```

(continues on next page)
1 0  3.0
dtype: Sparse[float64, nan]

Specifying dense_index=True will result in an index that is the Cartesian product of the row and columns coordinates of the matrix. Note that this will consume a significant amount of memory (relative to dense_index=False) if the sparse matrix is large (and sparse) enough.

```
In [77]: ss_dense = pd.Series.sparse.from_coo(A, dense_index=True)
In [78]: ss_dense
Out[78]:
0  0  NaN
  1  NaN
  2  1.0
  3  2.0
1  0  3.0
  1  NaN
  2  NaN
  3  NaN
2  0  NaN
  1  NaN
  2  NaN
  3  NaN
dtype: Sparse[float64, nan]
```

### 2.24 Frequently Asked Questions (FAQ)

#### 2.24.1 DataFrame memory usage

The memory usage of a DataFrame (including the index) is shown when calling the `info()`. A configuration option, display.memory_usage (see the list of options), specifies if the DataFrame’s memory usage will be displayed when invoking the df.info() method.

For example, the memory usage of the DataFrame below is shown when calling info():

```
In [1]: dtypes = ['int64', 'float64', 'datetime64[ns]', 'timedelta64[ns]',
            ...:   'complex128', 'object', 'bool']
            ...:

In [2]: n = 5000
In [3]: data = {t: np.random.randint(100, size=n).astype(t) for t in dtypes}
In [4]: df = pd.DataFrame(data)
In [5]: df['categorical'] = df['object'].astype('category')
In [6]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 8 columns):
# Column Non-Null Count Dtype
--- ------ -------------- -----
The `+` symbol indicates that the true memory usage could be higher, because pandas does not count the memory used by values in columns with `dtype=object`.

Passing `memory_usage='deep'` will enable a more accurate memory usage report, accounting for the full usage of the contained objects. This is optional as it can be expensive to do this deeper introspection.

By default the display option is set to `True` but can be explicitly overridden by passing the `memory_usage` argument when invoking `df.info()`.

The memory usage of each column can be found by calling the `memory_usage()` method. This returns a Series with an index represented by column names and memory usage of each column shown in bytes. For the DataFrame above, the memory usage of each column and the total memory usage can be found with the `memory_usage` method:

```python
In [8]: df.memory_usage()
```

```python
Out[8]:
Index       128
int64      40000
float64    40000
datetime64[ns]  40000
timedelta64[ns]  40000
complex128   80000
object      40000
bool        5000
categorical 10920
dtype: int64
```

# total memory usage of dataframe

(continues on next page)
In [9]: df.memory_usage().sum()
Out[9]: 296048

By default the memory usage of the DataFrame's index is shown in the returned Series, the memory usage of the index can be suppressed by passing the `index=False` argument:

In [10]: df.memory_usage(index=False)
Out[10]:
int64 40000
float64 40000
datetime64[ns] 40000
timedelta64[ns] 40000
complex128 80000
object 40000
bool 5000
categorical 10920
dtype: int64

The memory usage displayed by the `info()` method utilizes the `memory_usage()` method to determine the memory usage of a DataFrame while also formatting the output in human-readable units (base-2 representation; i.e. 1KB = 1024 bytes).

See also `Categorical Memory Usage`.

### 2.24.2 Using if/truth statements with pandas

pandas follows the NumPy convention of raising an error when you try to convert something to a `bool`. This happens in an `if`-statement or when using the boolean operations: `and`, `or`, and `not`. It is not clear what the result of the following code should be:

```python
>>> if pd.Series([False, True, False]):
...   pass
```

Should it be `True` because it's not zero-length, or `False` because there are `False` values? It is unclear, so instead, pandas raises a `ValueError`:

```python
>>> if pd.Series([False, True, False]):
...   print("I was true")
Traceback
...  ValueError: The truth value of an array is ambiguous. Use a.empty, a.any() or a.all().
```

You need to explicitly choose what you want to do with the DataFrame, e.g. use `any()`, `all()` or `empty()`. Alternatively, you might want to compare if the pandas object is `None`:

```python
>>> if pd.Series([False, True, False]) is not None:
...   print("I was not None")
I was not None
```

Below is how to check if any of the values are `True`:

```python
>>> if pd.Series([False, True, False]).any():
...   print("I am any")
I am any
```

To evaluate single-element pandas objects in a boolean context, use the method `bool()`:
In [11]: pd.Series([True]).bool()
Out[11]: True

In [12]: pd.Series([False]).bool()
Out[12]: False

In [13]: pd.DataFrame([[True]]).bool()
Out[13]: True

In [14]: pd.DataFrame([[False]]).bool()
Out[14]: False

### Bitwise boolean

Bitwise boolean operators like `==` and `!=` return a boolean Series, which is almost always what you want anyways.

```python
>>> s = pd.Series(range(5))
>>> s == 4
0    False
1    False
2    False
3    False
4     True
dtype: bool
```

See `boolean comparisons` for more examples.

### Using the `in` operator

Using the Python `in` operator on a Series tests for membership in the index, not membership among the values.

```python
In [15]: s = pd.Series(range(5), index=list('abcde'))
In [16]: 2 in s
Out[16]: False
In [17]: 'b' in s
Out[17]: True
```

If this behavior is surprising, keep in mind that using `in` on a Python dictionary tests keys, not values, and Series are dict-like. To test for membership in the values, use the method `isin()`:

```python
In [18]: s.isin([2])
Out[18]:
   a  False
   b  False
   c  True
   d  False
   e  False
dtype: bool

In [19]: s.isin([2]).any()
Out[19]: True
```

For DataFrames, likewise, `in` applies to the column axis, testing for membership in the list of column names.
### 2.24.3 NaN, Integer NA values and NA type promotions

#### Choice of NA representation

For lack of NA (missing) support from the ground up in NumPy and Python in general, we were given the difficult choice between either:

- A **masked array** solution: an array of data and an array of boolean values indicating whether a value is there or is missing.

- Using a special sentinel value, bit pattern, or set of sentinel values to denote NA across the dtypes.

For many reasons we chose the latter. After years of production use it has proven, at least in my opinion, to be the best decision given the state of affairs in NumPy and Python in general. The special value NaN (Not-A-Number) is used everywhere as the NA value, and there are API functions isna and notna which can be used across the dtypes to detect NA values.

However, it comes with it a couple of trade-offs which I most certainly have not ignored.

#### Support for integer NA

In the absence of high performance NA support being built into NumPy from the ground up, the primary casualty is the ability to represent NAs in integer arrays. For example:

```python
In [20]: s = pd.Series([1, 2, 3, 4, 5], index=list('abcde'))

In [21]: s
Out[21]:
   a    1
   b    2
   c    3
   d    4
   e    5
 dtype: int64

In [22]: s.dtype
Out[22]: dtype('int64')

In [23]: s2 = s.reindex(['a', 'b', 'c', 'f', 'u'])

In [24]: s2
Out[24]:
   a  1.0
   b  2.0
   c  3.0
   f  NaN
   u  NaN
 dtype: float64

In [25]: s2.dtype
Out[25]: dtype('float64')
```

This trade-off is made largely for memory and performance reasons, and also so that the resulting `Series` continues to be “numeric”.

If you need to represent integers with possibly missing values, use one of the nullable-integer extension dtypes provided by pandas.
• `Int8Dtype`
• `Int16Dtype`
• `Int32Dtype`
• `Int64Dtype`

In [26]: s_int = pd.Series([1, 2, 3, 4, 5], index=list('abcde'),
                      dtype=pd.Int64Dtype())

In [27]: s_int
Out[27]:
a 1
b 2
c 3
d 4
e 5
dtype: Int64

In [28]: s_int.dtype
Out[28]: Int64Dtype()

In [29]: s2_int = s_int.reindex(['a', 'b', 'c', 'f', 'u'])

In [30]: s2_int
Out[30]:
a 1
b 2
c 3
f <NA>
u <NA>
dtype: Int64

In [31]: s2_int.dtype
Out[31]: Int64Dtype()

See [Nullable integer data type](#) for more.

### NA type promotions

When introducing NAs into an existing `Series` or DataFrame via `reindex()` or some other means, boolean and integer types will be promoted to a different dtype in order to store the NAs. The promotions are summarized in this table:

<table>
<thead>
<tr>
<th>Typeclass</th>
<th>Promotion dtype for storing NAs</th>
</tr>
</thead>
<tbody>
<tr>
<td>floating</td>
<td>no change</td>
</tr>
<tr>
<td>object</td>
<td>no change</td>
</tr>
<tr>
<td>integer</td>
<td>cast to float64</td>
</tr>
<tr>
<td>boolean</td>
<td>cast to object</td>
</tr>
</tbody>
</table>

While this may seem like a heavy trade-off, I have found very few cases where this is an issue in practice i.e. storing values greater than $2^{**53}$. Some explanation for the motivation is in the next section.
**Why not make NumPy like R?**

Many people have suggested that NumPy should simply emulate the NA support present in the more domain-specific statistical programming language R. Part of the reason is the NumPy type hierarchy:

<table>
<thead>
<tr>
<th>Typeclass</th>
<th>Dtypes</th>
</tr>
</thead>
<tbody>
<tr>
<td>numpy.floating</td>
<td>float16, float32, float64, float128</td>
</tr>
<tr>
<td>numpy.integer</td>
<td>int8, int16, int32, int64</td>
</tr>
<tr>
<td>numpy.unsignedinteger</td>
<td>uint8, uint16, uint32, uint64</td>
</tr>
<tr>
<td>numpy.object_</td>
<td>object_</td>
</tr>
<tr>
<td>numpy.bool_</td>
<td>bool_</td>
</tr>
<tr>
<td>numpy.character</td>
<td>string_, unicode_</td>
</tr>
</tbody>
</table>

The R language, by contrast, only has a handful of built-in data types: integer, numeric (floating-point), character, and boolean. NA types are implemented by reserving special bit patterns for each type to be used as the missing value. While doing this with the full NumPy type hierarchy would be possible, it would be a more substantial trade-off (especially for the 8- and 16-bit data types) and implementation undertaking.

An alternate approach is that of using masked arrays. A masked array is an array of data with an associated boolean mask denoting whether each value should be considered NA or not. I am personally not in love with this approach as I feel that overall it places a fairly heavy burden on the user and the library implementer. Additionally, it exacts a fairly high performance cost when working with numerical data compared with the simple approach of using NaN. Thus, I have chosen the Pythonic “practicality beats purity” approach and traded integer NA capability for a much simpler approach of using a special value in float and object arrays to denote NA, and promoting integer arrays to floating when NAs must be introduced.

**2.24.4 Differences with NumPy**

For Series and DataFrame objects, var() normalizes by N−1 to produce unbiased estimates of the sample variance, while NumPy’s var normalizes by N, which measures the variance of the sample. Note that cov() normalizes by N−1 in both pandas and NumPy.

**2.24.5 Thread-safety**

As of pandas 0.11, pandas is not 100% thread safe. The known issues relate to the copy() method. If you are doing a lot of copying of DataFrame objects shared among threads, we recommend holding locks inside the threads where the data copying occurs.

See this link for more information.

**2.24.6 Byte-ordering issues**

Occasionally you may have to deal with data that were created on a machine with a different byte order than the one on which you are running Python. A common symptom of this issue is an error like:

```
Traceback
...
ValueError: Big-endian buffer not supported on little-endian compiler
```

To deal with this issue you should convert the underlying NumPy array to the native system byte order before passing it to Series or DataFrame constructors using something similar to the following:
2.25 Cookbook

This is a repository for short and sweet examples and links for useful pandas recipes. We encourage users to add to this documentation.

Adding interesting links and/or inline examples to this section is a great First Pull Request.

Simplified, condensed, new-user friendly, in-line examples have been inserted where possible to augment the StackOverflow and GitHub links. Many of the links contain expanded information, above what the in-line examples offer.

Pandas (pd) and Numpy (np) are the only two abbreviated imported modules. The rest are kept explicitly imported for newer users.

These examples are written for Python 3. Minor tweaks might be necessary for earlier python versions.

2.25.1 Idioms

These are some neat pandas idioms if-then/then-else on one column, and assignment to another one or more columns:

```python
In [1]: df = pd.DataFrame({'AAA': [4, 5, 6, 7],
        ...:                     'BBB': [10, 20, 30, 40],
        ...:                     'CCC': [100, 50, -30, -50]})

In [2]: df
Out[2]:
AAA  BBB  CCC
0    4    10   100
1    5    20    50
2    6    30   -30
3    7    40   -50

if-then...

An if-then on one column

In [3]: df.loc[df.AAA >= 5, 'BBB'] = -1

In [4]: df
Out[4]:
AAA  BBB  CCC
0    4    10   100
1    5    -1    50
```

See the NumPy documentation on byte order for more details.
An if-then with assignment to 2 columns:

```python
In [5]: df.loc[df.AAA >= 5, ['BBB', 'CCC']] = 555
In [6]: df
Out[6]:
     AAA BBB  CCC
0      4  10  100
1      5  555  555
2      6  555  555
3      7  555  555
```

Add another line with different logic, to do the -else

```python
In [7]: df.loc[df.AAA < 5, ['BBB', 'CCC']] = 2000
In [8]: df
Out[8]:
     AAA BBB  CCC
0      4  2000  2000
1      5  555  555
2      6  555  555
3      7  555  555
```

Or use pandas where after you’ve set up a mask

```python
In [10]: df.where(df_mask, -1000)
Out[10]:
     AAA  BBB  CCC
0      4 -1000  2000
1      5 -1000 -1000
2      6 -1000  555
3      7 -1000 -1000
```

if-then-else using numpy’s where()

```python
In [11]: df = pd.DataFrame({'AAA': [4, 5, 6, 7], 'BBB': [10, 20, 30, 40], 'CCC': [100, 50, -30, -50]})
In [12]: df
Out[12]:
     AAA  BBB  CCC
0      4    10  100
1      5     20   50
2      6     30  -30
3      7     40  -50
```
In [13]: df['logic'] = np.where(df['AAA'] > 5, 'high', 'low')

In [14]: df
Out[14]:
   AAA  BBB  CCC  logic
0   4   10  100    low
1   5   20   50    low
2   6   30  -30    high
3   7   40  -50    high

Splitting

Split a frame with a boolean criterion

In [15]: df = pd.DataFrame({'AAA': [4, 5, 6, 7],
                      'BBB': [10, 20, 30, 40],
                      'CCC': [100, 50, -30, -50]})

In [16]: df
Out[16]:
    AAA  BBB  CCC
0    4   10  100
1    5   20   50
2    6   30  -30
3    7   40  -50

In [17]: df[df.AAA <= 5]
Out[17]:
    AAA  BBB  CCC
0    4   10  100
1    5   20   50

In [18]: df[df.AAA > 5]
Out[18]:
    AAA  BBB  CCC
2    6   30  -30
3    7   40  -50

Building criteria

Select with multi-column criteria

In [19]: df = pd.DataFrame({'AAA': [4, 5, 6, 7],
                      'BBB': [10, 20, 30, 40],
                      'CCC': [100, 50, -30, -50]})

In [20]: df
Out[20]:
    AAA  BBB  CCC
0    4   10  100
1    5   20   50
... and (without assignment returns a Series)

In [21]: df.loc[(df['BBB'] < 25) & (df['CCC'] >= -40), 'AAA']
Out[21]:
0 4
1 5
Name: AAA, dtype: int64

... or (without assignment returns a Series)

In [22]: df.loc[(df['BBB'] > 25) | (df['CCC'] >= -40), 'AAA']
Out[22]:
0 4
1 5
2 6
3 7
Name: AAA, dtype: int64

... or (with assignment modifies the DataFrame.)

In [23]: df.loc[(df['BBB'] > 25) | (df['CCC'] >= 75), 'AAA'] = 0.1
In [24]:
Out[24]:
<table>
<thead>
<tr>
<th>AAA</th>
<th>BBB</th>
<th>CCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>10</td>
<td>100</td>
</tr>
<tr>
<td>5.0</td>
<td>20</td>
<td>50</td>
</tr>
<tr>
<td>0.1</td>
<td>30</td>
<td>-30</td>
</tr>
<tr>
<td>0.1</td>
<td>40</td>
<td>-50</td>
</tr>
</tbody>
</table>

Select rows with data closest to certain value using argsort

In [25]: df = pd.DataFrame({'AAA': [4, 5, 6, 7],
                        'BBB': [10, 20, 30, 40],
                        'CCC': [100, 50, -30, -50]})
In [26]:
Out[26]:
<table>
<thead>
<tr>
<th>AAA</th>
<th>BBB</th>
<th>CCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>10</td>
<td>100</td>
</tr>
<tr>
<td>5</td>
<td>20</td>
<td>50</td>
</tr>
<tr>
<td>6</td>
<td>30</td>
<td>-30</td>
</tr>
<tr>
<td>7</td>
<td>40</td>
<td>-50</td>
</tr>
</tbody>
</table>

In [27]: aValue = 43.0
In [28]: df.loc[(df.CCC - aValue).abs().argsort()]
Out[28]:
<table>
<thead>
<tr>
<th>AAA</th>
<th>BBB</th>
<th>CCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>10</td>
<td>100</td>
</tr>
<tr>
<td>5</td>
<td>20</td>
<td>50</td>
</tr>
<tr>
<td>6</td>
<td>30</td>
<td>-30</td>
</tr>
<tr>
<td>7</td>
<td>40</td>
<td>-50</td>
</tr>
</tbody>
</table>
Dynamically reduce a list of criteria using a binary operators

```
In [29]: df = pd.DataFrame({'AAA': [4, 5, 6, 7],
                          ....:                     'BBB': [10, 20, 30, 40],
                          ....:                     'CCC': [100, 50, -30, -50]})

In [30]: df
Out[30]:
     AAA  BBB  CCC
0   4    10   100
1   5    20    50
2   6    30   -30
3   7    40   -50

In [31]: Crit1 = df.AAA <= 5.5
In [32]: Crit2 = df.BBB == 10.0
In [33]: Crit3 = df.CCC > -40.0

One could hard code:
```
```
In [34]: AllCrit = Crit1 & Crit2 & Crit3

... Or it can be done with a list of dynamically built criteria
```
```
In [35]: import functools
In [36]: CritList = [Crit1, Crit2, Crit3]
In [37]: AllCrit = functools.reduce(lambda x, y: x & y, CritList)
In [38]: df[AllCrit]
Out[38]:
     AAA  BBB  CCC
0   4    10   100

2.25.2 Selection

Dataframes

The indexing docs.

Using both row labels and value conditionals
```
```
```
In [39]: df = pd.DataFrame({'AAA': [4, 5, 6, 7],
                          ....:                     'BBB': [10, 20, 30, 40],
                          ....:                     'CCC': [100, 50, -30, -50]})

In [40]: df
Out[40]:
     AAA  BBB  CCC
0   4    10   100
1   5    20    50

(continues on next page)
In [41]: df[(df.AAA <= 6) & (df.index.isin([0, 2, 4]))]
Out[41]:
   AAA  BBB  CCC
0  4   10  100
2  6   30  -30

Use loc for label-oriented slicing and iloc positional slicing

In [42]: df = pd.DataFrame({'AAA': [4, 5, 6, 7],
   ....:                 'BBB': [10, 20, 30, 40],
   ....:                 'CCC': [100, 50, -30, -50],
   ....:                 index=['foo', 'bar', 'boo', 'kar'])

There are 2 explicit slicing methods, with a third general case

1. Positional-oriented (Python slicing style : exclusive of end)
2. Label-oriented (Non-Python slicing style : inclusive of end)
3. General (Either slicing style : depends on if the slice contains labels or positions)

In [43]: df.loc['bar':'kar']  # Label
Out[43]:
      AAA  BBB  CCC
bar  5   20   50
boo  6   30  -30
kar  7   40  -50

# Generic
In [44]: df[0:3]
Out[44]:
      AAA  BBB  CCC
foo  4   10  100
bar  5   20   50
boo  6   30  -30

In [45]: df['bar':'kar']
Out[45]:
      AAA  BBB  CCC
bar  5   20   50
boo  6   30  -30
kar  7   40  -50

Ambiguity arises when an index consists of integers with a non-zero start or non-unit increment.

In [46]: data = {'AAA': [4, 5, 6, 7],
   ....:          'BBB': [10, 20, 30, 40],
   ....:          'CCC': [100, 50, -30, -50]}
   ....:  
In [47]: df2 = pd.DataFrame(data=data, index=[1, 2, 3, 4])  # Note index starts at 1.
In [48]: df2.iloc[1:3]  # Position-oriented
Out[48]:
   AAA  BBB  CCC
0  20  100  100
1  30  100  -30
Using inverse operator (~) to take the complement of a mask

```
In [50]: df = pd.DataFrame({'AAA': [4, 5, 6, 7],
                        'BBB': [10, 20, 30, 40],
                        'CCC': [100, 50, -30, -50]})

In [51]: df
Out[51]:
AAA  BBB  CCC
0   4    10   100
1   5    20    50
2   6    30   -30
3   7    40   -50

In [52]: df[~((df.AAA <= 6) & (df.index.isin([0, 2, 4])))]
```

New columns

Efficiently and dynamically creating new columns using *applymap*

```
In [53]: df = pd.DataFrame({'AAA': [1, 2, 1, 3],
                        'BBB': [1, 1, 2, 2],
                        'CCC': [2, 1, 3, 1]})

In [54]: df
Out[54]:
AAA  BBB  CCC
0   1    1    2
1   2    1    1
2   1    2    3
3   3    2    1

In [55]: source_cols = df.columns  # Or some subset would work too

In [56]: new_cols = [str(x) + "_cat" for x in source_cols]

In [57]: categories = {1: 'Alpha', 2: 'Beta', 3: 'Charlie'}
```
In [58]: df[new_cols] = df[source_cols].applymap(categories.get)

In [59]: df
Out[59]:
    AAA  BBB  CCC  AAA_cat  BBB_cat  CCC_cat
0   1    1    2    Alpha    Alpha    Beta
1   2    1    1    Beta     Alpha    Alpha
2   1    2    3    Alpha    Beta    Charlie
3   3    2    1    Charlie    Beta    Alpha

Keep other columns when using min() with groupby

In [60]: df = pd.DataFrame({'AAA': [1, 1, 1, 2, 2, 2, 3, 3],
                        'BBB': [2, 1, 3, 4, 5, 1, 2, 3]})

In [61]: df
Out[61]:
   AAA  BBB
0   1    2
1   1    1
2   1    3
3   2    4
4   2    5
5   2    1
6   3    2
7   3    3

Method 1: idxmin() to get the index of the minimums

In [62]: df.loc[df.groupby("AAA")["BBB"].idxmin()]
Out[62]:
   AAA  BBB
1   1    1
5   2    1
6   3    2

Method 2: sort then take first of each

In [63]: df.sort_values(by="BBB").groupby("AAA", as_index=False).first()
Out[63]:
   AAA  BBB
0   1    1
1   2    1
2   3    2

Notice the same results, with the exception of the index.
2.25.3 Multiindexing

The *multindexing* docs.

Creating a MultiIndex from a labeled frame

```
In [64]: df = pd.DataFrame({'row': [0, 1, 2],
       ....:               'One_X': [1.1, 1.1, 1.1],
       ....:               'One_Y': [1.2, 1.2, 1.2],
       ....:               'Two_X': [1.11, 1.11, 1.11],
       ....:               'Two_Y': [1.22, 1.22, 1.22]})

In [65]: df
Out[65]:
   row One_X  One_Y  Two_X  Two_Y
0    0     1.1    1.2    1.11   1.22
1    1     1.1    1.2    1.11   1.22
2    2     1.1    1.2    1.11   1.22

# As Labelled Index
In [66]: df = df.set_index('row')

In [67]: df
Out[67]:
     One_X  One_Y  Two_X  Two_Y
row
0     1.1    1.2    1.11   1.22
1     1.1    1.2    1.11   1.22
2     1.1    1.2    1.11   1.22

# With Hierarchical Columns
In [68]: df.columns = pd.MultiIndex.from_tuples([tuple(c.split('_'))
       ....:     for c in df.columns])

In [70]: df
Out[70]:
    One Two
row    X Y  X Y
0  One  1.1  1.2  1.11  1.22
1  One  1.1  1.2  1.11  1.22
2  One  1.1  1.2  1.11  1.22

# Now stack & Reset
In [71]: df = df.stack(0).reset_index(1)

In [71]: df
Out[71]:
   level_1  X  Y
row
0  One   1.10  1.20
0  Two   1.11  1.22
1  One   1.10  1.20
1  Two   1.11  1.22
2  One   1.10  1.20
2  Two   1.11  1.22
```

(continues on next page)
# And fix the labels (Notice the label 'level_1' got added automatically)
In [72]: df.columns = ['Sample', 'All_X', 'All_Y']

In [73]: df
Out[73]:
    Sample  All_X  All_Y
  0      One    1.10   1.20
  0      Two    1.11   1.22
  1      One    1.10   1.20
  1      Two    1.11   1.22
  2      One    1.10   1.20
  2      Two    1.11   1.22

Arithmetic

Performing arithmetic with a MultiIndex that needs broadcasting

In [74]: cols = pd.MultiIndex.from_tuples([(x, y) for x in ['A', 'B', 'C']
  ....:     for y in ['O', 'I']])
  ....:

In [75]: df = pd.DataFrame(np.random.randn(2, 6), index=['n', 'm'], columns=cols)

In [76]: df
Out[76]:
     A   B    C
   O  I  O  I  O  I
  n 0.469 -0.283 -1.510 -1.136 1.212 -0.173
  m 0.119 -1.044 -0.862 -2.105 -0.495  1.071

In [77]: df = df.div(df['C'], level=1)

In [78]: df
Out[78]:
     A   B    C
   O  I  O  I  O  I
  n 0.387 1.633 -1.245  6.556  1.0  1.0
  m -0.241 -0.974  1.741 -1.964  1.0  1.0

Slicing

Slicing a MultiIndex with xs

In [79]: coords = [('AA', 'one'), ('AA', 'six'), ('BB', 'one'), ('BB', 'two'),
  ....:     ('BB', 'six')]
  ....:

In [80]: index = pd.MultiIndex.from_tuples(coords)

In [81]: df = pd.DataFrame([11, 22, 33, 44, 55], index, ['MyData'])

In [82]: df
(continues on next page)
To take the cross section of the 1st level and 1st axis the index:

```python
# Note : level and axis are optional, and default to zero
In [83]: df.xs('BB', level=0, axis=0)
Out[83]:
      MyData
   one    33
   two    44
   six    55
```

... and now the 2nd level of the 1st axis.

```python
In [84]: df.xs('six', level=1, axis=0)
Out[84]:
      MyData
   AA    22
   BB    55
```

Slicing a MultiIndex with `xs`, method #2

```python
In [85]: import itertools

In [86]: index = list(itertools.product(['Ada', 'Quinn', 'Violet'],
                               ['Comp', 'Math', 'Sci']))

In [87]: headr = list(itertools.product(['Exams', 'Labs'], ['I', 'II']))

In [88]: indx = pd.MultiIndex.from_tuples(index, names=['Student', 'Course'])

In [89]: cols = pd.MultiIndex.from_tuples(headr)  # Notice these are un-named

In [90]: data = [[70 + x + y + (x * y) % 3 for x in range(4)] for y in range(9)]

In [91]: df = pd.DataFrame(data, indx, cols)

In [92]: df
Out[92]:
      Exams  Labs
    I    II  I    II
Student  Course
Ada  Comp  70    71  72    73
    Math  71    73  75    74
    Sci   72    75  75    75
Quinn   Comp  73    74  75    76
    Math  74    76  78    77
    Sci   75    78  78    78
Violet  Comp  76    77  78    79
    Math  77    79  81    80
```

(continues on next page)
Sci    78  81  81  81

In [93]: All = slice(None)

In [94]: df.loc[‘Violet’]
Out[94]:
   Exams  Labs
I   II  I   II
Course
Comp  76  77  78  79
Math  77  79  81  80
Sci   78  81  81  81

In [95]: df.loc[(All, ‘Math’), All]
Out[95]:
   Exams  Labs
I   II  I   II
Student Course
Ada  Math  71  73  75  74
Quinn Math  74  76  78  77
Violet Math  77  79  81  80

In [96]: df.loc[(slice(‘Ada’, ‘Quinn’), ‘Math’), All]
Out[96]:
   Exams  Labs
I   II  I   II
Student Course
Ada  Math  71  73  75  74
Quinn Math  74  76  78  77

In [97]: df.loc[(All, ‘Math’), (‘Exams’)]
Out[97]:
   I   II
Student Course
Ada  Math  71  73
Quinn Math  74  76
Violet Math  77  79

In [98]: df.loc[(All, ‘Math’), (All, ‘II’)]
Out[98]:
   Exams Labs
II  II
Student Course
Ada  Math  73  74
Quinn Math  76  77
Violet Math  79  80

Setting portions of a MultiIndex with xs
Sorting

Sort by specific column or an ordered list of columns, with a MultiIndex

In [99]: df.sort_values(by=('Labs', 'II'), ascending=False)
Out[99]:

<table>
<thead>
<tr>
<th>Student</th>
<th>Course</th>
<th>Exams</th>
<th>Labs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Violet</td>
<td>Sci</td>
<td>78</td>
<td>81</td>
</tr>
<tr>
<td></td>
<td>Math</td>
<td>77</td>
<td>81</td>
</tr>
<tr>
<td></td>
<td>Comp</td>
<td>76</td>
<td>78</td>
</tr>
<tr>
<td>Quinn</td>
<td>Sci</td>
<td>75</td>
<td>78</td>
</tr>
<tr>
<td></td>
<td>Math</td>
<td>74</td>
<td>78</td>
</tr>
<tr>
<td></td>
<td>Comp</td>
<td>73</td>
<td>76</td>
</tr>
<tr>
<td>Ada</td>
<td>Sci</td>
<td>72</td>
<td>75</td>
</tr>
<tr>
<td></td>
<td>Math</td>
<td>71</td>
<td>75</td>
</tr>
<tr>
<td></td>
<td>Comp</td>
<td>70</td>
<td>72</td>
</tr>
</tbody>
</table>

Partial selection, the need for sortedness;

Levels

Prepending a level to a multiindex

Flatten Hierarchical columns

2.25.4 Missing data

The missing data docs.

Fill forward a reversed timeseries

In [100]: df = pd.DataFrame(np.random.randn(6, 1),
                           index=pd.date_range('2013-08-01', periods=6, freq='B'),
                           columns=list('A'))
In [101]: df.loc[df.index[3], 'A'] = np.nan
In [102]: df.reindex(df.index[::-1]).ffill()
cumsum reset at NaN values

Replace

Using replace with backrefs

### 2.25.5 Grouping

The *grouping* docs.

Basic grouping with apply

Unlike agg, apply’s callable is passed a sub-DataFrame which gives you access to all the columns

```python
In [104]: df = pd.DataFrame({'animal': 'cat dog cat fish dog cat cat'.split(),
                             'size': list('SSMMMLL'),
                             'weight': [8, 10, 11, 1, 20, 12, 12],
                             'adult': [False] * 5 + [True] * 2})

In [105]: df
Out[105]:
   animal  size  weight  adult
0      cat    S      8  False
1      dog    S     10  False
2      cat    M     11  False
3      fish    M      1  False
4      dog    M     20  False
5      cat    L     12   True
6      cat    L     12   True

# List the size of the animals with the highest weight.
In [106]: df.groupby('animal').apply(lambda subf: subf['size'][subf['weight'].idxmax()])
Out[106]:
   animal
0      cat
1      dog
2      fish

Using get_group
```

```python
In [107]: gb = df.groupby(['animal'])

In [108]: gb.get_group('cat')
Out[108]:
   animal  size  weight  adult
0      cat    S      8  False
1      cat    M     11  False
```
Apply to different items in a group

```
In [109]: def GrowUp(x):
       :   avg_weight = sum(x[x['size'] == 'S'].weight * 1.5)
       :   avg_weight += sum(x[x['size'] == 'M'].weight * 1.25)
       :   avg_weight += sum(x[x['size'] == 'L'].weight)
       :   avg_weight /= len(x)
       :   return pd.Series(['L', avg_weight, True],
       :                      index=['size', 'weight', 'adult'])

In [110]: expected_df = gb.apply(GrowUp)

In [111]: expected_df
Out[111]:
size  weight  adult
animal
  cat    L   12.4375     True
  dog    L   20.0000     True
  fish   L    1.2500     True
```

Expanding apply

```
In [112]: S = pd.Series([i / 100.0 for i in range(1, 11)])

In [113]: def cum_ret(x, y):
       :   return x * (1 + y)

In [114]: def red(x):
       :   return functools.reduce(cum_ret, x, 1.0)

In [115]: S.expanding().apply(red, raw=True)
Out[115]:
   0    1.010000
   1    1.030200
   2    1.061106
   3    1.103550
   4    1.158728
   5    1.228251
   6    1.314229
   7    1.419367
   8    1.547110
   9    1.701821
   dtype: float64
```

Replacing some values with mean of the rest of a group

```
In [116]: df = pd.DataFrame({'A': [1, 1, 2, 2], 'B': [1, -1, 1, 2]})

In [117]: gb = df.groupby('A')

In [118]: def replace(g):
       :   return (g['B'] - g['B'].mean()).abs() < 1

In [119]: gb.agg(replace)
Out[119]:
  A
-1  True
  0  True
  1  True
  2  True
  3  True
```

In [119]: gb.transform(replace)
Out[119]:
   B
0  1.0
1 -1.0
2  1.5
3  1.5

Sort groups by aggregated data

In [120]: df = pd.DataFrame({'code': ['foo', 'bar', 'baz'] * 2,
       ....:                   'data': [0.16, -0.21, 0.33, 0.45, -0.59, 0.62],
       ....:                   'flag': [False, True] * 3})

In [121]: code_groups = df.groupby('code')
In [122]: agg_n_sort_order = code_groups[['data']].transform(sum).sort_values(by='data
˓→')
In [123]: sorted_df = df.loc[agg_n_sort_order.index]
In [124]: sorted_df
Out[124]:
   code  data  flag
0   foo   0.16 False
1   bar -0.21   True
2   bar -0.59   False
3   foo   0.45   True
4   baz   0.33   False
5   baz   0.62   True

Create multiple aggregated columns

In [125]: rng = pd.date_range(start="2014-10-07", periods=10, freq='2min')
In [126]: ts = pd.Series(data=list(range(10)), index=rng)
In [127]: def MyCust(x):
       ....:     if len(x) > 2:
       ....:         return x[1] * 1.234
       ....:     return pd.NaT

In [128]: mhc = {'Mean': np.mean, 'Max': np.max, 'Custom': MyCust}
In [129]: ts.resample("5min").apply(mhc)
Out[129]:
        Mean         Max
2014-10-07 00:00:00  1.0  8.5
2014-10-07 00:05:00  3.5
2014-10-07 00:10:00  6.0
2014-10-07 00:15:00  6.0
2014-10-07 00:20:00  NaT
2014-10-07 00:25:00  NaT
2014-10-07 00:30:00  NaT
2014-10-07 00:35:00  NaT
2014-10-07 00:40:00  NaT
2014-10-07 00:45:00  NaT
(continues on next page)
Create a value counts column and reassign back to the DataFrame

```
In [131]: df = pd.DataFrame({'Color': 'Red Red Red Blue'.split(),
       .....:         'Value': [100, 150, 50, 50]})

In [132]: df
Out[132]:
   Color  Value
0    Red   100
1    Red   150
2    Red    50
3   Blue    50
```

```
In [133]: df['Counts'] = df.groupby([ 'Color' ]).transform(len)

In [134]: df
Out[134]:
   Color  Value  Counts
0    Red   100      3
1    Red   150      3
2    Red    50      3
3   Blue    50      1
```

Shift groups of the values in a column based on the index

```
In [135]: df = pd.DataFrame({
     .....:     'line_race': [10, 10, 8, 10, 10, 8],
     .....:         'beyer': [99, 102, 103, 103, 88, 100],
     .....:     index=['Last Gunfighter', 'Last Gunfighter',
     .....:     'Last Gunfighter', 'Paynter', 'Paynter',
     .....:     'Paynter']})

In [136]: df
```
Select row with maximum value from each group

In [139]: df = pd.DataFrame({'host': ['other', 'other', 'that', 'this', 'this'],
                        'service': ['mail', 'web', 'mail', 'mail', 'web'],
                        'no': [1, 2, 1, 2, 1]}).set_index(['host', 'service'])

In [140]: mask = df.groupby(level=0).agg('idxmax')

In [141]: df_count = df.loc[mask['no']].reset_index()

In [142]: df_count
Out[142]:
   host  service  no
0   other      web  2
1     that    mail  1
2     this    mail  2

Grouping like Python’s itertools.groupby

In [143]: df = pd.DataFrame([0, 1, 0, 1, 1, 1, 0, 1, 1], columns=['A'])

In [144]: df['A'].groupby((df['A'] != df['A'].shift()).cumsum()).groups
Out[144]: {1: [0], 2: [1], 3: [2], 4: [3, 4, 5], 5: [6], 6: [7, 8]}

In [145]: df['A'].groupby((df['A'] != df['A'].shift()).cumsum()).cumsum()
Out[145]:
   0  1  2  3  4  5  6  7  8
0  0  1  2  3  4  5  6  7  8
Expanding data

Alignment and to-date

Rolling Computation window based on values instead of counts

Rolling Mean by Time Interval

Splitting

Splitting a frame

Create a list of dataframes, split using a delineation based on logic included in rows.

```python
In [146]: df = pd.DataFrame(data={'Case': ['A', 'A', 'A', 'B', 'A', 'A', 'B', 'A', 'A'], 'Data': np.random.randn(9)})
...

In [147]: dfs = list(zip(*df.groupby((1 * (df['Case'] == 'B')).cumsum()).rolling(window=3, min_periods=1).median()))[-1]

In [148]: dfs[0]
Out[148]:
   Case  Data
0     A  0.276232
1     A -1.087401
2     A -0.673690
3     B  0.113648

In [149]: dfs[1]
Out[149]:
   Case  Data
4     A -1.478427
5     A  0.524988
6     B  0.404705

In [150]: dfs[2]
Out[150]:
   Case  Data
7     A  0.577046
8     A -1.715002
```
Pivot

The *Pivot* docs.

Partial sums and subtotals

```python
In [151]: df = pd.DataFrame(data={'Province': ['ON', 'QC', 'BC', 'AL', 'AL', 'MN', 'ON'],
                             'City': ['Toronto', 'Montreal', 'Vancouver',
                                     'Calgary', 'Edmonton', 'Winnipeg',
                                     'Windsor'],
                             'Sales': [13, 6, 16, 8, 4, 3, 1]})

In [152]: table = pd.pivot_table(df, values=['Sales'], index=['Province'],
                            columns=['City'], aggfunc=np.sum, margins=True)

In [153]: table.stack('City')
Out[153]:
   Sales
Province City
   AL All   12.0
          Calgary  8.0
          Edmonton  4.0
   BC All   16.0
          Vancouver  6.0
... ...
   AL All   12.0
          Montreal  6.0
          Toronto  13.0
          Vancouver  6.0
          Windsor  1.0
          Winnipeg  3.0
[20 rows x 1 columns]
```

Frequency table like plyr in R

```python
In [154]: grades = [48, 99, 75, 80, 42, 80, 72, 68, 36, 78]

In [155]: df = pd.DataFrame({'ID': ["x%d" % r for r in range(10)],
                        'Gender': ['F', 'M', 'F', 'M', 'F',
                                   'M', 'F', 'M', 'M'],
                        'Class': ['algebra', 'stats', 'bio', 'algebra',
                                   'algebra', 'stats', 'stats', 'algebra',
                                   'bio', 'bio'],
                        'Participated': ['yes', 'yes', 'yes', 'yes', 'no',
                                         'yes', 'yes', 'yes', 'yes', 'yes'],
                        'Passed': ['yes' if x > 50 else 'no' for x in grades],
                        'Employed': [True, True, True, False,
                                     True, False, False, False, True, True],
                        'Grade': grades})

In [156]: df.groupby('ExamYear').agg({'Participated': lambda x: x.value_counts()['yes']})
```

(continues on next page)
Plot pandas DataFrame with year over year data

To create year and month cross tabulation:

```
In [157]: df = pd.DataFrame({'value': np.random.randn(36)},
       index=pd.date_range('2011-01-01', freq='M', periods=36))

In [158]: pd.pivot_table(df, index=df.index.month, columns=df.index.year,
       values='value', aggfunc='sum')
```

```
Out[158]:
   2011  2012  2013
0   1.64  3.54  2.14
1   0.77  0.17  0.27
2   0.29  0.49  0.39
3   0.46  0.56  0.66
4   0.56  0.66  0.76
5   0.66  0.76  0.86
6   0.76  0.86  0.96
7   0.86  0.96 1.06
8   0.96 1.06 1.16
9  1.06 1.16 1.26
10 1.16 1.26 1.36
```

Apply

Rolling apply to organize - Turning embedded lists into a MultiIndex frame

```
In [159]: df = pd.DataFrame(data=[['a', 'b', 'c'], ['jj', 'kk']],[i for i in range(100, 200)],
       index=[0, 1, 2])

In [160]: def SeriesFromSubList(aList):
       return pd.Series(aList)

In [161]: df_orgz = pd.concat({ind: row.apply(SeriesFromSubList)
       for ind, row in df.iterrows()})
```

```
Out[161]:
   0  1  2
0  0  1  2
1  3  4  5
2  6  7  8
3  9 10 11
```

(continues on next page)
Rolling apply with a DataFrame returning a Series

Rolling Apply to multiple columns where function calculates a Series before a Scalar from the Series is returned

```
In [163]: def gm(df, const):
    ...:     v = ((((df['A'] + df['B']) + 1).cumprod()) - 1) * const
    ...:     return v.iloc[-1]
    ...:

In [165]: df
Out[165]:
   A    B
2001-01-01 -0.000144 -0.000141
2001-01-02  0.000161  0.000102
2001-01-03  0.000057  0.000088
2001-01-04 -0.000221  0.000097
2001-01-05 -0.000201 -0.000041
   ...  ...  ...
2006-06-19  0.000040 -0.000235
2006-06-20 -0.000123 -0.000021
2006-06-21 -0.000113  0.000114
2006-06-22  0.000136  0.000109
2006-06-23  0.000027  0.000030
[2000 rows x 2 columns]
```

```
In [166]: s = pd.Series({df.index[i]: gm(df.iloc[i:min(i + 51, len(df) - 1)], 5)
                  for i in range(len(df) - 50))
                  ...
```

```
In [167]: s
Out[167]:
2001-01-01  0.000930
2001-01-02  0.002615
2001-01-03  0.001281
2001-01-04  0.001117
2001-01-05  0.002772
   ...  ...  ...
2006-04-30  0.003296
2006-05-01  0.002629
2006-05-02  0.002081
2006-05-03  0.004247
2006-05-04  0.003928
```

(continues on next page)
Rolling Apply to multiple columns where function returns a Scalar (Volume Weighted Average Price)

```
In [168]: rng = pd.date_range(start='2014-01-01', periods=100)

In [169]: df = pd.DataFrame({'Open': np.random.randn(len(rng)),
.....: 'Close': np.random.randn(len(rng)),
.....: 'Volume': np.random.randint(100, 2000, len(rng))},
.....: index=rng)

In [170]: df
Out[170]:
     Open   Close  Volume
2014-01-01 -1.611353 -0.492885  1219
2014-01-02 -3.000951  0.445794  1054
2014-01-03 -0.138359 -0.076081  1381
2014-01-04  0.301568  1.198259  1253
2014-01-05  0.276381 -0.669831  1728
...         ...         ... ...
2014-04-06 -0.040338  0.937843  1188
2014-04-07  0.359661 -0.285908  1864
2014-04-08  0.060978  1.714814   941
2014-04-09  1.759055 -0.455942  1065
2014-04-10  0.138185 -1.147008  1453
[100 rows x 3 columns]

In [171]: def vwap(bars):

In [172]: window = 5

In [173]: s = pd.concat([pd.Series(vwap(df.iloc[i:i + window]),
.....:                   index=df.index[i + window])
.....:                   for i in range(len(df) - window)])

In [174]: s.round(2)
Out[174]:
     2014-01-06  0.02
     2014-01-07  0.11
     2014-01-08  0.10
     2014-01-09  0.07
     2014-01-10 -0.29
     ...         ...
     2014-04-06 -0.63
     2014-04-07 -0.02
     2014-04-08 -0.03
     2014-04-09  0.34
     2014-04-10  0.29
Length: 95, dtype: float64
```
2.25.6 Timeseries

Between times
Using indexer between time
Constructing a datetime range that excludes weekends and includes only certain times
Vectorized Lookup
Aggregation and plotting time series
Turn a matrix with hours in columns and days in rows into a continuous row sequence in the form of a time series.
How to rearrange a Python pandas DataFrame?
Dealing with duplicates when reindexing a timeseries to a specified frequency
Calculate the first day of the month for each entry in a DatetimeIndex

```
In [175]: dates = pd.date_range('2000-01-01', periods=5)
In [176]: dates.to_period(freq='M').to_timestamp()
```

Out[176]:
```
              '2000-01-01'],
dtype='datetime64[ns]', freq=None)
```

Resampling

The Resample docs.
Using Grouper instead of TimeGrouper for time grouping of values
Time grouping with some missing values
Valid frequency arguments to Grouper Timeseries
Grouping using a MultiIndex
Using TimeGrouper and another grouping to create subgroups, then apply a custom function
Resampling with custom periods
Resample intraday frame without adding new days
Resample minute data
Resample with groupby

2.25.7 Merge

The Concat docs. The Join docs.
Append two dataframes with overlapping index (emulate R rbind)

```
In [177]: rng = pd.date_range('2000-01-01', periods=6)
In [178]: df1 = pd.DataFrame(np.random.randn(6, 3), index=rng, columns=['A', 'B', 'C'])
In [179]: df2 = df1.copy()
```
Depending on df construction, `ignore_index` may be needed

```python
In [180]: df = df1.append(df2, ignore_index=True)
In [181]: df
Out[181]:
     A         B         C
0 -0.870117 -0.479265 -0.790855
1  0.144817  1.726395 -0.464535
2 -0.821906  1.597605  0.187307
3 -1.128342 -1.511638 -0.289858
4  0.399194 -1.430030 -0.639760
5  1.115116 -2.012600  1.810662
6 -0.870117 -0.479265 -0.790855
7  0.144817  1.726395 -0.464535
8 -0.821906  1.597605  0.187307
9 -1.128342 -1.511638 -0.289858
10 0.399194 -1.430030 -0.639760
11 1.115116 -2.012600  1.810662
```

Self Join of a DataFrame

```python
In [182]: df = pd.DataFrame(data={'Area': ['A'] * 5 + ['C'] * 2,
                               ....: 'Bins': [110] * 2 + [160] * 3 + [40] * 2,
                               ....: 'Test_0': [0, 1, 0, 1, 2, 0, 1],
                               ....: 'Data': np.random.randn(7)})
In [183]: df
Out[183]:
     Area  Bins  Test_0  Data
0      A    110     0   -0.433937
1      A    110     1  -1.605522
2      A    160     0   0.744434
3      A    160     1  1.754213
4      A    160     2   0.000850
5      C     40     0   0.342243
6      C     40     1   1.070599
In [184]: df['Test_1'] = df['Test_0'] - 1
In [185]: pd.merge(df, df, left_on=['Bins', 'Area', 'Test_0'],
                   ....: right_on=['Bins', 'Area', 'Test_1'],
                   ....: suffixes=('_L', '_R'))
Out[185]:
     Area  Bins  Test_0_L  Data_L  Test_0_R  Data_R  Test_1_L  Test_1_R
0      A    110     0.433937   1       0.160552  0       -1       0
1      A    110     1.605522   1       1.754213  0       -1       0
2      A    160     0.744434   2       0.000850  1       0       1
3      A    160     1.754213  0       2       0.000850  1       0
4      A    160     0.000850  1       1       1.070599  0       0
5      C     40     0.342243   0       0       1.070599  0       0
```

How to set the index and join

KDB like asof join

Join with a criteria based on the values

Using `searchsorted` to merge based on values inside a range
2.25.8 Plotting

The Plotting docs.

Make Matplotlib look like R
Setting x-axis major and minor labels
Plotting multiple charts in an ipython notebook
Creating a multi-line plot
Plotting a heatmap
Annotate a time-series plot
Annotate a time-series plot #2
Generate Embedded plots in excel files using Pandas, Vincent and xlsxwriter

Boxplot for each quartile of a stratifying variable

```
In [186]: df = pd.DataFrame(
       ....:     {'stratifying_var': np.random.uniform(0, 100, 20),
       ....:      'price': np.random.normal(100, 5, 20))
       ....:

In [187]: df['quartiles'] = pd.qcut(
       ....:     df['stratifying_var'],
       ....:     4,
       ....:     labels=['0-25%', '25-50%', '50-75%', '75-100%'])
       ....:

In [188]: df.boxplot(column='price', by='quartiles')
Out[188]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe29449e9a0>
```
2.25.9 Data in/out

Performance comparison of SQL vs HDF5

CSV

The CSV docs
read_csv in action
appending to a csv
Reading a csv chunk-by-chunk
Reading only certain rows of a csv chunk-by-chunk
Reading the first few lines of a frame
Reading a file that is compressed but not by gzip/bz2 (the native compressed formats which read_csv understands). This example shows a WinZipped file, but is a general application of opening the file within a context manager and using that handle to read. See here
Inferring dtypes from a file
Dealing with bad lines
Dealing with bad lines II
Reading CSV with Unix timestamps and converting to local timezone
Write a multi-row index CSV without writing duplicates

**Reading multiple files to create a single DataFrame**

The best way to combine multiple files into a single DataFrame is to read the individual frames one by one, put all of the individual frames into a list, and then combine the frames in the list using `pd.concat()`:

```python
In [189]: for i in range(3):
.....:    data = pd.DataFrame(np.random.randn(10, 4))
.....:    data.to_csv('file_{}.csv'.format(i))
.....:
In [190]: files = ['file_0.csv', 'file_1.csv', 'file_2.csv']
In [191]: result = pd.concat([pd.read_csv(f) for f in files], ignore_index=True)
```

You can use the same approach to read all files matching a pattern. Here is an example using `glob`:

```python
In [192]: import glob
In [193]: import os
In [194]: files = glob.glob('file_*.csv')
In [195]: result = pd.concat([pd.read_csv(f) for f in files], ignore_index=True)
```

Finally, this strategy will work with the other `pd.read_*(...)` functions described in the `io docs`.

**Parsing date components in multi-columns**

Parsing date components in multi-columns is faster with a format

```python
In [196]: i = pd.date_range('20000101', periods=10000)
In [197]: df = pd.DataFrame({'year': i.year, 'month': i.month, 'day': i.day})
In [198]: df.head()
Out[198]:
   year  month  day
0  2000     1   1
1  2000     2   2
2  2000     3   3
3  2000     4   4
4  2000     5   5
In [199]: %timeit pd.to_datetime(df.year * 10000 + df.month * 100 + df.day, format='%Y-%m-%d')
.....:    ds = df.apply(lambda x: "%04d%02d%02d" % (x['year'], x['month'], x['day']), axis=1)
.....:    ds.head()
.....:    %timeit pd.to_datetime(ds)
```

(continues on next page)
Skip row between header and data

In [200]: data = ";;;;
   :;
   :;
   :;
   :;
   :;
   :;
   :;
   :;
   :;
   :;
   :;
   :;
   :;
   :;
   :;
   :;
   :;
   :;
   :;
   :;
   :;date;Param1;Param2;Param4;Param5
   :;m°C;m;m
   :;
   :;01.01.1990 00:00;1;1;2;3
   :;01.01.1990 01:00;5;3;4;5
   :;01.01.1990 02:00;9;5;6;7
   :;01.01.1990 03:00;13;7;8;9
   :;01.01.1990 04:00;17;9;10;11
   :;01.01.1990 05:00;21;11;12;13
   :="

Option 1: pass rows explicitly to skip rows

In [201]: from io import StringIO

In [202]: pd.read_csv(StringIO(data), sep=';', skiprows=[11, 12],
   index_col=0, parse_dates=True, header=10)

Out[202]:
   Param1  Param2  Param4  Param5
date
1990-01-01 00:00:00 1       1       2       3
1990-01-01 01:00:00 5       3       4       5
1990-01-01 02:00:00 9       5       6       7
1990-01-01 03:00:00 13      7       8       9
1990-01-01 04:00:00 17      9      10      11
1990-01-01 05:00:00 21      11      12      13
Option 2: read column names and then data

```python
In [203]: pd.read_csv(StringIO(data), sep=';', header=10, nrows=10).columns
Out[203]: Index(['date', 'Param1', 'Param2', 'Param4', 'Param5'], dtype='object')
In [204]: columns = pd.read_csv(StringIO(data), sep=';', header=10, nrows=10).columns
In [205]: pd.read_csv(StringIO(data), sep=';', index_col=0, header=12, parse_dates=True, names=columns)
```

<table>
<thead>
<tr>
<th>date</th>
<th>Param1</th>
<th>Param2</th>
<th>Param4</th>
<th>Param5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990-01-01 00:00:00</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>1990-01-01 01:00:00</td>
<td>5</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>1990-01-01 02:00:00</td>
<td>9</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>1990-01-01 03:00:00</td>
<td>13</td>
<td>7</td>
<td>8</td>
<td>9</td>
</tr>
<tr>
<td>1990-01-01 04:00:00</td>
<td>17</td>
<td>9</td>
<td>10</td>
<td>11</td>
</tr>
<tr>
<td>1990-01-01 05:00:00</td>
<td>21</td>
<td>11</td>
<td>12</td>
<td>13</td>
</tr>
</tbody>
</table>

**SQL**

The *SQL* docs

Reading from databases with SQL

**Excel**

The *Excel* docs

Reading from a filelike handle

Modifying formatting in XlsxWriter output

**HTML**

Reading HTML tables from a server that cannot handle the default request header

**HDFStore**

The *HDFStores* docs

Simple queries with a Timestamp Index

Managing heterogeneous data using a linked multiple table hierarchy

Merging on-disk tables with millions of rows

Avoiding inconsistencies when writing to a store from multiple processes/threads

De-duplicating a large store by chunks, essentially a recursive reduction operation. Shows a function for taking in data from csv file and creating a store by chunks, with date parsing as well. See here

Creating a store chunk-by-chunk from a csv file

Appending to a store, while creating a unique index

2.25. Cookbook
Large Data work flows
Reading in a sequence of files, then providing a global unique index to a store while appending
Groupby on a HDFStore with low group density
Groupby on a HDFStore with high group density
Hierarchical queries on a HDFStore
Counting with a HDFStore
Troubleshoot HDFStore exceptions
Setting min_itemsize with strings
Using ptrepack to create a completely-sorted-index on a store

**Storing Attributes to a group node**

```python
In [206]: df = pd.DataFrame(np.random.randn(8, 3))
In [207]: store = pd.HDFStore('test.h5')
In [208]: store.put('df', df)
# you can store a residual Python object via pickle
In [209]: store.get_storer('df').attrs.my_attribute = {'A': 10}
In [210]: store.get_storer('df').attrs.my_attribute
Out[210]: {'A': 10}
```

You can create or load a HDFStore in-memory by passing the `driver` parameter to PyTables. Changes are only written to disk when the HDFStore is closed.

```python
In [211]: store = pd.HDFStore('test.h5', 'w', driver='H5FD_CORE')
In [212]: df = pd.DataFrame(np.random.randn(8, 3))
In [213]: store['test'] = df
# only after closing the store, data is written to disk:
In [214]: store.close()
```

**Binary files**

pandas readily accepts NumPy record arrays, if you need to read in a binary file consisting of an array of C structs.
For example, given this C program in a file called `main.c` compiled with `gcc main.c -std=gnu99` on a 64-bit machine,

```c
#include <stdio.h>
#include <stdint.h>

typedef struct _Data
{
    int32_t count;
    double avg;
    float scale;
} Data;
```
int main(int argc, const char *argv[]) {
    size_t n = 10;
    Data d[n];

    for (int i = 0; i < n; ++i) {
        d[i].count = i;
        d[i].avg = i + 1.0;
        d[i].scale = (float) i + 2.0f;
    }

    FILE *file = fopen("binary.dat", "wb");
    fwrite(&d, sizeof(Data), n, file);
    fclose(file);
    return 0;
}

the following Python code will read the binary file 'binary.dat' into a pandas DataFrame, where each element of the struct corresponds to a column in the frame:

```python
names = 'count', 'avg', 'scale'

# note that the offsets are larger than the size of the type because of # struct padding
offsets = 0, 8, 16
formats = 'i4', 'f8', 'f4'
dt = np.dtype({'names': names, 'offsets': offsets, 'formats': formats},
              align=True)
df = pd.DataFrame(np.fromfile('binary.dat', dt))
```

**Note:** The offsets of the structure elements may be different depending on the architecture of the machine on which the file was created. Using a raw binary file format like this for general data storage is not recommended, as it is not cross platform. We recommended either HDF5 or parquet, both of which are supported by pandas’ IO facilities.

### 2.25.10 Computation

Numerical integration (sample-based) of a time series

**Correlation**

Often it’s useful to obtain the lower (or upper) triangular form of a correlation matrix calculated from `DataFrame.corr()`. This can be achieved by passing a boolean mask to `where` as follows:

```python
In [215]: df = pd.DataFrame(np.random.random(size=(100, 5)))
In [216]: corr_mat = df.corr()
In [217]: mask = np.tril(np.ones_like(corr_mat, dtype=np.bool), k=-1)
```
The method argument within DataFrame.corr can accept a callable in addition to the named correlation types. Here we compute the distance correlation matrix for a DataFrame object.

```python
In [219]: def distcorr(x, y):
    .....:     n = len(x)
    .....:     a = np.zeros(shape=(n, n))
    .....:     b = np.zeros(shape=(n, n))
    .....:     for i in range(n):
    .....:         for j in range(i + 1, n):
    .....:             a[i, j] = abs(x[i] - x[j])
    .....:             b[i, j] = abs(y[i] - y[j])
    .....:     a += a.T
    .....:     b += b.T
    .....:     a_bar = np.vstack([np.nanmean(a, axis=0)] * n)
    .....:     b_bar = np.vstack([np.nanmean(b, axis=0)] * n)
    .....:     A = a - a_bar - a_bar.T + np.full(shape=(n, n), fill_value=a_bar.mean())
    .....:     B = b - b_bar - b_bar.T + np.full(shape=(n, n), fill_value=b_bar.mean())
    .....:     cov_ab = np.sqrt(np.nansum(A * B)) / n
    .....:     std_a = np.sqrt(np.sqrt(np.nansum(A**2)) / n)
    .....:     std_b = np.sqrt(np.sqrt(np.nansum(B**2)) / n)
    .....:     return cov_ab / std_a / std_b

In [220]: df = pd.DataFrame(np.random.normal(size=(100, 3)))
In [221]: df.corr(method=distcorr)
Out[221]:
              0       1       2
0     1.000000  0.197613  0.216328
1  0.1976130 0.0000000  0.208749
2 0.2163280 0.2087490  0.000000
```

### 2.25.11 Timedeltas

The Timedeltas docs.

Using timedeltas

```python
In [222]: import datetime
In [223]: s = pd.Series(pd.date_range('2012-1-1', periods=3, freq='D'))
In [224]: s - s.max()
Out[224]:
0    -2 days
1    -1 days
```
Adding and subtracting deltas and dates

In [230]: deltas = pd.Series([datetime.timedelta(days=i) for i in range(3)])

In [231]: df = pd.DataFrame({'A': s, 'B': deltas})

In [232]: df
Out[232]:
       A         B
0 2012-01-01  0 days
1 2012-01-02  1 days
2 2012-01-03  2 days

In [233]: df['New Dates'] = df['A'] + df['B']

In [234]: df['Delta'] = df['A'] - df['New Dates']

In [235]: df
Out[235]:
Another example

Values can be set to NaT using np.nan, similar to datetime

```
In [237]: y = s - s.shift()
```

```
In [238]: y
Out[238]:
0  NaT
1   1 days
2   1 days
dtype: timedelta64[ns]
```

```
In [239]: y[1] = np.nan

In [240]: y
Out[240]:
0  NaT
1  NaT
2   1 days
dtype: timedelta64[ns]
```

### 2.25.12 Creating example data

To create a dataframe from every combination of some given values, like R’s `expand.grid()` function, we can create a dict where the keys are column names and the values are lists of the data values:

```
In [241]: def expand_grid(data_dict):
......:     rows = itertools.product(*data_dict.values())
......:     return pd.DataFrame.from_records(rows, columns=data_dict.keys())
......:

In [242]: df = expand_grid({'height': [60, 70],
......:                  'weight': [100, 140, 180],
......:                  'sex': ['Male', 'Female']})
```

```
In [243]: df
Out[243]:
   height  weight   sex
0     60      100   Male
1     60      100   Female
```
<table>
<thead>
<tr>
<th></th>
<th>Age</th>
<th>Height</th>
<th>Gender</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>60</td>
<td>140</td>
<td>Male</td>
</tr>
<tr>
<td>3</td>
<td>60</td>
<td>140</td>
<td>Female</td>
</tr>
<tr>
<td>4</td>
<td>60</td>
<td>180</td>
<td>Male</td>
</tr>
<tr>
<td>5</td>
<td>60</td>
<td>180</td>
<td>Female</td>
</tr>
<tr>
<td>6</td>
<td>70</td>
<td>100</td>
<td>Male</td>
</tr>
<tr>
<td>7</td>
<td>70</td>
<td>100</td>
<td>Female</td>
</tr>
<tr>
<td>8</td>
<td>70</td>
<td>140</td>
<td>Male</td>
</tr>
<tr>
<td>9</td>
<td>70</td>
<td>140</td>
<td>Female</td>
</tr>
<tr>
<td>10</td>
<td>70</td>
<td>180</td>
<td>Male</td>
</tr>
<tr>
<td>11</td>
<td>70</td>
<td>180</td>
<td>Female</td>
</tr>
</tbody>
</table>
This page gives an overview of all public pandas objects, functions and methods. All classes and functions exposed in `pandas.*` namespace are public.

Some subpackages are public which include `pandas.errors`, `pandas.plotting`, and `pandas.testing`. Public functions in `pandas.io` and `pandas.tseries` submodules are mentioned in the documentation. `pandas.api.types` subpackage holds some public functions related to data types in pandas.

**Warning:** The `pandas.core`, `pandas.compat`, and `pandas.util` top-level modules are PRIVATE. Stable functionality in such modules is not guaranteed.

### 3.1 Input/output

#### 3.1.1 Pickling

`read_pickle(filepath_or_buffer[, compression])` Load pickled pandas object (or any object) from file.

```python
pandas.read_pickle(filepath_or_buffer, compression='infer')
```

Load pickled pandas object (or any object) from file.

**Warning:** Loading pickled data received from untrusted sources can be unsafe. See here.

**Parameters**

- `filepath_or_buffer` [str, path object or file-like object] File path, URL, or buffer where the pickled object will be loaded from.

  Changed in version 1.0.0: Accept URL. URL is not limited to S3 and GCS.

- `compression` [{'infer', 'gzip', 'bz2', 'zip', 'xz', None}, default ‘infer’] If ‘infer’ and ‘path_or_url’ is path-like, then detect compression from the following extensions: ‘.gz’, ‘.bz2’, ‘.zip’, or ‘.xz’ (otherwise no compression) If ‘infer’ and ‘path_or_url’ is not path-like, then use None (= no decompression).

**Returns**
unpickled  [same type as object stored in file]

See also:

**DataFrame.to_pickle** Pickle (serialize) DataFrame object to file.

**Series.to_pickle** Pickle (serialize) Series object to file.

**read_hdf** Read HDF5 file into a DataFrame.

**read_sql** Read SQL query or database table into a DataFrame.

**read_parquet** Load a parquet object, returning a DataFrame.

Notes

read_pickle is only guaranteed to be backwards compatible to pandas 0.20.3.

Examples

```python
>>> original_df = pd.DataFrame({'foo': range(5), 'bar': range(5, 10)})
>>> original_df
   foo  bar
0    0    5
1    1    6
2    2    7
3    3    8
4    4    9
>>> pd.to_pickle(original_df, './dummy.pkl')

>>> unpickled_df = pd.read_pickle('./dummy.pkl')
>>> unpickled_df
   foo  bar
0    0    5
1    1    6
2    2    7
3    3    8
4    4    9

>>> import os
>>> os.remove('./dummy.pkl')
```

### 3.1.2 Flat file

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>read_table</code></td>
<td>Read general delimited file into DataFrame.</td>
</tr>
<tr>
<td><code>read_csv</code></td>
<td>Read a comma-separated values (csv) file into DataFrame.</td>
</tr>
<tr>
<td><code>read_fwf</code></td>
<td>Read a table of fixed-width formatted lines into DataFrame.</td>
</tr>
</tbody>
</table>
pandas.read_table

**pandas.read_table** (filepath_or_buffer,  
sep='\t',  
delimiter=None,  
header='infer',  
names=None,  
index_col=None,  
usecols=None,  
squeeze=False,  
prefix=None,  
mangle_dupe_cols=True,  
dtype=None,  
engine=None,  
converters=None,  
true_values=None,  
false_values=None,  
skipinitialspace=False,  
skiprows=None,  
skipfooter=0,  
nrows=None,  
na_values=None,  
keep_default_na=True,  
na_filter=True,  
verbose=False,  
skip_blank_lines=True,  
parsing engine can, meaning the latter will be used and automatically detect the separator by Python's builtin sniffer tool, **csv.Sniffer**. In addition, separators longer than 1 character and different from '\s+' will be interpreted as regular expressions and will also force the use of the Python parsing engine. Note that regex delimiters are prone to ignoring quoted data. Regex example: ' \r\t'.

delim_whitespace=False,  
float_precision=None)  
Read general delimited file into DataFrame.  
Also supports optionally iterating or breaking of the file into chunks.  
Additional help can be found in the online docs for **IO Tools**.

**Parameters**

- **filepath_or_buffer** [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, gs, and file. For file URLs, a host is expected. A local file could be: file://localhost/path/to/table.csv.

If you want to pass in a path object, pandas accepts any **os.PathLike**.  
By file-like object, we refer to objects with a **read()** method, such as a file handler (e.g. via built-in **open** function) or **StringIO**.

- **sep** [str, default '\t' (tab-stop)] Delimiter to use. If sep is None, the C engine cannot automatically detect the separator, but the Python parsing engine can, meaning the latter will be used and automatically detect the separator by Python’s built-in sniffer tool, **csv.Sniffer**. In addition, separators longer than 1 character and different from '\s+' will be interpreted as regular expressions and will also force the use of the Python parsing engine. Note that regex delimiters are prone to ignoring quoted data. Regex example: '\r\t'.

- **delimiter** [str, default None] Alias for sep.

- **header** [int, list of int, default ‘infer’] Row number(s) to use as the column names, and the start of the data. Default behavior is to infer the column names: if no names are passed the behavior is identical to header=0 and column names are inferred from the first line of the file, if column names are passed explicitly then the behavior is identical to header=None. Explicitly pass header=0 to be able to replace existing names. The header can be a list of integers that specify row locations for a multi-index on the columns e.g. [0,1,3]. Intervening rows that are not specified will be skipped (e.g. 2 in this example is skipped). Note that this parameter ignores commented lines and empty lines if **skip_blank_lines=True**, so header=0 denotes the first line of data rather than the first line of the file.

- **names** [array-like, optional] List of column names to use. If the file contains a header row, then you should explicitly pass header=0 to override the column names. Duplicates in this list are not allowed.

- **index_col** [int, str, sequence of int / str, or False, default None] Column(s) to use as the row labels of the **DataFrame**, either given as string name or column index. If a sequence of int / str is given, a MultiIndex is used.
Note: `index_col=False` can be used to force pandas to not use the first column as the index, e.g. when you have a malformed file with delimiters at the end of each line.

`usecols` [list-like or callable, optional] Return a subset of the columns. If list-like, all elements must either be positional (i.e. integer indices into the document columns) or strings that correspond to column names provided either by the user in `names` or inferred from the document header row(s). For example, a valid list-like `usecols` parameter would be `[0, 1, 2]` or `['foo', 'bar', 'baz']`. Element order is ignored, so `usecols=[0, 1]` is the same as `[1, 0]`. To instantiate a DataFrame from data with element order preserved use `pd.read_csv(data, usecols=['foo', 'bar'])[['foo', 'bar']]` for columns in `['foo', 'bar']` order or `pd.read_csv(data, usecols=['foo', 'bar'])[['bar', 'foo']]` for `['bar', 'foo']` order.

If callable, the callable function will be evaluated against the column names, returning names where the callable function evaluates to True. An example of a valid callable argument would be `lambda x: x.upper() in ['AAA', 'BBB', 'DDD']`. Using this parameter results in much faster parsing time and lower memory usage.

`squeeze` [bool, default False] If the parsed data only contains one column then return a Series.

`prefix` [str, optional] Prefix to add to column numbers when no header, e.g. ‘X’ for X0, X1, ...

`mangle_dupe_cols` [bool, default True] Duplicate columns will be specified as ‘X’, ‘X.1’, … ‘X.N’, rather than ‘X’…‘X’. Passing in False will cause data to be overwritten if there are duplicate names in the columns.

`dtype` [Type name or dict of column -> type, optional] Data type for data or columns. E.g. `{‘a’: np.float64, ‘b’: np.int32, ‘c’: ‘Int64’}` Use `str or object` together with suitable `na_values` settings to preserve and not interpret dtype. If converters are specified, they will be applied INSTEAD of dtype conversion.

`engine` [{‘c’, ‘python’}, optional] Parser engine to use. The C engine is faster while the python engine is currently more feature-complete.

`converters` [dict, optional] Dict of functions for converting values in certain columns. Keys can either be integers or column labels.

`true_values` [list, optional] Values to consider as True.

`false_values` [list, optional] Values to consider as False.

`skipinitialspace` [bool, default False] Skip spaces after delimiter.

`skiprows` [list-like, int or callable, optional] Line numbers to skip (0-indexed) or number of lines to skip (int) at the start of the file.

If callable, the callable function will be evaluated against the row indices, returning True if the row should be skipped and False otherwise. An example of a valid callable argument would be `lambda x: x in [0, 2]`.

`skipfooter` [int, default 0] Number of lines at bottom of file to skip (Unsupported with engine='c').

`nrows` [int, optional] Number of rows of file to read. Useful for reading pieces of large files.

`na_values` [scalar, str, list-like, or dict, optional] Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values. By default the following values are interpreted as NaN: ‘’, '#N/A', '#N/A N/A', 'NA', '-1.#IND', '-1.#QNAN', '-NaN', '-nan', '1.#IND', '1.#QNAN', '<NaN>', 'N/A', 'NA', 'NULL', 'NaN', 'n/a', 'nan', 'null'.

`keep_default_na` [bool, default True] Whether or not to include the default NaN values when parsing the data. Depending on whether `na_values` is passed in, the behavior is as follows:
• If `keep_default_na` is True, and `na_values` are specified, `na_values` is appended to the
default NaN values used for parsing.

• If `keep_default_na` is True, and `na_values` are not specified, only the default NaN values
are used for parsing.

• If `keep_default_na` is False, and `na_values` are specified, only the NaN values specified
`na_values` are used for parsing.

• If `keep_default_na` is False, and `na_values` are not specified, no strings will be parsed as
NaN.

Note that if `na_filter` is passed in as False, the `keep_default_na` and `na_values` parameters
will be ignored.

`na_filter` [bool, default True] Detect missing value markers (empty strings and the value of
`na_values`). In data without any NAs, passing `na_filter=False` can improve the performance
of reading a large file.

`verbose` [bool, default False] Indicate number of NA values placed in non-numeric columns.

`skip_blank_lines` [bool, default True] If True, skip over blank lines rather than interpreting as
NaN values.

`parse_dates` [bool or list of int or names or list of lists or dict, default False] The behavior is as
follows:

• boolean. If True -> try parsing the index.

• list of int or names. e.g. If [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date
column.

• list of lists. e.g. If [[1, 3]] -> combine columns 1 and 3 and parse as a single date column.

• dict, e.g. {'foo': [1, 3]} -> parse columns 1, 3 as date and call result ‘foo’

If a column or index cannot be represented as an array of datetimes, say because of an
unparseable value or a mixture of timezones, the column or index will be returned unal-
t ered as an object data type. For non-standard datetime parsing, use `pd.to_datetime` after
`pd.read_csv`. To parse an index or column with a mixture of timezones, specify
date_parser to be a partially-applied `pandas.to_datetime()` with utc=True. See
Parsing a CSV with mixed timezones for more.

Note: A fast-path exists for iso8601-formatted dates.

`infer_datetime_format` [bool, default False] If True and `parse_dates` is enabled, pandas will
attempt to infer the format of the datetime strings in the columns, and if it can be inferred,
switch to a faster method of parsing them. In some cases this can increase the parsing speed
by 5-10x.

`keep_date_col` [bool, default False] If True and `parse_dates` specifies combining multiple
columns then keep the original columns.

`date_parser` [function, optional] Function to use for converting a sequence of string columns to
an array of datetime instances. The default uses `dateutil.parser.parser` to do the
conversion. Pandas will try to call `date_parser` in three different ways, advancing to the next
if an exception occurs: 1) Pass one or more arrays (as defined by `parse_dates`) as arguments;
2) concatenate (row-wise) the string values from the columns defined by `parse_dates` into
a single array and pass that; and 3) call `date_parser` once for each row using one or more
strings (corresponding to the columns defined by `parse_dates`) as arguments.

`dayfirst` [bool, default False] DD/MM format dates, international and European format.
**cache_dates** [bool, default True] If True, use a cache of unique, converted dates to apply the
datetime conversion. May produce significant speed-up when parsing duplicate date strings,
especially ones with timezone offsets.

New in version 0.25.0.

**iterator** [bool, default False] Return TextFileReader object for iteration or getting chunks with
get_chunk().

**chunksize** [int, optional] Return TextFileReader object for iteration. See the IO Tools docs for
more information on iterator and chunksize.

**compression** ['infer', 'gzip', 'bz2', 'zip', 'xz', None], default 'infer'] For on-the-fly decom-
pression of on-disk data. If 'infer' and filepath_or_buffer is path-like, then detect compres-
sion from the following extensions: '.gz', '.bz2', '.zip', or '.xz' (otherwise no decompres-
sion). If using 'zip', the ZIP file must contain only one data file to be read in. Set to None
for no decompression.

**thousands** [str, optional] Thousands separator.

**decimal** [str, default '.'] Character to recognize as decimal point (e.g. use ',' for European data).

**lineterminator** [str (length 1), optional] Character to break file into lines. Only valid with C
parser.

**quotechar** [str (length 1), optional] The character used to denote the start and end of a quoted
item. Quoted items can include the delimiter and it will be ignored.

**quoting** [int or csv.QUOTE_* instance, default 0] Control field quoting behavior per
csv.QUOTE_* constants. Use one of QUOTE_MINIMAL (0), QUOTE_ALL (1),
QUOTE_NONNUMERIC (2) or QUOTE_NONE (3).

**doublequote** [bool, default True] When quotechar is specified and quoting is not
QUOTE_NONE, indicate whether or not to interpret two consecutive quotechar elements
INSIDE a field as a single quotechar element.

**escapechar** [str (length 1), optional] One-character string used to escape other characters.

**comment** [str, optional] Indicates remainder of line should not be parsed. If found at the begin-
nning of a line, the line will be ignored altogether. This parameter must be a single character.
Like empty lines (as long as skip_blank_lines=True), fully commented lines are
ignored by the parameter header but not by skiprows. For example, if comment='#',
parsing #empty
a,b,c
1,2,3 with header=0 will result in 'a,b,c' being treated
as the header.

**encoding** [str, optional] Encoding to use for UTF when reading/writing (ex. ‘utf-8’). List of
Python standard encodings.

**dialect** [str or csv.Dialect, optional] If provided, this parameter will override values (default
or not) for the following parameters: delimiter, doublequote, escapechar, skipinitialspace,
quotechar, and quoting. If it is necessary to override values, a ParserWarning will be issued.
See csv.Dialect documentation for more details.

**error_bad_lines** [bool, default True] Lines with too many fields (e.g. a csv line with too many
commas) will by default cause an exception to be raised, and no DataFrame will be returned.
If False, then these “bad lines” will dropped from the DataFrame that is returned.

**warn_bad_lines** [bool, default True] If error_bad_lines is False, and warn_bad_lines is True, a
warning for each “bad line” will be output.
**delim_whitespace** [bool, default False] Specifies whether or not whitespace (e.g. ' ' or '
') will be used as the sep. Equivalent to setting `sep='\s+'`. If this option is set to True, nothing should be passed in for the `delimiter` parameter.

**low_memory** [bool, default True] Internally process the file in chunks, resulting in lower memory use while parsing, but possibly mixed type inference. To ensure no mixed types either set False, or specify the type with the `dtype` parameter. Note that the entire file is read into a single DataFrame regardless, use the `chunksize` or `iterator` parameter to return the data in chunks. (Only valid with C parser).

**memory_map** [bool, default False] If a filepath is provided for `filepath_or_buffer`, map the file object directly onto memory and access the data directly from there. Using this option can improve performance because there is no longer any I/O overhead.

**float_precision** [str, optional] Specifies which converter the C engine should use for floating-point values. The options are `None` for the ordinary converter, `high` for the high-precision converter, and `round_trip` for the round-trip converter.

**Returns**

- **DataFrame or TextParser** A comma-separated values (csv) file is returned as a two-dimensional data structure with labeled axes.

**See also:**

- `DataFrame.to_csv` Write DataFrame to a comma-separated values (csv) file.
- `read_csv` Read a comma-separated values (csv) file into DataFrame.
- `read_fwf` Read a table of fixed-width formatted lines into DataFrame.

**Examples**

```python
>>> pd.read_table('data.csv')
```

**pandas.read_csv**

- **pandas.read_csv** (filepath_or_buffer, sep=':', delimiter=None, header='infer', names=None, index_col=None, usecols=None, squeeze=False, prefix=None, mangle_dupe_cols=True, dtype=None, engine=None, converters=None, true_values=None, false_values=None, skipinitialspace=False, skiprows=None, skipfooter=0, nrows=None, na_values=None, keep_default_na=True, na_filter=True, verbose=False, skip_blank_lines=True, parse_dates=False, infer_datetime_format=False, keep_date_col=False, date_parser=None, dayfirst=False, cache_dates=True, iterator=False, chunksize=None, compression='infer', thousands=None, decimal='.', lineterminator=None, comment=None, encoding=None, dialect=None, error_bad_lines=True, warn_bad_lines=True, delim_whitespace=False, low_memory=True, memory_map=False, float_precision=None)

Read a comma-separated values (csv) file into DataFrame.

Also supports optionally iterating or breaking of the file into chunks.

Additional help can be found in the online docs for IO Tools.

**Parameters**
filepath_or_buffer  [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, gs, and file. For file URLs, a host is expected. A local file could be: file://localhost/path/to/table.csv.

If you want to pass in a path object, pandas accepts any os.PathLike.

By file-like object, we refer to objects with a read() method, such as a file handler (e.g. via builtin open function) or StringIO.

sep  [str, default ‘’] Delimiter to use. If sep is None, the C engine cannot automatically detect the separator, but the Python parsing engine can, meaning the latter will be used and automatically detect the separator by Python’s builtin sniffer tool, csv.Sniffer. In addition, separators longer than 1 character and different from \s+ will be interpreted as regular expressions and will also force the use of the Python parsing engine. Note that regex delimiters are prone to ignoring quoted data. Regex example: '\r\t'.

delimiter  [str, default None] Alias for sep.

header  [int, list of int, default ‘infer’] Row number(s) to use as the column names, and the start of the data. Default behavior is to infer the column names: if no names are passed the behavior is identical to header=0 and column names are inferred from the first line of the file, if column names are passed explicitly then the behavior is identical to header=None. Explicitly pass header=0 to be able to replace existing names. The header can be a list of integers that specify row locations for a multi-index on the columns e.g. [0,1,3]. Intervening rows that are not specified will be skipped (e.g. 2 in this example is skipped). Note that this parameter ignores commented lines and empty lines if skip_blank_lines=True, so header=0 denotes the first line of data rather than the first line of the file.

names  [array-like, optional] List of column names to use. If the file contains a header row, then you should explicitly pass header=0 to override the column names. Duplicates in this list are not allowed.

index_col  [int, str, sequence of int / str, or False, default None] Column(s) to use as the row labels of the DataFrame, either given as string name or column index. If a sequence of int / str is given, a MultiIndex is used.

Note: index_col=False can be used to force pandas to not use the first column as the index, e.g. when you have a malformed file with delimiters at the end of each line.

usecols  [list-like or callable, optional] Return a subset of the columns. If list-like, all elements must either be positional (i.e. integer indices into the document columns) or strings that correspond to column names provided either by the user in names or inferred from the document header row(s). For example, a valid list-like usecols parameter would be [0, 1, 2] or ['foo', 'bar', 'baz']. Element order is ignored, so usecols=[0, 1] is the same as [1, 0]. To instantiate a DataFrame from data with element order preserved use pd.read_csv(data, usecols=['foo', 'bar'])[['foo', 'bar']] for columns in ['foo', 'bar'] order or pd.read_csv(data, usecols=['foo', 'bar'])[['bar', 'foo']] for ['bar', 'foo'] order.

If callable, the callable function will be evaluated against the column names, returning names where the callable function evaluates to True. An example of a valid callable argument would be lambda x: x.upper() in ['AAA', 'BBB', 'DDD']. Using this parameter results in much faster parsing time and lower memory usage.

squeeze  [bool, default False] If the parsed data only contains one column then return a Series.

prefix  [str, optional] Prefix to add to column numbers when no header, e.g. ‘X’ for X0, X1, …

mangle_dupe_cols  [bool, default True] Duplicate columns will be specified as ‘X’, ‘X.1’, … ‘X.N’, rather than ‘X’… ‘X’. Passing in False will cause data to be overwritten if there
are duplicate names in the columns.

**dtype** [Type name or dict of column -> type, optional] Data type for data or columns. E.g. `{‘a’: np.float64, ‘b’: np.int32, ‘c’: ‘Int64’}` Use `str` or `object` together with suitable `na_values` settings to preserve and not interpret dtype. If converters are specified, they will be applied **INSTEAD** of dtype conversion.

**engine** [‘c’, ‘python’], optional] Parser engine to use. The C engine is faster while the python engine is currently more feature-complete.

**converters** [dict, optional] Dict of functions for converting values in certain columns. Keys can either be integers or column labels.

**true_values** [list, optional] Values to consider as True.

**false_values** [list, optional] Values to consider as False.

**skipinitialspace** [bool, default False] Skip spaces after delimiter.

**skiprows** [list-like, int or callable, optional] Line numbers to skip (0-indexed) or number of lines to skip (int) at the start of the file.

If callable, the callable function will be evaluated against the row indices, returning True if the row should be skipped and False otherwise. An example of a valid callable argument would be `lambda x: x in [0, 2]`.

**skipfooter** [int, default 0] Number of lines at bottom of file to skip (Unsupported with engine='c').

**nrows** [int, optional] Number of rows of file to read. Useful for reading pieces of large files.

**na_values** [scalar, str, list-like, or dict, optional] Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values. By default the following values are interpreted as NaN: ‘’, ‘#N/A’, ‘#N/A N/A’, ‘#NA’, ‘-1.#IND’, ‘-1.#QNAN’, ‘-NaN’, ‘-nan’, ‘1.#IND’, ‘1.#QNAN’, ‘<NA>’, ‘N/A’, ‘NA’, ‘NULL’, ‘NaN’, ‘n/a’, ‘nan’, ‘null’.

**keep_default_na** [bool, default True] Whether or not to include the default NaN values when parsing the data. Depending on whether `na_values` is passed in, the behavior is as follows:

- If `keep_default_na` is True, and `na_values` are specified, `na_values` is appended to the default NaN values used for parsing.
- If `keep_default_na` is True, and `na_values` are not specified, only the default NaN values are used for parsing.
- If `keep_default_na` is False, and `na_values` are specified, only the NaN values specified `na_values` are used for parsing.
- If `keep_default_na` is False, and `na_values` are not specified, no strings will be parsed as NaN.

Note that if `na_filter` is passed in as False, the `keep_default_na` and `na_values` parameters will be ignored.

**na_filter** [bool, default True] Detect missing value markers (empty strings and the value of `na_values`). In data without any NAs, passing `na_filter=False` can improve the performance of reading a large file.

**verbose** [bool, default False] Indicate number of NA values placed in non-numeric columns.

**skip_blank_lines** [bool, default True] If True, skip over blank lines rather than interpreting as NaN values.
parse_dates [bool or list of int or names or list of lists or dict, default False] The behavior is as follows:

- boolean. If True -> try parsing the index.
- list of int or names. e.g. If [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column.
- list of lists. e.g. If [[1, 3]] -> combine columns 1 and 3 and parse as a single date column.
- dict, e.g. `{‘foo’ : [1, 3]}` -> parse columns 1, 3 as date and call result ‘foo’

If a column or index cannot be represented as an array of datetimes, say because of an unparsable value or a mixture of timezones, the column or index will be returned unaltered as an object data type. For non-standard datetime parsing, use `pd.to_datetime` after `pd.read_csv`. To parse an index or column with a mixture of timezones, specify `date_parser` to be a partially-applied `pandas.to_datetime()` with `utc=True`. See Parsing a CSV with mixed timezones for more.

Note: A fast-path exists for iso8601-formatted dates.

infer_datetime_format [bool, default False] If True and `parse_dates` is enabled, pandas will attempt to infer the format of the datetime strings in the columns, and if it can be inferred, switch to a faster method of parsing them. In some cases this can increase the parsing speed by 5-10x.

keep_date_col [bool, default False] If True and `parse_dates` specifies combining multiple columns then keep the original columns.

date_parser [function, optional] Function to use for converting a sequence of string columns to an array of datetime instances. The default uses `dateutil.parser.parser` to do the conversion. Pandas will try to call `date_parser` in three different ways, advancing to the next if an exception occurs: 1) Pass one or more arrays (as defined by `parse_dates`) as arguments; 2) concatenate (row-wise) the string values from the columns defined by `parse_dates` into a single array and pass that; and 3) call `date_parser` once for each row using one or more strings (corresponding to the columns defined by `parse_dates`) as arguments.

dayfirst [bool, default False] DD/MM format dates, international and European format.

cache_dates [bool, default True] If True, use a cache of unique, converted dates to apply the datetime conversion. May produce significant speed-up when parsing duplicate date strings, especially ones with timezone offsets.

New in version 0.25.0.

iterator [bool, default False] Return TextFileReader object for iteration or getting chunks with `get_chunk()`.

chunksize [int, optional] Return TextFileReader object for iteration. See the IO Tools docs for more information on `iterator` and `chunksize`.

compression [{‘infer’, ‘gzip’, ‘bz2’, ‘zip’, ‘xz’, None}, default ‘infer’] For on-the-fly decompression of on-disk data. If ‘infer’ and `filepath_or_buffer` is path-like, then detect compression from the following extensions: ‘.gz’, ‘.bz2’, ‘.zip’, or ‘.xz’ (otherwise no decompression). If using ‘zip’, the ZIP file must contain only one data file to be read in. Set to None for no decompression.

thousands [str, optional] Thousands separator.

decimal [str, default ‘.’] Character to recognize as decimal point (e.g. use ‘,’ for European data).

lineterminator [str (length 1), optional] Character to break file into lines. Only valid with C parser.
quotechar  [str (length 1), optional] The character used to denote the start and end of a quoted item. Quoted items can include the delimiter and it will be ignored.

quoting  [int or csv.QUOTE_* instance, default 0] Control field quoting behavior per csv.QUOTE_* constants. Use one of QUOTE_MINIMAL (0), QUOTE_ALL (1), QUOTE_NONNUMERIC (2) or QUOTE_NONE (3).

doublequote  [bool, default True] When quotechar is specified and quoting is not QUOTE_NONE, indicate whether or not to interpret two consecutive quotechar elements INSIDE a field as a single quotechar element.

escapechar  [str (length 1), optional] One-character string used to escape other characters.

comment  [str, optional] Indicates remainder of line should not be parsed. If found at the beginning of a line, the line will be ignored altogether. This parameter must be a single character. Like empty lines (as long as skip_blank_lines=True), fully commented lines are ignored by the parameter header but not by skiprows. For example, if comment='#', parsing '#empty
a,b,c
1,2,3' with header=0 will result in 'a,b,c' being treated as the header.

encoding  [str, optional] Encoding to use for UTF when reading/writing (ex. ‘utf-8’). List of Python standard encodings .

dialect  [str or csv.Dialect, optional] If provided, this parameter will override values (default or not) for the following parameters: delimiter, doublequote, escapechar, skipinitialspace, quotechar, and quoting. If it is necessary to override values, a ParserWarning will be issued. See csv.Dialect documentation for more details.

error_bad_lines  [bool, default True] Lines with too many fields (e.g. a csv line with too many commas) will by default cause an exception to be raised, and no DataFrame will be returned. If False, then these “bad lines” will dropped from the DataFrame that is returned.

warn_bad_lines  [bool, default True] If error_bad_lines is False, and warn_bad_lines is True, a warning for each “bad line” will be output.

delim_whitespace  [bool, default False] Specifies whether or not whitespace (e.g. ' ' or '
') will be used as the sep. Equivalent to setting sep='\s+'. If this option is set to True, nothing should be passed in for the delimiter parameter.

low_memory  [bool, default True] Internally process the file in chunks, resulting in lower memory use while parsing, but possibly mixed type inference. To ensure no mixed types either set False, or specify the type with the dtype parameter. Note that the entire file is read into a single DataFrame regardless, use the chunksize or iterator parameter to return the data in chunks. (Only valid with C parser).

memory_map  [bool, default False] If a filepath is provided for filepath_or_buffer, map the file object directly onto memory and access the data directly from there. Using this option can improve performance because there is no longer any I/O overhead.

float_precision  [str, optional] Specifies which converter the C engine should use for floating-point values. The options are None for the ordinary converter, high for the high-precision converter, and round_trip for the round-trip converter.

Returns

DataFrame or TextParser  A comma-separated values (csv) file is returned as two-dimensional data structure with labeled axes.

See also:

DataFrame.to_csv  Write DataFrame to a comma-separated values (csv) file.
**read_csv**  Read a comma-separated values (csv) file into DataFrame.

**read_fwf**  Read a table of fixed-width formatted lines into DataFrame.

**Examples**

```python
>>> pd.read_csv('data.csv')
```

### pandas.read_fwf

```python
def pandas.read_fwf(filepath_or_buffer, colspecs='infer', widths=None, infer_nrows=100, **kwds)
```

Read a table of fixed-width formatted lines into DataFrame.

Also supports optionally iterating or breaking of the file into chunks.

Additional help can be found in the online docs for IO Tools.

**Parameters**

- `filepath_or_buffer` [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: file://localhost/path/to/table.csv.
  
  If you want to pass in a path object, pandas accepts any `os.PathLike`.

  By file-like object, we refer to objects with a `read()` method, such as a file handler (e.g. via builtin `open` function) or `StringIO`.

- `colspecs` [list of tuple (int, int) or ‘infer’, optional] A list of tuples giving the extents of the fixed-width fields of each line as half-open intervals (i.e., [from, to[). String value ‘infer’ can be used to instruct the parser to try detecting the column specifications from the first 100 rows of the data which are not being skipped via `skiprows` (default=‘infer’).

- `widths` [list of int, optional] A list of field widths which can be used instead of `colspecs` if the intervals are contiguous.

- `infer_nrows` [int, default 100] The number of rows to consider when letting the parser determine the `colspecs`.
  
  New in version 0.24.0.

- `**kwds` [optional] Optional keyword arguments can be passed to `TextFileReader`.

**Returns**

- `DataFrame` or `TextParser`  A comma-separated values (csv) file is returned as two-dimensional data structure with labeled axes.

**See also:**

- `DataFrame.to_csv`  Write DataFrame to a comma-separated values (csv) file.

- `read_csv`  Read a comma-separated values (csv) file into DataFrame.
### 3.1.3 Clipboard

**pandas.read_clipboard**

```
pandas.read_clipboard(sep='\s+', **kwargs)
```

Read text from clipboard and pass to read_csv.

**Parameters**

- `sep` [str, default 's+'] A string or regex delimiter. The default of ‘s+’ denotes one or more whitespace characters.
- `**kwargs` See read_csv for the full argument list.

**Returns**

- `DataFrame` A parsed DataFrame object.

### 3.1.4 Excel

**pandas.read_excel**

```
pandas.read_excel(*args, **kwargs)
```

Read an Excel file into a pandas DataFrame.

Supports xls, xlsx, xslm, xslb, odf, ods and odt file extensions read from a local filesystem or URL. Supports an option to read a single sheet or a list of sheets.

**Parameters**

- `io` [str, bytes, ExcelFile, xlrd.Book, path object, or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: file://localhost/path/to/table.xlsx.

  If you want to pass in a path object, pandas accepts any os.PathLike.

  By file-like object, we refer to objects with a read() method, such as a file handler (e.g. via builtin open function) or StringIO.

- `sheet_name` [str, int, list, or None, default 0] Strings are used for sheet names. Integers are used in zero-indexed sheet positions. Lists of strings/integers are used to request multiple sheets. Specify None to get all sheets.
Available cases:

- Defaults to 0: 1st sheet as a DataFrame
- 1: 2nd sheet as a DataFrame
- "Sheet1": Load sheet with name “Sheet1”
- [0, 1, "Sheet5"]: Load first, second and sheet named “Sheet5” as a dict of DataFrame
- None: All sheets.

header [int, list of int, default 0] Row (0-indexed) to use for the column labels of the parsed DataFrame. If a list of integers is passed those row positions will be combined into a MultiIndex. Use None if there is no header.

names [array-like, default None] List of column names to use. If file contains no header row, then you should explicitly pass header=None.

index_col [int, list of int, default None] Column (0-indexed) to use as the row labels of the DataFrame. Pass None if there is no such column. If a list is passed, those columns will be combined into a MultiIndex. If a subset of data is selected with usecols, index_col is based on the subset.

usecols [int, str, list-like, or callable default None]

- If None, then parse all columns.
- If str, then indicates comma separated list of Excel column letters and column ranges (e.g. “A:E” or “A,C,E:F”). Ranges are inclusive of both sides.
- If list of int, then indicates list of column numbers to be parsed.
- If list of string, then indicates list of column names to be parsed.

    New in version 0.24.0.

- If callable, then evaluate each column name against it and parse the column if the callable returns True.

    Returns a subset of the columns according to behavior above.

    New in version 0.24.0.

squeeze [bool, default False] If the parsed data only contains one column then return a Series.

dtype [Type name or dict of column -> type, default None] Data type for data or columns.

E.g. {'a': np.float64, 'b': np.int32} Use object to preserve data as stored in Excel and not interpret dtype. If converters are specified, they will be applied INSTEAD of dtype conversion.

engine [str, default None] If io is not a buffer or path, this must be set to identify io. Supported engines: “xlrd”, “openpyxl”, “odf”, “pyxlsb”, default “xlrd”. Engine compatibility:

- “xlrd” supports most old/new Excel file formats.
- “openpyxl” supports newer Excel file formats.
- “odf” supports OpenDocument file formats (.odf, .ods, .odt).
- “pyxlsb” supports Binary Excel files.

converters [dict, default None] Dict of functions for converting values in certain columns. Keys can either be integers or column labels, values are functions that take one input argument, the Excel cell content, and return the transformed content.

true_values [list, default None] Values to consider as True.

false_values [list, default None] Values to consider as False.
skiprows [list-like] Rows to skip at the beginning (0-indexed).

nrows [int, default None] Number of rows to parse.

New in version 0.23.0.

na_values [scalar, str, list-like, or dict, default None] Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values. By default the following values are interpreted as NaN: ' ', '#N/A', '#N/A NA', '#NA', '-1.#IND', '-1.#QNAN', '-NaN', '-nan', '1.#IND', '1.#QNAN', '<NA>', 'N/A', 'NA', 'NULL', 'NaN', 'n/a', 'nan', 'null'.

keep_default_na [bool, default True] Whether or not to include the default NaN values when parsing the data. Depending on whether na_values is passed in, the behavior is as follows:

• If keep_default_na is True, and na_values are specified, na_values is appended to the default NaN values used for parsing.

• If keep_default_na is True, and na_values are not specified, only the default NaN values are used for parsing.

• If keep_default_na is False, and na_values are specified, only the NaN values specified na_values are used for parsing.

• If keep_default_na is False, and na_values are not specified, no strings will be parsed as NaN.

Note that if na_filter is passed in as False, the keep_default_na and na_values parameters will be ignored.

na_filter [bool, default True] Detect missing value markers (empty strings and the value of na_values). In data without any NAs, passing na_filter=False can improve the performance of reading a large file.

verbose [bool, default False] Indicate number of NA values placed in non-numeric columns.

parse_dates [bool, list-like, or dict, default False] The behavior is as follows:

• bool. If True -> try parsing the index.

• list of int or names. e.g. If [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column.

• list of lists. e.g. If [[1, 3]] -> combine columns 1 and 3 and parse as a single date column.

• dict, e.g. {'foo' : [1, 3]} -> parse columns 1, 3 as date and call result ‘foo’

If a column or index contains an unparseable date, the entire column or index will be returned unaltered as an object data type. If you don’t want to parse some cells as date just change their type in Excel to “Text”. For non-standard datetime parsing, use pd.to_datetime after pd.read_excel.

Note: A fast-path exists for iso8601-formatted dates.

date_parser [function, optional] Function to use for converting a sequence of string columns to an array of datetime instances. The default uses dateutil.parser.parser to do the conversion. Pandas will try to call date_parser in three different ways, advancing to the next if an exception occurs: 1) Pass one or more arrays (as defined by parse_dates) as arguments; 2) concatenate (row-wise) the string values from the columns defined by parse_dates into a single array and pass that; and 3) call date_parser once for each row using one or more strings (corresponding to the columns defined by parse_dates) as arguments.

thousands [str, default None] Thousands separator for parsing string columns to numeric. Note that this parameter is only necessary for columns stored as TEXT in Excel, any numeric columns will automatically be parsed, regardless of display format.
comment [str, default None] Comments out remainder of line. Pass a character or characters to this argument to indicate comments in the input file. Any data between the comment string and the end of the current line is ignored.

skipfooter [int, default 0] Rows at the end to skip (0-indexed).

convert_float [bool, default True] Convert integral floats to int (i.e., 1.0 → 1). If False, all numeric data will be read in as floats: Excel stores all numbers as floats internally.

mangle_dupe_cols [bool, default True] Duplicate columns will be specified as ‘X’, ‘X.1’, ‘X.2’, ..., ‘X.N’, rather than ‘X’...‘X’. Passing in False will cause data to be overwritten if there are duplicate names in the columns.

Returns

DataFrame or dict of DataFrames DataFrame from the passed in Excel file. See notes in sheet_name argument for more information on when a dict of DataFrames is returned.

See also:

DataFrame.to_excel Write DataFrame to an Excel file.

DataFrame.to_csv Write DataFrame to a comma-separated values (csv) file.

read_csv Read a comma-separated values (csv) file into DataFrame.

read_fwf Read a table of fixed-width formatted lines into DataFrame.

Examples

The file can be read using the file name as string or an open file object:

```python
>>> pd.read_excel('tmp.xlsx', index_col=0)
   Name  Value
0 string1  1
1 string2  2
2 #Comment  3
```

```python
>>> pd.read_excel(open('tmp.xlsx', 'rb'),
... sheet_name='Sheet3')
   Unnamed: 0       Name  Value
0         0  string1  1
1         1  string2  2
2         2 #Comment  3
```

Index and header can be specified via the index_col and header arguments

```python
>>> pd.read_excel('tmp.xlsx', index_col=None, header=None)
   0  1  2
0 NaN  Name  Value
1 0.0 string1  1
2 1.0 string2  2
3 2.0 #Comment  3
```

Column types are inferred but can be explicitly specified

```python
>>> pd.read_excel('tmp.xlsx', index_col=0,
...                  dtype={'Name': str, 'Value': float})
   Name  Value
```

(continues on next page)
True, False, and NA values, and thousands separators have defaults, but can be explicitly specified, too. Supply the values you would like as strings or lists of strings!

```python
>>> pd.read_excel('tmp.xlsx', index_col=0,
...                na_values=['string1', 'string2'])
```

Comment lines in the excel input file can be skipped using the `comment` kwarg

```python
>>> pd.read_excel('tmp.xlsx', index_col=0, comment='#')
```

### pandas.ExcelFile.parse

ExcelFile.parse(sheet_name=0, header=0, names=None, index_col=None, usecols=None, squeeze=False, converters=None, true_values=None, false_values=None, skiprows=None, nrows=None, na_values=None, parse_dates=False, date_parser=None, thousands=None, comment=None, skipfooter=0, convert_float=True, mangle_dupe_cols=True, **kwds)

Parse specified sheet(s) into a DataFrame.

Equivalent to read_excel(ExcelFile, ...) See the read_excel docstring for more info on accepted parameters.

**Returns**

DataFrame or dict of DataFrames: DataFrame from the passed in Excel file.

### pandas.ExcelWriter

class pandas.ExcelWriter(path[, engine])

Class for writing DataFrame objects into excel sheets.

Default is to use xlwt for xls, openpyxl forxlsx, odf for ods. See DataFrame.to_excel for typical usage.

**Parameters**

- **path** [str] Path to xls or xlsx or ods file.
- **engine** [str (optional)] Engine to use for writing. If None, defaults to io.excel.<extension>.writer. NOTE: can only be passed as a keyword argument.
- **date_format** [str, default None] Format string for dates written into Excel files (e.g. ‘YYYY-MM-DD’).
datetime_format  [str, default None] Format string for datetime objects written into Excel files. (e.g. ‘YYYY-MM-DD HH:MM:SS’).

mode  [‘w’, ‘a’], default ‘w’] File mode to use (write or append).

New in version 0.24.0.

Notes

None of the methods and properties are considered public.

For compatibility with CSV writers, ExcelWriter serializes lists and dicts to strings before writing.

Examples

Default usage:

```python
>>> with ExcelWriter('path_to_file.xlsx') as writer:
    ...     df.to_excel(writer)
```

To write to separate sheets in a single file:

```python
>>> with ExcelWriter('path_to_file.xlsx') as writer:
    ...     df1.to_excel(writer, sheet_name='Sheet1')
    ...     df2.to_excel(writer, sheet_name='Sheet2')
```

You can set the date format or datetime format:

```python
>>> with ExcelWriter('path_to_file.xlsx',
    ...     date_format='YYYY-MM-DD',
    ...     datetime_format='YYYY-MM-DD HH:MM:SS') as writer:
    ...     df.to_excel(writer)
```

You can also append to an existing Excel file:

```python
>>> with ExcelWriter('path_to_file.xlsx', mode='a') as writer:
    ...     df.to_excel(writer, sheet_name='Sheet3')
```
3.1.5 JSON

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>read_json(*args, **kwargs)</td>
<td>Convert a JSON string to pandas object.</td>
</tr>
<tr>
<td>json_normalize(data[, record_path, meta, ...])</td>
<td>Normalize semi-structured JSON data into a flat table.</td>
</tr>
</tbody>
</table>

**pandas.read_json**

```python
pandas.read_json(*args, **kwargs)
```

Convert a JSON string to pandas object.

**Parameters**

- **path_or_buf** [a valid JSON str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: file://localhost/path/to/table.json.

  If you want to pass in a path object, pandas accepts any `os.PathLike`.

  By file-like object, we refer to objects with a `read()` method, such as a file handler (e.g. via built-in `open` function) or `StringIO`.

- **orient** [str] Indication of expected JSON string format. Compatible JSON strings can be produced by `to_json()` with a corresponding orient value. The set of possible orients is:
  - `'split'`: dict like `{index -> [index], columns -> [columns], data -> [values]}`
  - `'records'`: list like `[{column -> value}, ..., {column -> value}]`
  - `'index'`: dict like `{index -> {column -> value}}`
  - `'columns'`: dict like `{column -> {index -> value}}`
  - `'values'`: just the values array

  The allowed and default values depend on the value of the `typ` parameter.

  - when `typ == 'series'`,
    - allowed orients are `{split', 'records', 'index'}`
    - default is `'index'`
    - The Series index must be unique for orient `'index'`.
  - when `typ == 'frame'`,
    - allowed orients are `{split', 'records', 'index', 'columns', 'values', 'table'}`
    - default is `'columns'`
    - The DataFrame index must be unique for orients `'index'` and `'columns'`.
    - The DataFrame columns must be unique for orients `'index'`, `'columns'`, and `'records'`.

New in version 0.23.0: ‘table’ as an allowed value for the `orient` argument

- **typ** [{‘frame’, ‘series’}, default ‘frame’] The type of object to recover.
dtype [bool or dict, default None] If True, infer dtypes; if a dict of column to dtype, then use those; if False, then don’t infer dtypes at all, applies only to the data.

   For all orient values except 'table', default is True.
   Changed in version 0.25.0: Not applicable for orient='table'.

convert_axes [bool, default None] Try to convert the axes to the proper dtypes.

   For all orient values except 'table', default is True.
   Changed in version 0.25.0: Not applicable for orient='table'.

convert_dates [bool or list of str, default True] If True then default datelike columns may be converted (depending on keep_default_dates). If False, no dates will be converted. If a list of column names, then those columns will be converted and default datelike columns may also be converted (depending on keep_default_dates).

keep_default_dates [bool, default True] If parsing dates (convert_dates is not False), then try to parse the default datelike columns. A column label is datelike if

   • it ends with '_at',
   • it ends with '_time',
   • it begins with 'timestamp',
   • it is 'modified', or
   • it is 'date'.

numpy [bool, default False] Direct decoding to numpy arrays. Supports numeric data only, but non-numeric column and index labels are supported. Note also that the JSON ordering MUST be the same for each term if numpy=True.

   Deprecated since version 1.0.0.

precise_float [bool, default False] Set to enable usage of higher precision (strtod) function when decoding string to double values. Default (False) is to use fast but less precise builtin functionality.

date_unit [str, default None] The timestamp unit to detect if converting dates. The default behaviour is to try and detect the correct precision, but if this is not desired then pass one of 's', 'ms', 'us' or 'ns' to force parsing only seconds, milliseconds, microseconds or nanoseconds respectively.

encoding [str, default is 'utf-8'] The encoding to use to decode py3 bytes.

lines [bool, default False] Read the file as a json object per line.

chunksize [int, optional] Return JsonReader object for iteration. See the line-delimited json docs for more information on chunksize. This can only be passed if lines=True. If this is None, the file will be read into memory all at once.

compression [{'infer', 'gzip', 'bz2', 'zip', 'xz', None}, default 'infer'] For on-the-fly decompression of on-disk data. If 'infer', then use gzip, bz2, zip or xz if path_or_buf is a string ending in '.gz', '.bz2', '.zip', or 'xz', respectively, and no decompression otherwise. If using 'zip', the ZIP file must contain only one data file to be read in. Set to None for no decompression.

nrows [int, optional] The number of lines from the line-delimited jsonfile that has to be read. This can only be passed if lines=True. If this is None, all the rows will be returned.

New in version 1.1.
Returns

Series or DataFrame The type returned depends on the value of typ.

See also:

DataFrame.to_json Convert a DataFrame to a JSON string.
Series.to_json Convert a Series to a JSON string.

Notes

Specific to orient='table', if a DataFrame with a literal Index name of index gets written with to_json(), the subsequent read operation will incorrectly set the Index name to None. This is because index is also used by DataFrame.to_json() to denote a missing Index name, and the subsequent read_json() operation cannot distinguish between the two. The same limitation is encountered with a MultiIndex and any names beginning with 'level_'.

Examples

```python
>>> df = pd.DataFrame([['a', 'b'], ['c', 'd']],
                    index=['row 1', 'row 2'],
                    columns=['col 1', 'col 2'])
Encoding/decoding a Dataframe using 'split' formatted JSON:

```python
>>> df.to_json(orient='split')
'{"columns": ["col 1", "col 2"],
 "index": ["row 1", "row 2"],
 "data": ["a", "b"], ["c", "d"]}'
```

```python
>>> pd.read_json(_, orient='split')
   col 1 col 2
row 1    a    b
row 2    c    d
```

Encoding/decoding a Dataframe using 'index' formatted JSON:

```python
>>> df.to_json(orient='index')
'{"row 1": {"col 1": "a", "col 2": "b"},
 "row 2": {"col 1": "c", "col 2": "d"}}'
```

```python
>>> pd.read_json(_, orient='index')
   col 1 col 2
row 1    a    b
row 2    c    d
```

Encoding/decoding a Dataframe using 'records' formatted JSON. Note that index labels are not preserved with this encoding.

```python
>>> df.to_json(orient='records')
'[{"col 1": "a", "col 2": "b"}, {"col 1": "c", "col 2": "d"}]
```

```python
>>> pd.read_json(_, orient='records')
   col 1 col 2
0    a    b
1    c    d
```

Encoding with Table Schema
```python
>>> df.to_json(orient='table')
"{"schema": {"fields": [{"name": "index", "type": "string"},
  {"name": "col 1", "type": "string"},
  {"name": "col 2", "type": "string"}],
  "primaryKey": "index",
  "pandas_version": "0.20.0"},
  "data": [{"index": "row 1", "col 1": "a", "col 2": "b"},
              {"index": "row 2", "col 1": "c", "col 2": "d"}]}"
```

**pandas.json_normalize**

`pandas.json_normalize(data, record_path=None, meta=None, meta_prefix=None, record_prefix=None, errors='raise', sep='.', max_level=None)`

Normalize semi-structured JSON data into a flat table.

**Parameters**

- **data** [dict or list of dicts] Unserialized JSON objects.
- **record_path** [str or list of str, default None] Path in each object to list of records. If not passed, data will be assumed to be an array of records.
- **meta** [list of paths (str or list of str), default None] Fields to use as metadata for each record in resulting table.
- **meta_prefix** [str, default None] If True, prefix records with dotted (?) path, e.g. foo.bar.field if meta is ['foo', 'bar'].
- **record_prefix** [str, default None] If True, prefix records with dotted (?) path, e.g. foo.bar.field if path to records is ['foo', 'bar'].
- **errors** [{'raise', 'ignore'}, default 'raise'] Configures error handling.
  - ‘ignore’ : will ignore KeyError if keys listed in meta are not always present.
  - ‘raise’ : will raise KeyError if keys listed in meta are not always present.
- **sep** [str, default '.'] Nested records will generate names separated by sep. e.g., for sep='.', {'foo': {'bar': 0}} -> foo.bar.
- **max_level** [int, default None] Max number of levels(depth of dict) to normalize. if None, normalizes all levels.

**Returns**

- **frame** [DataFrame]

  Normalize semi-structured JSON data into a flat table.
Examples

```python
>>> data = [{'id': 1, 'name': {'first': 'Coleen', 'last': 'Volk'}},
          ...  
          ... {'id': 2, 'name': 'Faye Raker'}]
>>> pandas.json_normalize(data)
    id  name  name.family  name.first  name.given  name.last
0  1.0  NaN         NaN         NaN         NaN  Volk
1  NaN  NaN         Regner      NaN         Mose  NaN
2  2.0  Faye Raker  NaN         NaN         NaN  NaN
```

```python
>>> data = [{'id': 1, 'name': 'Cole Volk', 'fitness': {'height': 130, 'weight': 60}},
          ...  
          ... {'name': 'Mose Reg', 'fitness': {'height': 130, 'weight': 60}},
          ...  
          ... {'id': 2, 'name': 'Faye Raker', 'fitness': {'height': 130, 'weight': 60}}]
>>> json_normalize(data, max_level=0)
   id  name
0  1.0  Cole Volk
1  NaN  Mose Reg
2  2.0  Faye Raker
```

Normalizes nested data up to level 1.

```python
>>> data = [{'id': 1, 'name': 'Cole Volk', 'fitness': {'height': 130, 'weight': 60}},
          ...  
          ... {'name': 'Mose Reg', 'fitness': {'height': 130, 'weight': 60}},
          ...  
          ... {'id': 2, 'name': 'Faye Raker', 'fitness': {'height': 130, 'weight': 60}}]
>>> json_normalize(data, max_level=1)
   fitness.height  fitness.weight  id  name
0               130             60  1.0  Cole Volk
1               130             60  NaN  Mose Reg
2               130             60  2.0  Faye Raker
```

```python
>>> data = [{'state': 'Florida', 'shortname': 'FL', 'info': {'governor': 'Rick Scott'}},
          ...  
          ... {'state': 'Ohio', 'shortname': 'OH', 'info': {'governor': 'John Kasich'}}]
>>> result = json_normalize(data, 'counties', ['state', 'shortname', 
                                                      ...  
                                                      ... ['info', 'governor']])
>>> result
   name  population  state  shortname  info.governor
0  Dade  12345      Florida  FL        Rick Scott
1  Broward  40000  Florida  FL        Rick Scott
2 Palm Beach  60000  Florida  FL        Rick Scott
```

(continues on next page)
3 Summit 1234 Ohio OH John Kasich
4 Cuyahoga 1337 Ohio OH John Kasich

```python
>>> data = {'A': [1, 2]}
>>> json_normalize(data, 'A', record_prefix='Prefix."
Prefix.0
  0 1
  1 2
```

Returns normalized data with columns prefixed with the given string.

```python
pd.io.json.build_table_schema(data[, index, ...]) Create a Table schema from data.
```

**pd.io.json.build_table_schema**

Create a Table schema from `data`.

**Parameters**

- `data` [Series, DataFrame]
- `index` [bool, default True] Whether to include `data.index` in the schema.
- `primary_key` [bool or None, default True] Column names to designate as the primary key. The default `None` will set `primaryKey` to the index level or levels if the index is unique.
- `version` [bool, default True] Whether to include a field `pandas_version` with the version of pandas that generated the schema.

**Returns**

- `schema` [dict]

**Notes**

See Table Schema for conversion types. Timedeltas as converted to ISO8601 duration format with 9 decimal places after the seconds field for nanosecond precision.

Categoricals are converted to the `any` dtype, and use the `enum` field constraint to list the allowed values. The `ordered` attribute is included in an `ordered` field.

**Examples**

```python
>>> df = pd.DataFrame(
...     {'A': [1, 2, 3],
...      'B': ['a', 'b', 'c'],
...      'C': pd.date_range('2016-01-01', freq='d', periods=3),
...     }, index=pd.Index(range(3), name='idx'))
>>> build_table_schema(df)
{'fields': [{'name': 'idx', 'type': 'integer'},
            {'name': 'A', 'type': 'integer'},
            {'name': 'B', 'type': 'string'},
            {'name': 'C', 'type': 'datetime'}],
```
3.1.6 HTML

```
pandas.read_html(*args, **kwargs)
```

Read HTML tables into a list of DataFrame objects.

**Parameters**

- `io` [str, path object or file-like object] A URL, a file-like object, or a raw string containing HTML. Note that lxml only accepts the http, ftp and file url protocols. If you have a URL that starts with `https` you might try removing the `s`.

- `match` [str or compiled regular expression, optional] The set of tables containing text matching this regex or string will be returned. Unless the HTML is extremely simple you will probably need to pass a non-empty string here. Defaults to `.+` (match any non-empty string). The default value will return all tables contained on a page. This value is converted to a regular expression so that there is consistent behavior between Beautiful Soup and lxml.

- `flavor` [str, optional] The parsing engine to use. `bs4` and `html5lib` are synonymous with each other, they are both there for backwards compatibility. The default of `None` tries to use lxml to parse and if that fails it falls back on `bs4 + html5lib`.

- `header` [int or list-like, optional] The row (or list of rows for a `MultiIndex`) to use to make the columns headers.

- `index_col` [int or list-like, optional] The column (or list of columns) to use to create the index.

- `skiprows` [int, list-like or slice, optional] Number of rows to skip after parsing the column integer. 0-based. If a sequence of integers or a slice is given, will skip the rows indexed by that sequence. Note that a single element sequence means ‘skip the nth row’ whereas an integer means ‘skip n rows’.

- `attrs` [dict, optional] This is a dictionary of attributes that you can pass to use to identify the table in the HTML. These are not checked for validity before being passed to lxml or Beautiful Soup. However, these attributes must be valid HTML table attributes to work correctly. For example,

```
attrs = {'id': 'table'}
```

is a valid attribute dictionary because the ‘id’ HTML tag attribute is a valid HTML attribute for any HTML tag as per this document.

```
attrs = {'asdf': 'table'}
```

is not a valid attribute dictionary because ‘asdf’ is not a valid HTML attribute even if it is a valid XML attribute. Valid HTML 4.01 table attributes can be found here. A working draft
of the HTML 5 spec can be found here. It contains the latest information on table attributes for the modern web.

**parse_dates** [bool, optional] See `read_csv()` for more details.

**thousands** [str, optional] Separator to use to parse thousands. Defaults to ‘,’.

**encoding** [str, optional] The encoding used to decode the web page. Defaults to `None`. "None" preserves the previous encoding behavior, which depends on the underlying parser library (e.g., the parser library will try to use the encoding provided by the document).

**decimal** [str, default '.'] Character to recognize as decimal point (e.g. use ',' for European data).

**converters** [dict, default None] Dict of functions for converting values in certain columns. Keys can either be integers or column labels, values are functions that take one input argument, the cell (not column) content, and return the transformed content.

**na_values** [iterable, default None] Custom NA values.

**keep_default_na** [bool, default True] If na_values are specified and keep_default_na is False the default NaN values are overridden, otherwise they’re appended to.

**displayed_only** [bool, default True] Whether elements with “display: none” should be parsed.

**Returns**

- **dfs** A list of DataFrames.

**See also:**

- `read_csv` Read a comma-separated values (csv) file into DataFrame.

**Notes**

Before using this function you should read the [gotchas about the HTML parsing libraries](#).

Expect to do some cleanup after you call this function. For example, you might need to manually assign column names if the column names are converted to NaN when you pass the `header=0` argument. We try to assume as little as possible about the structure of the table and push the idiosyncrasies of the HTML contained in the table to the user.

This function searches for `<table>` elements and only for `<tr>` and `<th>` rows and `<td>` elements within each `<tr>` or `<th>` element in the table. `<td>` stands for “table data”. This function attempts to properly handle `colspan` and `rowspan` attributes. If the function has a `<thead>` argument, it is used to construct the header, otherwise the function attempts to find the header within the body (by putting rows with only `<th>` elements into the header).

Similar to `read_csv()` the `header` argument is applied after `skiprows` is applied.

This function will *always* return a list of `DataFrame` or it will fail, e.g., it will *not* return an empty list.
Examples

See the *read_html documentation in the IO section of the docs* for some examples of reading in HTML tables.

### 3.1.7 HDFStore: PyTables (HDF5)

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>read_hdf</td>
<td>Read from the store, close it if we opened it.</td>
</tr>
<tr>
<td>HDFStore.put</td>
<td>Store object in HDFStore.</td>
</tr>
<tr>
<td>HDFStore.append</td>
<td>Append to Table in file.</td>
</tr>
<tr>
<td>HDFStore.get</td>
<td>Retrieve pandas object stored in file.</td>
</tr>
<tr>
<td>HDFStore.select</td>
<td>Retrieve pandas object stored in file, optionally based on where criteria.</td>
</tr>
<tr>
<td>HDFStore.info</td>
<td>Print detailed information on the store.</td>
</tr>
<tr>
<td>HDFStore.keys</td>
<td>Return a list of keys corresponding to objects stored in HDFStore.</td>
</tr>
<tr>
<td>HDFStore.groups</td>
<td>Return a list of all the top-level nodes.</td>
</tr>
<tr>
<td>HDFStore.walk</td>
<td>Walk the pytables group hierarchy for pandas objects.</td>
</tr>
</tbody>
</table>

**pandas.read_hdf**

```python
pandas.read_hdf(path_or_buf, key=None, mode='r', errors='strict', where=None, start=None, stop=None, columns=None, iterator=False, chunksize=None, **kwargs)
```

Read from the store, close it if we opened it.

Retrieve pandas object stored in file, optionally based on where criteria.

*Warning:* Pandas uses PyTables for reading and writing HDF5 files, which allows serializing object-dtype data with pickle when using the “fixed” format. Loading pickled data received from untrusted sources can be unsafe.

See: https://docs.python.org/3/library/pickle.html for more.

**Parameters**

- **path_or_buf** [str, path object, pandas.HDFStore or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: file://localhost/path/to/table.h5.

  If you want to pass in a path object, pandas accepts any os.PathLike.

  Alternatively, pandas accepts an open pandas.HDFStore object.

  By file-like object, we refer to objects with a `read()` method, such as a file handler (e.g. via builtin `open` function) or `StringIO`.

- **key** [object, optional] The group identifier in the store. Can be omitted if the HDF file contains a single pandas object.

- **mode** [{'r', 'r+', 'a'}, default 'r'] Mode to use when opening the file. Ignored if `path_or_buf` is a pandas.HDFStore. Default is 'r'.

- **errors** [str, default 'strict'] Specifies how encoding and decoding errors are to be handled. See the errors argument for `open()` for a full list of options.
where  [list, optional] A list of Term (or convertible) objects.
start  [int, optional] Row number to start selection.
stop  [int, optional] Row number to stop selection.
columns  [list, optional] A list of columns names to return.
iterator  [bool, optional] Return an iterator object.
chunksize  [int, optional] Number of rows to include in an iteration when using an iterator.
**kwargs Additional keyword arguments passed to HDFStore.

Returns
  item  [object] The selected object. Return type depends on the object stored.

See also:
  DataFrame.to_hdf Write a HDF file from a DataFrame.
  HDFStore Low-level access to HDF files.

Examples

```python
>>> df = pd.DataFrame([[1, 1.0, 'a']], columns=['x', 'y', 'z'])
>>> df.to_hdf('./store.h5', 'data')
>>> reread = pd.read_hdf('./store.h5')
```

pandas.HDFStore.put

HDFStore.put(key, value, format=None, index=True, append=False, complib=None, complevel=None, min_itemsize=None, nan_rep=None, data_columns=None, encoding=None, errors='strict', track_times=True)

Store object in HDFStore.

Parameters
  key  [str]
  value  ([Series, DataFrame])
  format  ['fixed(f)|table(t)', default is 'fixed'] Format to use when storing object in HDFStore.
  Value can be one of:
    'fixed' Fixed format. Fast writing/reading. Not-appendable, nor searchable.
    'table' Table format. Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data.
  append  [bool, default False] This will force Table format, append the input data to the existing.
  data_columns  [list, default None] List of columns to create as data columns, or True to use all columns. See here.
  encoding  [str, default None] Provide an encoding for strings.
  dropna  [bool, default False, do not write an ALL nan row to] The store settable by the option ‘io.hdf.dropna_table’.
track_times [bool, default True] Parameter is propagated to ‘create_table’ method of ‘PyTables’. If set to False it enables to have the same h5 files (same hashes) independent on creation time.

New in version 1.1.0.

pandas.HDFStore.append

HDFStore.append(key, value, format=None, axes=None, index=True, append=True, complevel=None, columns=None, min_itemsize=None, nan_rep=None, chunksize=None, expectedrows=None, dropna=None, data_columns=None, encoding=None, errors='strict')

Append to Table in file. Node must already exist and be Table format.

Parameters

- key [str]
- value [{Series, DataFrame}]
- format ['table' is the default] Format to use when storing object in HDFStore. Value can be one of:
  - 'table': Table format. Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data.
- append [bool, default True] Append the input data to the existing.
- data_columns [list of columns, or True, default None] List of columns to create as indexed data columns for on-disk queries, or True to use all columns. By default only the axes of the object are indexed. See here.
- min_itemsize [dict of columns that specify minimum str sizes]
- nan_rep [str to use as str nan representation]
- chunksize [size to chunk the writing]
- expectedrows [expected TOTAL row size of this table]
- encoding [default None, provide an encoding for str]
- dropna [bool, default False] Do not write an ALL nan row to the store settable by the option 'io.hdf.dropna_table'.

Notes

Does not check if data being appended overlaps with existing data in the table, so be careful.

pandas.HDFStore.get

HDFStore.get(key)

Retrieve pandas object stored in file.

Parameters

- key [str]

Returns

- object Same type as object stored in file.
pandas.HDFStore.select

HDFStore.select(key, where=None, start=None, stop=None, columns=None, iterator=False, chunksize=None, auto_close=False)

Retrieve pandas object stored in file, optionally based on where criteria.

**Warning:** Pandas uses PyTables for reading and writing HDF files, which allows serializing object-dtype data with pickle when using the “fixed” format. Loading pickled data received from untrusted sources can be unsafe.

See: https://docs.python.org/3/library/pickle.html for more.

**Parameters**

- **key** [str] Object being retrieved from file.
- **where** [list, default None] List of Term (or convertible) objects, optional.
- **start** [int, default None] Row number to start selection.
- **stop** [int, default None] Row number to stop selection.
- **columns** [list, default None] A list of columns that if not None, will limit the return columns.
- **iterator** [bool, default False] Returns an iterator.
- **chunksize** [int, default None] Number or rows to include in iteration, return an iterator.
- **auto_close** [bool, default False] Should automatically close the store when finished.

**Returns**

- **object** Retrieved object from file.

pandas.HDFStore.info

HDFStore.info()

Print detailed information on the store.

**Returns**

- **str**

pandas.HDFStore.keys

HDFStore.keys(include='pandas')

Return a list of keys corresponding to objects stored in HDFStore.

**Parameters**

- **include** [str, default ‘pandas’] When kind equals ‘pandas’ return pandas objects When kind equals ‘native’ return native HDF5 Table objects

New in version 1.1.0.

**Returns**

- **list** List of ABSOLUTE path-names (e.g. have the leading ‘/’).
raises ValueError if kind has an illegal value

**pandas.HDFStore.groups**

HDFStore.

**groups** ()

Return a list of all the top-level nodes.

Each node returned is not a pandas storage object.

**Returns**

list List of objects.

**pandas.HDFStore.walk**

HDFStore.

**walk** (where='/')

Walk the pytables group hierarchy for pandas objects.

This generator will yield the group path, subgroups and pandas object names for each group.

Any non-pandas PyTables objects that are not a group will be ignored.

The where group itself is listed first (preorder), then each of its child groups (following an alphanumerical order) is also traversed, following the same procedure.

New in version 0.24.0.

**Parameters**

where [str, default ‘/’] Group where to start walking.

**Yields**

path [str] Full path to a group (without trailing ‘/’).

groups [list] Names (strings) of the groups contained in path.

leaves [list] Names (strings) of the pandas objects contained in path.

---

**3.1.8 Feather**

**read_feather**(path[, columns, use_threads]) Load a feather-format object from the file path.

**pandas.read_feather**

pandas.

**read_feather** (path, columns=None, use_threads=True)

Load a feather-format object from the file path.

**Parameters**

path [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: file://localhost/path/to/table.feather.

If you want to pass in a path object, pandas accepts any os.PathLike.

By file-like object, we refer to objects with a read() method, such as a file handler (e.g. via builtin open function) or StringIO.
columns [sequence, default None] If not provided, all columns are read.

    New in version 0.24.0.

use_threads [bool, default True]

    Whether to parallelize reading using multiple threads.

    New in version 0.24.0.

Returns

type of object stored in file

3.1.9 Parquet

read_parquet(path[, engine, columns])

Load a parquet object from the file path, returning a DataFrame.

pandas.read_parquet

pandas.read_parquet (path, engine='auto', columns=None, **kwargs)

Load a parquet object from the file path, returning a DataFrame.

Parameters

    path [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: file://localhost/path/to/table.parquet. A file URL can also be a path to a directory that contains multiple partitioned parquet files. Both pyarrow and fastparquet support paths to directories as well as file URLs. A directory path could be: file://localhost/path/to/tables or s3://bucket/partition_dir

    If you want to pass in a path object, pandas accepts any os.PathLike.

    By file-like object, we refer to objects with a read() method, such as a file handler (e.g. via builtins.open function) or StringIO.

    engine [{‘auto’, ‘pyarrow’, ‘fastparquet’}, default ‘auto’] Parquet library to use. If ‘auto’, then the option io.parquet.engine is used. The default io.parquet.engine behavior is to try ‘pyarrow’, falling back to ‘fastparquet’ if ‘pyarrow’ is unavailable.

    columns [list, default=None] If not None, only these columns will be read from the file.

    **kwargs Any additional kwargs are passed to the engine.

Returns

    DataFrame
3.1.10 ORC

```
read_orc(path[, columns])
```

Load an ORC object from the file path, returning a DataFrame.

**pandas.read_orc**

```
pandas.read_orc(path, columns=None, **kwargs)
```

Load an ORC object from the file path, returning a DataFrame.

New in version 1.0.0.

**Parameters**

- `path` [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: `file:///localhost/path/to/table.orc`. If you want to pass in a path object, pandas accepts any `os.PathLike`.
  
  By file-like object, we refer to objects with a `read()` method, such as a file handler (e.g. via built-in open function) or `StringIO`.

- `columns` [list, default None] If not None, only these columns will be read from the file.

- `**kwargs` Any additional kwargs are passed to pyarrow.

**Returns**

DataFrame

3.1.11 SAS

```
read_sas()
```

Read SAS files stored as either XPORT or SAS7BDAT format files.

**pandas.read_sas**

```
```

Read SAS files stored as either XPORT or SAS7BDAT format files.

**Parameters**

- `filepath_or_buffer` [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: `file:///localhost/path/to/table.sas`. If you want to pass in a path object, pandas accepts any `os.PathLike`.
  
  By file-like object, we refer to objects with a `read()` method, such as a file handler (e.g. via built-in open function) or `StringIO`.  

3.1. Input/output
format [str {'xport', 'sas7bdat'} or None] If None, file format is inferred from file extension. If 'xport' or 'sas7bdat', uses the corresponding format.

index [identifier of index column, defaults to None] Identifier of column that should be used as index of the DataFrame.

encoding [str, default is None] Encoding for text data. If None, text data are stored as raw bytes.

chunksize [int] Read file chunksize lines at a time, returns iterator.

iterator [bool, defaults to False] If True, returns an iterator for reading the file incrementally.

Returns

DataFrame if iterator=False and chunksize=None, else SAS7BDATReader or XportReader

3.1.12 SPSS

read_spss(path[, usecols, convert_categoricals]) Load an SPSS file from the file path, returning a DataFrame.

pandas.read_spss

pandas.read_spss(path, usecols=None, convert_categoricals=True)
Load an SPSS file from the file path, returning a DataFrame.

New in version 0.25.0.

Parameters

path [str or Path] File path.
usecols [list-like, optional] Return a subset of the columns. If None, return all columns.
convert_categoricals [bool, default is True] Convert categorical columns into pd.Categorical.

Returns

DataFrame

3.1.13 SQL

read_sql_table() Read SQL database table into a DataFrame.
read_sql_query() Read SQL query into a DataFrame.
read_sql() Read SQL query or database table into a DataFrame.
pandas.read_sql_table

pandas.read_sql_table (table_name, con, schema='None', index_col='None', coerce_float='True',
parse_dates='None', columns='None', chunksize:  None = 'None') → DataFrame
pandas.read_sql_table (table_name, con, schema='None', index_col='None', coerce_float='True',
parse_dates='None', columns='None', chunksize:  int = '1') → Iterator[DataFrame]

Read SQL database table into a DataFrame.

Given a table name and a SQLAlchemy connectable, returns a DataFrame. This function does not support
DBAPI connections.

Parameters

  table_name  [str] Name of SQL table in database.
  con         [SQLAlchemy connectable or str] A database URI could be provided as as str. SQLite
              DBAPI connection mode not supported.
  schema      [str, default None] Name of SQL schema in database to query (if database flavor sup-
              ports this). Uses default schema if None (default).
  index_col   [str or list of str, optional, default: None] Column(s) to set as index(MultiIndex).
  coerce_float [bool, default True] Attempts to convert values of non-string, non-numeric objects
              (like decimal.Decimal) to floating point. Can result in loss of Precision.
  parse_dates [list or dict, default None]
    • List of column names to parse as dates.
    • Dict of {column_name: format string} where format string is strftime compat-
      ible in case of parsing string times or is one of (D, s, ns, ms, us) in case of parsing integer
      timestamps.
    • Dict of {column_name: arg dict}, where the arg dict corresponds to the keyword
      arguments of pandas.to_datetime() Especially useful with databases without na-
      tive Datetime support, such as SQLite.
  columns     [list, default None] List of column names to select from SQL table.
  chunksize   [int, default None] If specified, returns an iterator where chunksize is the number of
              rows to include in each chunk.

Returns

  DataFrame or Iterator[DataFrame]  A SQL table is returned as two-dimensional data struc-
                                  ture with labeled axes.

See also:

read_sql_query  Read SQL query into a DataFrame.
read_sql    Read SQL query or database table into a DataFrame.

3.1. Input/output
Notes

Any datetime values with time zone information will be converted to UTC.

Examples

```python
>>> pd.read_sql_table('table_name', 'postgres:///db_name')
```

**pandas.read_sql_query**

```python
pandas.read_sql_query(sql, con, index_col='None', coerce_float='True', params='None', parse_dates='None', chunksize=None) -> DataFrame
pandas.read_sql_query(sql, con, index_col='None', coerce_float='True', params='None', parse_dates='None', chunksize: int = '1') -> Iterator[DataFrame]
```

Read SQL query into a DataFrame.

Returns a DataFrame corresponding to the result set of the query string. Optionally provide an `index_col` parameter to use one of the columns as the index, otherwise default integer index will be used.

**Parameters**

- `sql` [str SQL query or SQLAlchemy Selectable (select or text object)] SQL query to be executed.
- `con` [SQLAlchemy connectable, str, or sqlite3 connection] Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.
- `index_col` [str or list of str, optional, default: None] Column(s) to set as index(MultiIndex).
- `coerce_float` [bool, default True] Attempts to convert values of non-string, non-numeric objects (like decimal.Decimal) to floating point. Useful for SQL result sets.
- `params` [list, tuple or dict, optional, default: None] List of parameters to pass to execute method. The syntax used to pass parameters is database driver dependent. Check your database driver documentation for which of the five syntax styles, described in PEP 249’s paramstyle, is supported. Eg. for psycopg2, uses %(name)s so use params={'name': 'value'}.
- `parse_dates` [list or dict, default: None] List of column names to parse as dates.
  - Dict of {column_name: format_string} where format_string is strftime compatible in case of parsing string times, or is one of (D, s, ns, ms, us) in case of parsing integer timestamps.
  - Dict of {column_name: arg dict}, where the arg dict corresponds to the keyword arguments of `pandas.to_datetime()` Especially useful with databases without native Datetime support, such as SQLite.
- `chunksize` [int, default None] If specified, return an iterator where chunksize is the number of rows to include in each chunk.

**Returns**

DataFrame or Iterator[DataFrame]

**See also:**

- `read_sql_table` Read SQL database table into a DataFrame.
**read_sql** Read SQL query or database table into a DataFrame.

**Notes**

Any datetime values with time zone information parsed via the `parse_dates` parameter will be converted to UTC.

```python
def read_sql(sql, con, index_col='None', coerce_float='True', params='None', parse_dates='None', columns='None', chunksize: int = '1') -> DataFrame
```

Read SQL query or database table into a DataFrame.

This function is a convenience wrapper around `read_sql_table` and `read_sql_query` (for backward compatibility). It will delegate to the specific function depending on the provided input. A SQL query will be routed to `read_sql_query`, while a database table name will be routed to `read_sql_table`. Note that the delegated function might have more specific notes about their functionality not listed here.

**Parameters**

- `sql` [str or SQLAlchemySelectable (select or text object)] SQL query to be executed or a table name.
- `con` [SQLAlchemy connectable, str, or sqlite3 connection] Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported. The user is responsible for engine disposal and connection closure for the SQLAlchemy connectable. See [here](#).
- `index_col` [str or list of str, optional, default: None] Column(s) to set as index(MultiIndex).
- `coerce_float` [bool, default True] Attempts to convert values of non-string, non-numeric objects (like decimal.Decimal) to floating point, useful for SQL result sets.
- `params` [list, tuple or dict, optional, default: None] List of parameters to pass to execute method. The syntax used to pass parameters is database driver dependent. Check your database driver documentation for which of the five syntax styles, described in PEP 249’s paramstyle, is supported. Eg. for psycopg2, uses %(name)s so use params={'name': 'value'}.
- `parse_dates` [list or dict, default: None]  
  - List of column names to parse as dates.
  - Dict of {column_name: format string} where format string is strftime compatible in case of parsing string times, or is one of (D, s, ns, ms, us) in case of parsing integer timestamps.
  - Dict of {column_name: arg dict}, where the arg dict corresponds to the keyword arguments of `pandas.to_datetime()` Especially useful with databases without native Datetime support, such as SQLite.
- `columns` [list, default: None] List of column names to select from SQL table (only used when reading a table).
- `chunksize` [int, default None] If specified, return an iterator where `chunksize` is the number of rows to include in each chunk.

**Returns**
DataFrame or Iterator[DataFrame]

See also:

read_sql_table  Read SQL database table into a DataFrame.
read_sql_query  Read SQL query into a DataFrame.

3.1.14 Google BigQuery

read_gbq(query[, project_id, index_col, ...])  Load data from Google BigQuery.

pandas.read_gbq

pandas.read_gbq(query, project_id=None, index_col=None, col_order=None, reauth=False, auth_local_webserver=False, dialect=None, location=None, configuration=None, credentials=None, use_bqstorage_api=None, max_results=None, private_key=None, verbose=None, progress_bar_type=None)

Load data from Google BigQuery.

This function requires the pandas-gbq package.

See the How to authenticate with Google BigQuery guide for authentication instructions.

Parameters

query  [str] SQL-Like Query to return data values.
project_id  [str, optional] Google BigQuery Account project ID. Optional when available from the environment.
index_col  [str, optional] Name of result column to use for index in results DataFrame.
col_order  [list(str), optional] List of BigQuery column names in the desired order for results DataFrame.
reauth  [bool, default False] Force Google BigQuery to re-authenticate the user. This is useful if multiple accounts are used.
auth_local_webserver  [bool, default False] Use the local webserver flow instead of the console flow when getting user credentials.
New in version 0.2.0 of pandas-gbq.
dialect  [str, default ‘legacy’] Note: The default value is changing to ‘standard’ in a future version.
SQL syntax dialect to use. Value can be one of:
‘legacy’  Use BigQuery’s legacy SQL dialect. For more information see BigQuery Legacy SQL Reference.
‘standard’  Use BigQuery’s standard SQL, which is compliant with the SQL 2011 standard. For more information see BigQuery Standard SQL Reference.
Changed in version 0.24.0.
location  [str, optional] Location where the query job should run. See the BigQuery locations documentation for a list of available locations. The location must match that of any datasets used in the query.
New in version 0.5.0 of pandas-gbq.

**configuration** [dict, optional] Query config parameters for job processing. For example:

```python
configuration = {'query': {'useQueryCache': False}}
```

For more information see BigQuery REST API Reference.

**credentials** [google.auth.credentials.Credentials, optional] Credentials for accessing Google APIs. Use this parameter to override default credentials, such as to use Compute Engine google.auth.compute_engine.Credentials or Service Account google.oauth2.service_account.Credentials directly.

New in version 0.8.0 of pandas-gbq.

New in version 0.24.0.

**use_bqstorage_api** [bool, default False] Use the BigQuery Storage API to download query results quickly, but at an increased cost. To use this API, first enable it in the Cloud Console. You must also have the bigquery.readsessions.create permission on the project you are billing queries to.

This feature requires version 0.10.0 or later of the pandas-gbq package. It also requires the google-cloud-bigquery-storage and fastavro packages.

New in version 0.25.0.

**max_results** [int, optional] If set, limit the maximum number of rows to fetch from the query results.

New in version 0.12.0 of pandas-gbq.

New in version 1.1.0.

**progress_bar_type** [Optional, str] If set, use the tqdm library to display a progress bar while the data downloads. Install the tqdm package to use this feature.

Possible values of **progress_bar_type** include:

- **None** No progress bar.
- **tqdm** Use the tqdm.tqdm() function to print a progress bar to sys.stderr.
- **tqdm_notebook** Use the tqdm.tqdm_notebook() function to display a progress bar as a Jupyter notebook widget.
- **tqdm_gui** Use the tqdm.tqdm_gui() function to display a progress bar as a graphical dialog box.

Note that his feature requires version 0.12.0 or later of the pandas-gbq package. And it requires the tqdm package. Slightly different than pandas-gbq, here the default is **None**.

New in version 1.0.0.

Returns

**df**: DataFrame DataFrame representing results of query.

See also:

- **pandas_gbq.read_gbq** This function in the pandas-gbq library.
- **DataFrame.to_gbq** Write a DataFrame to Google BigQuery.
3.1.15 STATA

`read_stata(filepath_or_buffer[, ...])` Read Stata file into DataFrame.

**pandas.read_stata**

`pandas.read_stata(filepath_or_buffer, convert_dates=True, convert_categoricals=True, index_col=None, convert_missing=False, preserve_dtypes=True, columns=None, order_categoricals=True, chunksize=None, iterator=False)`

Read Stata file into DataFrame.

**Parameters**

- `filepath_or_buffer` [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: `file://localhost/path/to/table.dta`. If you want to pass in a path object, pandas accepts any `os.PathLike`.

  By file-like object, we refer to objects with a `read()` method, such as a file handler (e.g. via built-in `open` function) or `StringIO`.

- `convert_dates` [bool, default True] Convert date variables to DataFrame time values.

- `convert_categoricals` [bool, default True] Read value labels and convert columns to Categorical/Factor variables.

- `index_col` [str, optional] Column to set as index.

- `convert_missing` [bool, default False] Flag indicating whether to convert missing values to their Stata representations. If False, missing values are replaced with `nan`. If True, columns containing missing values are returned with object data types and missing values are represented by StataMissingValue objects.

- `preserve_dtypes` [bool, default True] Preserve Stata datatypes. If False, numeric data are upcast to pandas default types for foreign data (float64 or int64).

- `columns` [list or None] Columns to retain. Columns will be returned in the given order. None returns all columns.

- `order_categoricals` [bool, default True] Flag indicating whether converted categorical data are ordered.

- `chunksize` [int, default None] Return StataReader object for iterations, returns chunks with given number of lines.

- `iterator` [bool, default False] Return StataReader object.

**Returns**

- DataFrame or StataReader

See also:

- `io.stata.StataReader` Low-level reader for Stata data files.

- `DataFrame.to_stata` Export Stata data files.
Notes

Categorical variables read through an iterator may not have the same categories and dtype. This occurs when a variable stored in a DTA file is associated to an incomplete set of value labels that only label a strict subset of the values.

Examples

Read a Stata dta file:

```python
>>> df = pd.read_stata('filename.dta')
```

Read a Stata dta file in 10,000 line chunks:

```python
>>> itr = pd.read_stata('filename.dta', chunksize=10000)
>>> for chunk in itr:
...     do_something(chunk)
```

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>StataReader.data_label</td>
<td>Return data label of Stata file.</td>
</tr>
<tr>
<td>StataReader.value_labels()</td>
<td>Return a dict, associating each variable name a dict, associating each value its corresponding label.</td>
</tr>
<tr>
<td>StataReader.variable_labels()</td>
<td>Return variable labels as a dict, associating each variable name with corresponding label.</td>
</tr>
<tr>
<td>StataWriter.write_file()</td>
<td></td>
</tr>
</tbody>
</table>
### 3.2 General functions

#### 3.2.1 Data manipulations

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>melt(frame[, id_vars, value_vars, var_name, ...])</td>
<td>Unpivot a DataFrame from wide to long format, optionally leaving identifiers set.</td>
</tr>
<tr>
<td>pivot(data[, index, columns, values])</td>
<td>Return reshaped DataFrame organized by given index / column values.</td>
</tr>
<tr>
<td>pivot_table(data[, values, index, columns, ...])</td>
<td>Create a spreadsheet-style pivot table as a DataFrame.</td>
</tr>
<tr>
<td>crosstab(index, columns[, values, rownames, ...])</td>
<td>Compute a simple cross tabulation of two (or more) factors.</td>
</tr>
<tr>
<td>cut(x, bins[, right, labels, retbins, ...])</td>
<td>Bin values into discrete intervals.</td>
</tr>
<tr>
<td>qcut(x, q[, labels, retbins, precision, ...])</td>
<td>Quantile-based discretization function.</td>
</tr>
<tr>
<td>merge(left, right[, how, on, left_on, ...])</td>
<td>Merge DataFrame or named Series objects with a database-style join.</td>
</tr>
<tr>
<td>merge_ordered(left, right[, on, left_on, ...])</td>
<td>Perform merge with optional filling/interpolation.</td>
</tr>
<tr>
<td>merge_asof(left, right[, on, left_on, ...])</td>
<td>Perform an asof merge.</td>
</tr>
<tr>
<td>concat()</td>
<td>Concatenate pandas objects along a particular axis with optional set logic along the other axes.</td>
</tr>
<tr>
<td>get_dummies(data[, prefix, prefix_sep, ...])</td>
<td>Convert categorical variable into dummy/indicator variables.</td>
</tr>
<tr>
<td>factorize(values[, sort, na_sentinel, ...])</td>
<td>Encode the object as an enumerated type or categorical variable.</td>
</tr>
<tr>
<td>unique(values)</td>
<td>Hash table-based unique.</td>
</tr>
<tr>
<td>wide_to_long(df, stubnames, i, j[, sep, suffix])</td>
<td>Wide panel to long format.</td>
</tr>
</tbody>
</table>

**pandas.melt**

pandas.melt (frame, id_vars=None, value_vars=None, var_name=None, value_name='value', col_level=None, ignore_index=True)

Unpivot a DataFrame from wide to long format, optionally leaving identifiers set.

This function is useful to massage a DataFrame into a format where one or more columns are identifier variables (id_vars), while all other columns, considered measured variables (value_vars), are “unpivoted” to the row axis, leaving just two non-identifier columns, ‘variable’ and ‘value’.

**Parameters**

- **id_vars** [tuple, list, or ndarray, optional] Column(s) to use as identifier variables.
- **value_vars** [tuple, list, or ndarray, optional] Column(s) to unpivot. If not specified, uses all columns that are not set as id_vars.
- **var_name** [scalar] Name to use for the ‘variable’ column. If None it uses frame.columns.name or ‘variable’.
- **value_name** [scalar, default ‘value’] Name to use for the ‘value’ column.
- **col_level** [int or str, optional] If columns are a MultiIndex then use this level to melt.
**ignore_index** [bool, default True] If True, original index is ignored. If False, the original index is retained. Index labels will be repeated as necessary.

New in version 1.1.0.

**Returns**

**DataFrame** Unpivoted DataFrame.

**See also:**

**DataFrame.melt** Identical method.

**pivot_table** Create a spreadsheet-style pivot table as a DataFrame.

**DataFrame.pivot** Return reshaped DataFrame organized by given index / column values.

**DataFrame.explode** Explode a DataFrame from list-like columns to long format.

**Examples**

```python
>>> df = pd.DataFrame({'A': {0: 'a', 1: 'b', 2: 'c'},
...                     'B': {0: 1, 1: 3, 2: 5},
...                     'C': {0: 2, 1: 4, 2: 6}})
>>> df
      A  B  C
0    a  1  2
1    b  3  4
2    c  5  6

>>> pd.melt(df, id_vars=['A'], value_vars=['B'])
   A    variable  value
0  a         B   1
1  b         B   3
2  c         B   5

>>> pd.melt(df, id_vars=['A'], value_vars=['B', 'C'])
   A    variable  value
0  a         B   1
1  b         B   3
2  c         B   5
3  a         C   2
4  b         C   4
5  c         C   6

The names of ‘variable’ and ‘value’ columns can be customized:

```python
>>> pd.melt(df, id_vars=['A'], value_vars=['B'],
...          var_name='myVarname', value_name='myValname')
   A    myVarname  myValname
0  a         B   1
1  b         B   3
2  c         B   5
```

Original index values can be kept around:

```python
... var_name='myVarname', value_name='myValname')
   A    myVarname  myValname
0  a         B   1
1  b         B   3
2  c         B   5
```
```python
>>> pd.melt(df, id_vars=['A'], value_vars=['B', 'C'], ignore_index=False)
    A  variable  value
0  a       B     1
1  b       B     3
2  c       B     5
0  a       C     2
1  b       C     4
2  c       C     6

If you have multi-index columns:

```python
>>> df.columns = [list('ABC'), list('DEF')]
>>> df
   A  B  C  D  E  F
0  a  1  2  
1  b  3  4  
2  c  5  6  
```python
>>> pd.melt(df, col_level=0, id_vars=['A'], value_vars=['B'])
    A  variable  value
0  a       B     1
1  b       B     3
2  c       B     5
```python
>>> pd.melt(df, id_vars=[('A', 'D')], value_vars=[('B', 'E')])
   (A, D)  variable_0  variable_1  value
0  a      B       E       1
1  b      B       E       3
2  c      B       E       5

pandas.pivot

pandas.pivot(data, index=None, columns=None, values=None)

Return reshaped DataFrame organized by given index / column values.

Reshape data (produce a “pivot” table) based on column values. Uses unique values from specified index / columns to form axes of the resulting DataFrame. This function does not support data aggregation, multiple values will result in a MultiIndex in the columns. See the User Guide for more on reshaping.

Parameters

data  [DataFrame]

index  [str or object or a list of str, optional] Column to use to make new frame’s index. If None, uses existing index.

    Changed in version 1.1.0: Also accept list of index names.

columns  [str or object or a list of str] Column to use to make new frame’s columns.

    Changed in version 1.1.0: Also accept list of columns names.

values  [str, object or a list of the previous, optional] Column(s) to use for populating new frame’s values. If not specified, all remaining columns will be used and the result will have hierarchically indexed columns.

    Changed in version 0.23.0: Also accept list of column names.
Returns

**DataFrame** Returns reshaped DataFrame.

Raises

**ValueError**: When there are any *index*, *columns* combinations with multiple values. *DataFrame.pivot_table* when you need to aggregate.

See also:

*DataFrame.pivot_table* Generalization of pivot that can handle duplicate values for one index/column pair.

*DataFrame.unstack* Pivot based on the index values instead of a column.

Notes

For finer-tuned control, see hierarchical indexing documentation along with the related stack/unstack methods.

Examples

```python
>>> df = pd.DataFrame({'foo': ['one', 'one', 'one', 'two', 'two', ...
...   'two'],
...   'bar': ['A', 'B', 'C', 'A', 'B', 'C'],
...   'baz': [1, 2, 3, 4, 5, 6],
...   'zoo': ['x', 'y', 'z', 'q', 'w', 't']})
>>> df
   foo  bar  baz  zoo
0  one   A    1   x
1  one   B    2   y
2  one   C    3   z
3  two   A    4   q
4  two   B    5   w
5  two   C    6   t

>>> df.pivot(index='foo', columns='bar', values='baz')
   bar
foo
one  A  B  C
  1  2  3
two 4  5  6

>>> df.pivot(index='foo', columns='bar')['baz']
   bar
foo
one  A  B  C
  1  2  3
two 4  5  6

>>> df.pivot(index='foo', columns='bar', values=['baz', 'zoo'])
   baz  zoo
bar
foo
one  A  B  C
  1  2  3  x  y  z
two 4  5  6  q  w  t
```

You could also assign a list of column names or a list of index names.
```python
>>> df = pd.DataFrame({
...     "lev1": [1, 1, 2, 2, 2],
...     "lev2": [1, 1, 2, 1, 2],
...     "lev3": [1, 2, 1, 2, 2],
...     "lev4": [1, 2, 3, 4, 5],
...     "values": [0, 1, 2, 3, 4]})

>>> df
lev1 lev2 lev3 lev4 values
0 1 1 1 1 0
1 1 1 2 2 1
2 1 2 1 3 2
3 2 1 2 4 3
4 2 1 1 5 4
5 2 2 2 6 5

>>> df.pivot(index="lev1", columns=["lev2", "lev3"],values="values")
lev2 1 2
lev3 1 2 1 2
lev1
1 0.0 1.0 2.0 NaN
2 4.0 3.0 NaN 5.0

>>> df.pivot(index=["lev1", "lev2"], columns=["lev3"],values="values")
lev3 1 2
lev1 lev2
1 1 0.0 1.0
2 2.0 NaN
2 1 4.0 3.0
2 NaN 5.0

A ValueError is raised if there are any duplicates.

>>> df = pd.DataFrame({"foo": ['one', 'one', 'two', 'two'],
...     "bar": ['A', 'A', 'B', 'C'],
...     "baz": [1, 2, 3, 4]})

>>> df
foo bar baz
0 one A 1
1 one A 2
2 two B 3
3 two C 4

Notice that the first two rows are the same for our index and columns arguments.

>>> df.pivot(index='foo', columns='bar', values='baz')
Traceback (most recent call last):
...
ValueError: Index contains duplicate entries, cannot reshape
```
pandas.pivot_table

```python
pandas.pivot_table(data, values=None, index=None, columns=None, aggfunc='mean', fill_value=None, margins=False, dropna=True, margins_name='All', observed=False)
```

Create a spreadsheet-style pivot table as a DataFrame.

The levels in the pivot table will be stored in MultiIndex objects (hierarchical indexes) on the index and columns of the result DataFrame.

**Parameters**

- **data** [DataFrame]
  - [column to aggregate, optional]

- **values** [column to aggregate, optional]

- **index** [column, Grouper, array, or list of the previous]
  - If an array is passed, it must be the same length as the data. The list can contain any of the other types (except list). Keys to group by on the pivot table index. If an array is passed, it is being used as the same manner as column values.

- **columns** [column, Grouper, array, or list of the previous]
  - If an array is passed, it must be the same length as the data. The list can contain any of the other types (except list). Keys to group by on the pivot table column. If an array is passed, it is being used as the same manner as column values.

- **aggfunc** [function, list of functions, dict, default numpy.mean]
  - If list of functions passed, the resulting pivot table will have hierarchical columns whose top level are the function names (inferred from the function objects themselves) If dict is passed, the key is column to aggregate and value is function or list of functions.

- **fill_value** [scalar, default None]
  - Value to replace missing values with (in the resulting pivot table, after aggregation).

- **margins** [bool, default False]
  - Add all row / columns (e.g. for subtotal / grand totals).

- **dropna** [bool, default True]
  - Do not include columns whose entries are all NaN.

- **margins_name** [str, default ‘All’]
  - Name of the row / column that will contain the totals when margins is True.

- **observed** [bool, default False]
  - This only applies if any of the groupers are Categoricals. If True: only show observed values for categorical groupers. If False: show all values for categorical groupers.

changed in version 0.25.0.

**Returns**

- **DataFrame** An Excel style pivot table.

**See also:**

- `DataFrame.pivot` Pivot without aggregation that can handle non-numeric data.
### Examples

```python
>>> df = pd.DataFrame(
    {
        "A": ["foo", "foo", "foo", "foo", "foo", "bar", "bar", "bar", "bar"],
        "B": ["one", "one", "one", "two", "two", "one", "one", "two", "two"],
        "C": ["small", "large", "large", "small", "small", "large", "small", "small", "large"],
        "D": [1, 2, 2, 3, 3, 4, 5, 6, 7],
        "E": [2, 4, 5, 5, 6, 6, 8, 9, 9]
    },
    index=[0, 1, 2, 3, 4, 5, 6, 7, 8])
```

This first example aggregates values by taking the sum.

```python
>>> table = pd.pivot_table(df, values='D', index=['A', 'B'], columns=['C'], aggfunc=np.sum)
```

```
<table>
<thead>
<tr>
<th>C</th>
<th>large</th>
<th>small</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>B</td>
<td></td>
</tr>
<tr>
<td>bar</td>
<td>one</td>
<td>4.0</td>
</tr>
<tr>
<td>two</td>
<td>7.0</td>
<td>6.0</td>
</tr>
<tr>
<td>foo</td>
<td>one</td>
<td>4.0</td>
</tr>
<tr>
<td>two</td>
<td>NaN</td>
<td>6.0</td>
</tr>
</tbody>
</table>
```

We can also fill missing values using the `fill_value` parameter.

```python
>>> table = pd.pivot_table(df, values='D', index=['A', 'B'], columns=['C'], aggfunc=np.sum, fill_value=0)
```

```
<table>
<thead>
<tr>
<th>C</th>
<th>large</th>
<th>small</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>B</td>
<td></td>
</tr>
<tr>
<td>bar</td>
<td>one</td>
<td>4</td>
</tr>
<tr>
<td>two</td>
<td>7</td>
<td>6</td>
</tr>
<tr>
<td>foo</td>
<td>one</td>
<td>4</td>
</tr>
<tr>
<td>two</td>
<td>0</td>
<td>6</td>
</tr>
</tbody>
</table>
```

The next example aggregates by taking the mean across multiple columns.

```python
>>> table = pd.pivot_table(df, values=['D', 'E'], index=['A', 'C'], aggfunc={'D': np.mean, 'E': np.mean})
```

```
<table>
<thead>
<tr>
<th>A</th>
<th>C</th>
<th>D</th>
<th>E</th>
</tr>
</thead>
<tbody>
<tr>
<td>bar</td>
<td>large</td>
<td>5.500</td>
<td>7.5000</td>
</tr>
<tr>
<td></td>
<td>small</td>
<td>5.500</td>
<td>8.5000</td>
</tr>
</tbody>
</table>
```

(continues on next page)
We can also calculate multiple types of aggregations for any given value column.

```py
>>> table = pd.pivot_table(df, values=['D', 'E'], index=['A', 'C'],
                        aggfunc={'D': np.mean,
                                 'E': [min, max, np.mean]})
```

```py
>>> table

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>D</td>
<td>E</td>
<td></td>
</tr>
<tr>
<td></td>
<td>mean</td>
<td>max</td>
<td>mean</td>
</tr>
<tr>
<td>A</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>bar</td>
<td>5.5</td>
<td>9.0</td>
<td>7.5</td>
</tr>
<tr>
<td>small</td>
<td>5.5</td>
<td>9.0</td>
<td>8.5</td>
</tr>
<tr>
<td>foo</td>
<td>2.0</td>
<td>5.0</td>
<td>4.5</td>
</tr>
<tr>
<td>small</td>
<td>2.3</td>
<td>6.0</td>
<td>4.3</td>
</tr>
</tbody>
</table>
```

**pandas.crosstab**

`pandas.crosstab` (index, columns, values=None, rownames=None, colnames=None, aggfunc=None, margins=False, margins_name='All', dropna=True, normalize=False)

Compute a simple cross tabulation of two (or more) factors. By default computes a frequency table of the factors unless an array of values and an aggregation function are passed.

**Parameters**

- **index** [array-like, Series, or list of arrays/Series] Values to group by in the rows.
- **columns** [array-like, Series, or list of arrays/Series] Values to group by in the columns.
- **values** [array-like, optional] Array of values to aggregate according to the factors. Requires `aggfunc` be specified.
- **rownames** [sequence, default None] If passed, must match number of row arrays passed.
- **colnames** [sequence, default None] If passed, must match number of column arrays passed.
- **aggfunc** [function, optional] If specified, requires `values` be specified as well.
- **margins** [bool, default False] Add row/column margins (subtotals).
- **margins_name** [str, default ‘All’] Name of the row/column that will contain the totals when `margins` is True.
- **dropna** [bool, default True] Do not include columns whose entries are all NaN.
- **normalize** [bool, {'all', 'index', 'columns'}, or {0,1}, default False] Normalize by dividing all values by the sum of values.
  - If passed ‘all’ or `True`, will normalize over all values.
  - If passed ‘index’ will normalize over each row.
  - If passed ‘columns’ will normalize over each column.
  - If margins is `True`, will also normalize margin values.

**Returns**

- **DataFrame** Cross tabulation of the data.

See also:
**DataFrame.pivot**  Reshape data based on column values.

**pivot_table**  Create a pivot table as a DataFrame.

**Notes**

Any Series passed will have their name attributes used unless row or column names for the cross-tabulation are specified.

Any input passed containing Categorical data will have all of its categories included in the cross-tabulation, even if the actual data does not contain any instances of a particular category.

In the event that there aren’t overlapping indexes an empty DataFrame will be returned.

**Examples**

```python
>>> a = np.array(["foo", "foo", "foo", "foo", "bar", "bar",
...                  "bar", "bar", "foo", "foo"], dtype=object)
>>> b = np.array(["one", "one", "one", "two", "one", "one",
...                  "one", "two", "two", "one"], dtype=object)
>>> c = np.array(["dull", "dull", "shiny", "dull", "dull", "shiny",
...                  "shiny", "dull", "shiny", "shiny", "shiny"],
...                  dtype=object)
>>> pd.crosstab(a, [b, c], rownames=["a"], colnames=["b", "c"])
    b    one    two
  c      dull  shiny  dull  shiny
bar     1      2     1      0
foo     2      2     1      2
```

Here ‘c’ and ‘f’ are not represented in the data and will not be shown in the output because dropna is True by default. Set dropna=False to preserve categories with no data.

```python
>>> foo = pd.Categorical(["a", "b"], categories=["a", "b", "c"])
>>> bar = pd.Categorical(["d", "e"], categories=["d", "e", "f"])
>>> pd.crosstab(foo, bar)
    col_0  d  e  f
row_0
a     1  0  0
b     0  1  0
c     0  0  0
```

```python
>>> pd.crosstab(foo, bar, dropna=\texttt{False})
    col_0  d  e  f
row_0
a     1  0  0
b     0  1  0
c     0  0  0
```
pandas.cut

pandas.cut(x, bins, right=True, labels=None, retbins=False, precision=3, include_lowest=False, duplicates='raise', ordered=True)

Bin values into discrete intervals.

Use cut when you need to segment and sort data values into bins. This function is also useful for going from a continuous variable to a categorical variable. For example, cut could convert ages to groups of age ranges. Supports binning into an equal number of bins, or a pre-specified array of bins.

Parameters

x [array-like] The input array to be binned. Must be 1-dimensional.

bins [int, sequence of scalars, or IntervalIndex] The criteria to bin by.

• int : Defines the number of equal-width bins in the range of x. The range of x is extended by .1% on each side to include the minimum and maximum values of x.

• sequence of scalars : Defines the bin edges allowing for non-uniform width. No extension of the range of x is done.

• IntervalIndex : Defines the exact bins to be used. Note that IntervalIndex for bins must be non-overlapping.

right [bool, default True] Indicates whether bins includes the rightmost edge or not. If right == True (the default), then the bins [1, 2, 3, 4] indicate (1,2], (2,3], (3,4]. This argument is ignored when bins is an IntervalIndex.

labels [array or False, default None] Specifies the labels for the returned bins. Must be the same length as the resulting bins. If False, returns only integer indicators of the bins. This affects the type of the output container (see below). This argument is ignored when bins is an IntervalIndex. If True, raises an error. When ordered=False, labels must be provided.

retbins [bool, default False] Whether to return the bins or not. Useful when bins is provided as a scalar.

precision [int, default 3] The precision at which to store and display the bins labels.

include_lowest [bool, default False] Whether the first interval should be left-inclusive or not.

duplicates [{default ‘raise’, ‘drop’}, optional] If bin edges are not unique, raise ValueError or drop non-uniclues.

New in version 0.23.0.

ordered [bool, default True] Whether the labels are ordered or not. Applies to returned types Categorical and Series (with Categorical dtype). If True, the resulting categorical will be ordered. If False, the resulting categorical will be unordered (labels must be provided).

New in version 1.1.0.

Returns

out [Categorical, Series, or ndarray] An array-like object representing the respective bin for each value of x. The type depends on the value of labels.

• True (default) : returns a Series for Series x or a Categorical for all other inputs. The values stored within are Interval dtype.

• sequence of scalars : returns a Series for Series x or a Categorical for all other inputs. The values stored within are whatever the type in the sequence is.

• False : returns an ndarray of integers.
bins [numpy.ndarray or IntervalIndex.] The computed or specified bins. Only returned when retbins=True. For scalar or sequence bins, this is an ndarray with the computed bins. If set duplicates=drop, bins will drop non-unique bin. For an IntervalIndex bins, this is equal to bins.

See also:

qcut Discretize variable into equal-sized buckets based on rank or based on sample quantiles.

Categorical Array type for storing data that come from a fixed set of values.

Series One-dimensional array with axis labels (including time series).

IntervalIndex Immutable Index implementing an ordered, sliceable set.

Notes

Any NA values will be NA in the result. Out of bounds values will be NA in the resulting Series or Categorical object.

Examples

Discretize into three equal-sized bins.

```python
>>> pd.cut(np.array([1, 7, 5, 4, 6, 3]), 3)
...
[(0.994, 3.0], (5.0, 7.0], (3.0, 5.0], (3.0, 5.0], (5.0, 7.0], ...
Categories (3, interval[float64]): [(0.994, 3.0) < (3.0, 5.0) ...
```

```python
>>> pd.cut(np.array([1, 7, 5, 4, 6, 3]), 3, retbins=True)
...
[(0.994, 3.0], (5.0, 7.0], (3.0, 5.0], (3.0, 5.0], (5.0, 7.0], ...
Categories (3, interval[float64]): [(0.994, 3.0) < (3.0, 5.0) ...
array([0.994, 3. , 5. , 7. ]))
```

Discover the same bins, but assign them specific labels. Notice that the returned Categorical’s categories are labels and is ordered.

```python
>>> pd.cut(np.array([1, 7, 5, 4, 6, 3]), 3, labels=['bad', 'medium', 'good'])
['bad', 'good', 'medium', 'medium', 'good', 'bad']
Categories (3, object): ['bad' < 'medium' < 'good']
```

ordered=False will result in unordered categories when labels are passed. This parameter can be used to allow non-unique labels:

```python
>>> pd.cut(np.array([1, 7, 5, 4, 6, 3]), 3, labels=['B', 'A', 'B'], ordered=False)
['B', 'B', 'A', 'B', 'B', 'B']
Categories (2, object): ['A', 'B']
```

labels=False implies you just want the bins back.

```python
>>> pd.cut([0, 1, 1, 2], bins=4, labels=False)
array([0, 1, 1, 3])
```

Passing a Series as an input returns a Series with categorical dtype:
>>> s = pd.Series(np.array([2, 4, 6, 8, 10]),
...          index=['a', 'b', 'c', 'd', 'e'])
>>> pd.cut(s, 3)
...  
...  a (1.992, 4.667]
...  b (1.992, 4.667]
...  c (4.667, 7.333]
...  d (7.333, 10.0]
...  e (7.333, 10.0]
  dtype: category
  Categories (3, interval[float64]): 
[(1.992, 4.667] < (4.667, ...  

Passing a Series as an input returns a Series with mapping value. It is used to map numerically to intervals based on bins.

>>> s = pd.Series(np.array([2, 4, 6, 8, 10]),
...          index=['a', 'b', 'c', 'd', 'e'])
>>> pd.cut(s, [0, 2, 4, 6, 8, 10], labels=False, retbins=True, right=False)
...  
...  a 1.0
...  b 2.0
...  c 3.0
...  d 4.0
...  e NaN
dtype: float64,
array([ 0, 2, 4, 6, 8, 10])

Use drop optional when bins is not unique

>>> pd.cut(s, [0, 2, 4, 6, 10, 10], labels=False, retbins=True, right=False, duplicates='drop')
...  
...  a 1.0
...  b 2.0
...  c 3.0
...  d 3.0
...  e NaN
dtype: float64,
array([ 0, 2, 4, 6, 10])

Passing an IntervalIndex for bins results in those categories exactly. Notice that values not covered by the IntervalIndex are set to NaN. 0 is to the left of the first bin (which is closed on the right), and 1.5 falls between two bins.

>>> bins = pd.IntervalIndex.from_tuples([(0, 1), (2, 3), (4, 5)])
>>> pd.cut([0, 0.5, 1.5, 2.5, 4.5], bins)
[NaN, 0.0, 1.0], NaN, (2.0, 3.0], (4.0, 5.0]
Categories (3, interval[int64]): [(0, 1] < (2, 3] < (4, 5]]
pandas.qcut

Quantile-based discretization function.
Discretize variable into equal-sized buckets based on rank or based on sample quantiles. For example 1000 values for 10 quantiles would produce a Categorical object indicating quantile membership for each data point.

Parameters

- **x** [1d ndarray or Series]: Number of quantiles. 10 for deciles, 4 for quartiles, etc. Alternately array of quantiles, e.g. [0, .25, .5, .75, 1.] for quartiles.
- **q** [int or list-like of float]: Number of quantiles. 10 for deciles, 4 for quartiles, etc. Alternately array of quantiles, e.g. [0, .25, .5, .75, 1.] for quartiles.
- **labels** [array or False, default None]: Used as labels for the resulting bins. Must be of the same length as the resulting bins. If False, return only integer indicators of the bins. If True, raises an error.
- **retbins** [bool, optional]: Whether to return the (bins, labels) or not. Can be useful if bins is given as a scalar.
- **precision** [int, optional]: The precision at which to store and display the bins labels.
- **duplicates** [default 'raise', 'drop', optional]: If bin edges are not unique, raise ValueError or drop non-uniques.

Returns

- **out** [Categorical or Series or array of integers if labels is False]: The return type (Categorical or Series) depends on the input: a Series of type category if input is a Series else Categorical. Bins are represented as categories when categorical data is returned.
- **bins** [ndarray of floats]: Returned only if retbins is True.

Notes

Out of bounds values will be NA in the resulting Categorical object

Examples

```python
>>> pd.qcut(range(5), 4)
...
[(-0.001, 1.0], (-0.001, 1.0], (1.0, 2.0], (2.0, 3.0], (3.0, 4.0]]
Categories (4, interval[float64]): [(-0.001, 1.0] < (1.0, 2.0] ...
```

```python
>>> pd.qcut(range(5), 3, labels=["good", "medium", "bad"])
...
[good, good, medium, bad, bad]
Categories (3, object): [good < medium < bad]
```

```python
>>> pd.qcut(range(5), 4, labels=False)
array([0, 0, 1, 2, 3])
```
pandas.merge

pandas.merge(left, right, how='inner', on=None, left_on=None, right_on=None, left_index=False, right_index=False, sort=False, suffixes='_x', '_y', copy=True, indicator=False, validate=None)

Merge DataFrame or named Series objects with a database-style join.

The join is done on columns or indexes. If joining columns on columns, the DataFrame indexes will be ignored. Otherwise if joining indexes on indexes or indexes on a column or columns, the index will be passed on.

Parameters

left [DataFrame]
right [DataFrame or named Series] Object to merge with.
how [{‘left’, ‘right’, ‘outer’, ‘inner’}, default ‘inner’] Type of merge to be performed.
  • left: use only keys from left frame, similar to a SQL left outer join; preserve key order.
  • right: use only keys from right frame, similar to a SQL right outer join; preserve key order.
  • outer: use union of keys from both frames, similar to a SQL full outer join; sort keys lexicographically.
  • inner: use intersection of keys from both frames, similar to a SQL inner join; preserve the order of the left keys.
on [label or list] Column or index level names to join on. These must be found in both DataFrames. If on is None and not merging on indexes then this defaults to the intersection of the columns in both DataFrames.
left_on [label or list, or array-like] Column or index level names to join on in the left DataFrame. Can also be an array or list of arrays of the length of the left DataFrame. These arrays are treated as if they are columns.
right_on [label or list, or array-like] Column or index level names to join on in the right DataFrame. Can also be an array or list of arrays of the length of the right DataFrame. These arrays are treated as if they are columns.
left_index [bool, default False] Use the index from the left DataFrame as the join key(s). If it is a MultiIndex, the number of keys in the other DataFrame (either the index or a number of columns) must match the number of levels.
right_index [bool, default False] Use the index from the right DataFrame as the join key. Same caveats as left_index.
sort [bool, default False] Sort the join keys lexicographically in the result DataFrame. If False, the order of the join keys depends on the join type (how keyword).
suffixes [list-like, default is (“_x”, “_y”) ] A length-2 sequence where each element is optionally a string indicating the suffix to add to overlapping column names in left and right respectively. Pass a value of None instead of a string to indicate that the column name from left or right should be left as-is, with no suffix. At least one of the values must not be None.
copy [bool, default True] If False, avoid copy if possible.
indicator [bool or str, default False] If True, adds a column to the output DataFrame called “_merge” with information on the source of each row. The column can be given a different name by providing a string argument. The column will have a Categorical type with the value of “left_only” for observations whose merge key only appears in the left DataFrame,
“right_only” for observations whose merge key only appears in the right DataFrame, and
“both” if the observation’s merge key is found in both DataFrames.

validate [str, optional] If specified, checks if merge is of specified type.

• “one_to_one” or “1:1”: check if merge keys are unique in both left and right datasets.
• “one_to_many” or “1:m”: check if merge keys are unique in left dataset.
• “many_to_one” or “m:1”: check if merge keys are unique in right dataset.
• “many_to_many” or “m:m”: allowed, but does not result in checks.

Returns

DataFrame A DataFrame of the two merged objects.

See also:

merge_ordered Merge with optional filling/interpolation.
merge_asof Merge on nearest keys.
DataFrame.join Similar method using indices.

Notes

Support for specifying index levels as the on, left_on, and right_on parameters was added in version 0.23.0
Support for merging named Series objects was added in version 0.24.0

Examples

```python
>>> df1 = pd.DataFrame({"lkey": ["foo", 'bar', 'baz', 'foo'],
...     'value': [1, 2, 3, 5]})
>>> df2 = pd.DataFrame({"rkey": ["foo", 'bar', 'baz', 'foo'],
...     'value': [5, 6, 7, 8]})
>>> df1
lkey  value
0  foo     1
1  bar     2
2  baz     3
3  foo     5
>>> df2
rkey  value
0  foo     5
1  bar     6
2  baz     7
3  foo     8

Merge df1 and df2 on the lkey and rkey columns. The value columns have the default suffixes, _x and _y,
appended.

>>> df1.merge(df2, left_on='lkey', right_on='rkey')
lkey  value_x  rkey  value_y
0  foo       1   foo       5
1  foo       1   foo       8
2  foo       5   foo       5
3  foo       5   foo       8
```

(continues on next page)
Merge DataFrames df1 and df2 with specified left and right suffixes appended to any overlapping columns.

```py
>>> df1.merge(df2, left_on='lkey', right_on='rkey',
             suffixes=('_left', '_right'))
lkey  value_left  rkey  value_right
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>foo</td>
<td>1</td>
<td>foo</td>
</tr>
<tr>
<td>1</td>
<td>foo</td>
<td>1</td>
<td>foo</td>
</tr>
<tr>
<td>2</td>
<td>foo</td>
<td>5</td>
<td>foo</td>
</tr>
<tr>
<td>3</td>
<td>foo</td>
<td>5</td>
<td>foo</td>
</tr>
<tr>
<td>4</td>
<td>bar</td>
<td>2</td>
<td>bar</td>
</tr>
<tr>
<td>5</td>
<td>baz</td>
<td>3</td>
<td>baz</td>
</tr>
</tbody>
</table>
```

Merge DataFrames df1 and df2, but raise an exception if the DataFrames have any overlapping columns.

```py
>>> df1.merge(df2, left_on='lkey', right_on='rkey', suffixes=(False, False))
Traceback (most recent call last):
...  
ValueError: columns overlap but no suffix specified:
  Index(['value'], dtype='object')
```

**pandas.merge_ordered**

`pandas.merge_ordered(left, right, on=None, left_on=None, right_on=None, left_by=None, right_by=None, fill_method=None, suffixes='_x', '_y', how='outer')`

Perform merge with optional filling/interpolation.

Designed for ordered data like time series data. Optionally perform group-wise merge (see examples).

**Parameters**

- `left` [DataFrame]
- `right` [DataFrame]
- `on` [label or list] Field names to join on. Must be found in both DataFrames.
- `left_on` [label or list, or array-like] Field names to join on in left DataFrame. Can be a vector or list of vectors of the length of the DataFrame to use a particular vector as the join key instead of columns.
- `right_on` [label or list, or array-like] Field names to join on in right DataFrame or vector/list of vectors per left_on docs.
- `left_by` [column name or list of column names] Group left DataFrame by group columns and merge piece by piece with right DataFrame.
- `right_by` [column name or list of column names] Group right DataFrame by group columns and merge piece by piece with left DataFrame.
- `fill_method` [{‘ffill’, None}, default None] Interpolation method for data.
- `suffixes` [list-like, default is ("_x", "_y") A length-2 sequence where each element is optionally a string indicating the suffix to add to overlapping column names in left and right respectively. Pass a value of None instead of a string to indicate that the column name from left or right should be left as-is, with no suffix. At least one of the values must not be None.

Changed in version 0.25.0.
pandas: powerful Python data analysis toolkit, Release 1.1.1

how ['left', 'right', 'outer', 'inner'], default 'outer'

- left: use only keys from left frame (SQL: left outer join)
- right: use only keys from right frame (SQL: right outer join)
- outer: use union of keys from both frames (SQL: full outer join)
- inner: use intersection of keys from both frames (SQL: inner join).

Returns

Dataframe The merged DataFrame output type will be the same as 'left', if it is a subclass of DataFrame.

See also:

merge Merge with a database-style join.
merge_asof Merge on nearest keys.

Examples

```python
>>> df1 = pd.DataFrame({
...     "key": ["a", "c", "e", "a", "c", "e"],
...     "lvalue": [1, 2, 3, 1, 2, 3],
...     "group": ["a", "a", "a", "b", "b", "b"]
... })
>>> df1
     key  lvalue group
0     a      1   a
1     c      2   a
2     e      3   a
3     a      1   b
4     c      2   b
5     e      3   b
```

```python
>>> df2 = pd.DataFrame({"key": ["b", "c", "d"], "rvalue": [1, 2, 3]})
>>> df2
     key rvalue
0     b      1
1     c      2
2     d      3
```

```python
>>> merge_ordered(df1, df2, fill_method="ffill", left_by="group")
     key  lvalue group  rvalue
0     a      1   a     NaN
1     b      1   a     1.0
2     c      2   a     2.0
3     d      2   a     3.0
4     e      3   a     3.0
5     a      1   b     NaN
6     b      1   b     1.0
7     c      2   b     2.0
8     d      2   b     3.0
9     e      3   b     3.0
```
Pandas: powerful Python data analysis toolkit, Release 1.1.1

Pandas.merge_asof

Pandas.merge_asof(left, right, on=None, left_on=None, right_on=None, left_index=False, right_index=False, by=None, left_by=None, right_by=None, suffixes=('_x', '_y'), tolerance=None, allow_exact_matches=True, direction='backward')

Perform an asof merge.

This is similar to a left-join except that we match on nearest key rather than equal keys. Both DataFrames must be sorted by the key.

For each row in the left DataFrame:

- A “backward” search selects the last row in the right DataFrame whose ‘on’ key is less than or equal to the left’s key.
- A “forward” search selects the first row in the right DataFrame whose ‘on’ key is greater than or equal to the left’s key.
- A “nearest” search selects the row in the right DataFrame whose ‘on’ key is closest in absolute distance to the left’s key.

The default is “backward” and is compatible in versions below 0.20.0. The direction parameter was added in version 0.20.0 and introduces “forward” and “nearest”.

Optionally match on equivalent keys with ‘by’ before searching with ‘on’.

Parameters

left [DataFrame]
right [DataFrame]
on [label] Field name to join on. Must be found in both DataFrames. The data MUST be ordered. Furthermore this must be a numeric column, such as datetimelike, integer, or float. On or left_on/right_on must be given.
left_on [label] Field name to join on in left DataFrame.
right_on [label] Field name to join on in right DataFrame.
left_index [bool] Use the index of the left DataFrame as the join key.
right_index [bool] Use the index of the right DataFrame as the join key.
by [column name or list of column names] Match on these columns before performing merge operation.
left_by [column name] Field names to match on in the left DataFrame.
right_by [column name] Field names to match on in the right DataFrame.
suffixes [2-length sequence (tuple, list, …)] Suffix to apply to overlapping column names in the left and right side, respectively.
tolerance [int or Timedelta, optional, default None] Select asof tolerance within this range; must be compatible with the merge index.
allow_exact_matches [bool, default True]
  - If True, allow matching with the same ‘on’ value (i.e. less-than-or-equal-to / greater-than-or-equal-to)
  - If False, don’t match the same ‘on’ value (i.e., strictly less-than / strictly greater-than).
direction ['backward' (default), ‘forward’, or ‘nearest’] Whether to search for prior, subsequent, or closest matches.
Returns

merged [DataFrame]

See also:

merge Merge with a database-style join.
merge_ordered Merge with optional filling/interpolation.

Examples

```python
>>> left = pd.DataFrame({"a": [1, 5, 10], "left_val": ["a", "b", "c"]})
>>> left
    a  left_val
0  1  a
1  5  b
2 10  c

>>> right = pd.DataFrame({"a": [1, 2, 3, 6, 7], "right_val": [1, 2, 3, 6, 7]})
>>> right
    a  right_val
0  1       1
1  2       2
2  3       3
3  6       6
4  7       7

>>> pd.merge_asof(left, right, on="a")
    a  left_val  right_val
0  1    a        1
1  5    b        3
2 10   c        NaN

>>> pd.merge_asof(left, right, on="a", allow_exact_matches=False)
    a  left_val  right_val
0  1    a        NaN
1  5    b        3.0
2 10   c        7.0

>>> pd.merge_asof(left, right, on="a", direction="forward")
    a  left_val  right_val
0  1    a        1.0
1  5    b        6.0
2 10   c        NaN

>>> pd.merge_asof(left, right, on="a", direction="nearest")
    a  left_val  right_val
0  1    a        1
1  5    b        6
2 10   c        7

We can use indexed DataFrames as well.
```
```python
>>> left = pd.DataFrame({"left_val": ["a", "b", "c"], index=[1, 5, 10])
>>> left
     left_val
0       a
5       b
10      c

>>> right = pd.DataFrame({"right_val": [1, 2, 3, 6, 7], index=[1, 2, 3, 6, 7])
>>> right
     right_val
0        1
1        2
2        3
3        6
4        7

>>> pd.merge_asof(left, right, left_index=True, right_index=True)
     left_val  right_val
0       a        1
5       b        3
10      c        7

Here is a real-world times-series example
```

```python
>>> quotes = pd.DataFrame(
... {...
...     "time": [
...         pd.Timestamp("2016-05-25 13:30:00.023"),
...         pd.Timestamp("2016-05-25 13:30:00.023"),
...         pd.Timestamp("2016-05-25 13:30:00.030"),
...         pd.Timestamp("2016-05-25 13:30:00.041"),
...         pd.Timestamp("2016-05-25 13:30:00.048"),
...         pd.Timestamp("2016-05-25 13:30:00.049"),
...         pd.Timestamp("2016-05-25 13:30:00.072"),
...         pd.Timestamp("2016-05-25 13:30:00.075")
...     ],
...     "ticker": [
...         "GOOG",
...         "MSFT",
...         "MSFT",
...         "GOOG",
...         "AAPL",
...         "GOOG",
...         "MSFT"
...     ],
...     "bid": [720.50, 51.95, 51.97, 51.99, 720.50, 97.99, 720.50, 52.01],
...     "ask": [720.93, 51.96, 51.98, 52.00, 720.93, 98.01, 720.88, 52.03]
... })
>>> quotes
     time     ticker  bid  ask
0 2016-05-25 13:30:00.023  GOOG  720.50  720.93
1 2016-05-25 13:30:00.023  MSFT  51.95   51.96
2 2016-05-25 13:30:00.030  MSFT  51.97   51.98
3 2016-05-25 13:30:00.041  MSFT  51.99   52.00
4 2016-05-25 13:30:00.048  GOOG  720.50  720.93
(continues on next page)
```
5 2016-05-25 13:30:00.049  AAPL  97.99  98.01
6 2016-05-25 13:30:00.072  GOOG  720.50  720.88
7 2016-05-25 13:30:00.075  MSFT  52.01  52.03

```python
>>> trades = pd.DataFrame(
...     {
...         "time": [pd.Timestamp("2016-05-25 13:30:00.023"),
...                  pd.Timestamp("2016-05-25 13:30:00.038"),
...                  pd.Timestamp("2016-05-25 13:30:00.048"),
...                  pd.Timestamp("2016-05-25 13:30:00.048"),
...                  pd.Timestamp("2016-05-25 13:30:00.048"),
...                  ],
...         "ticker": ["MSFT", "MSFT", "GOOG", "GOOG", "AAPL"],
...         "price": [51.95, 51.95, 720.77, 720.92, 98.0],
...         "quantity": [75, 155, 100, 100, 100]
...     }
... )
```

```python
>>> trades
  time  ticker  price  quantity
0 13:30:00.023  MSFT  51.95       75
1 13:30:00.038  MSFT  51.95      155
2 13:30:00.048  GOOG  720.77      100
3 13:30:00.048  GOOG  720.92      100
4 13:30:00.048  AAPL  98.00      100
```

By default we are taking the asof of the quotes

```python
>>> pd.merge_asof(trades, quotes, on="time", by="ticker")
  time  ticker  price  quantity  bid  ask
0 13:30:00.023  MSFT  51.95       75  51.95  51.96
1 13:30:00.038  MSFT  51.95      155  51.97  51.98
2 13:30:00.048  GOOG  720.77      100  720.50  720.93
3 13:30:00.048  GOOG  720.92      100  720.50  720.93
4 13:30:00.048  AAPL  98.00      100      NaN   NaN
```

We only asof within 2ms between the quote time and the trade time

```python
>>> pd.merge_asof(trades, quotes, on="time", by="ticker", tolerance=pd.Timedelta("2ms"))
  time  ticker  price  quantity  bid  ask
0 13:30:00.023  MSFT  51.95       75  51.95  51.96
1 13:30:00.038  MSFT  51.95      155  51.97  51.98
2 13:30:00.048  GOOG  720.77      100  720.50  720.93
3 13:30:00.048  GOOG  720.92      100  720.50  720.93
4 13:30:00.048  AAPL  98.00      100      NaN   NaN
```

We only asof within 10ms between the quote time and the trade time and we exclude exact matches on time. However prior data will propagate forward

```python
>>> pd.merge_asof(
...     trades, quotes, on="time", by="ticker", tolerance=pd.Timedelta("10ms"))
... )
```

(continues on next page)
... tolerance=pd.Timedelta("10ms"),
... allow_exact_matches=False
...

<table>
<thead>
<tr>
<th>time</th>
<th>ticker</th>
<th>price</th>
<th>quantity</th>
<th>bid</th>
<th>ask</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 2016-05-25 13:30:00.023</td>
<td>MSFT</td>
<td>51.95</td>
<td>75</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>1 2016-05-25 13:30:00.038</td>
<td>MSFT</td>
<td>51.95</td>
<td>155</td>
<td>51.97</td>
<td>51.98</td>
</tr>
<tr>
<td>2 2016-05-25 13:30:00.048</td>
<td>GOOG</td>
<td>720.77</td>
<td>100</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>3 2016-05-25 13:30:00.048</td>
<td>GOOG</td>
<td>720.92</td>
<td>100</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>4 2016-05-25 13:30:00.048</td>
<td>AAPL</td>
<td>98.00</td>
<td>100</td>
<td>NaN</td>
<td>NaN</td>
</tr>
</tbody>
</table>

pandas.concat


Concatenate pandas objects along a particular axis with optional set logic along the other axes.

Can also add a layer of hierarchical indexing on the concatenation axis, which may be useful if the labels are the same (or overlapping) on the passed axis number.

**Parameters**

- **objs** [a sequence or mapping of Series or DataFrame objects] If a mapping is passed, the sorted keys will be used as the keys argument, unless it is passed, in which case the values will be selected (see below). Any None objects will be dropped silently unless they are all None in which case a ValueError will be raised.

- **axis** [{0/’index’, 1/’columns’}, default 0] The axis to concatenate along.

- **join** [{‘inner’, ‘outer’}, default ‘outer’] How to handle indexes on other axis (or axes).

- **ignore_index** [bool, default False] If True, do not use the index values along the concatenation axis. The resulting axis will be labeled 0, ..., n - 1. This is useful if you are concatenating objects where the concatenation axis does not have meaningful indexing information. Note the index values on the other axes are still respected in the join.

- **keys** [sequence, default None] If multiple levels passed, should contain tuples. Construct hierarchical index using the passed keys as the outermost level.

- **levels** [list of sequences, default None] Specific levels (unique values) to use for constructing a MultiIndex. Otherwise they will be inferred from the keys.

- **names** [list, default None] Names for the levels in the resulting hierarchical index.

- **verify_integrity** [bool, default False] Check whether the new concatenated axis contains duplicates. This can be very expensive relative to the actual data concatenation.

- **sort** [bool, default False] Sort non-concatenation axis if it is not already aligned when join is ‘outer’. This has no effect when join='inner', which already preserves the order of the non-concatenation axis.

New in version 0.23.0.

Changed in version 1.0.0: Changed to not sort by default.

- **copy** [bool, default True] If False, do not copy data unnecessarily.
Returns

**object, type of objs** When concatenating all *Series* along the index (axis=0), a *Series* is returned. When *objs* contains at least one *DataFrame*, a *DataFrame* is returned. When concatenating along the columns (axis=1), a *DataFrame* is returned.

See also:

*Series.append* Concatenate *Series*.

*DataFrame.append* Concatenate *DataFrames*.

*DataFrame.join* Join *DataFrames* using indexes.

*DataFrame.merge* Merge *DataFrames* by indexes or columns.

Notes

The keys, levels, and names arguments are all optional.

A walkthrough of how this method fits in with other tools for combining pandas objects can be found [here](#).

Examples

Combine two *Series*.

```python
>>> s1 = pd.Series(['a', 'b'])
>>> s2 = pd.Series(['c', 'd'])
>>> pd.concat([s1, s2])
0   a
1   b
0   c
1   d
dtype: object
```

Clear the existing index and reset it in the result by setting the `ignore_index` option to `True`.

```python
>>> pd.concat([s1, s2], ignore_index=True)
0   a
1   b
2   c
3   d
dtype: object
```

Add a hierarchical index at the outermost level of the data with the `keys` option.

```python
>>> pd.concat([s1, s2], keys=['s1', 's2'])
s1 0   a
   1   b
s2 0   c
   1   d
dtype: object
```

Label the index keys you create with the `names` option.
Combine two DataFrame objects with identical columns.

```python
>>> df1 = pd.DataFrame([[1], [2]], columns=['letter', 'number'])
>>> df2 = pd.DataFrame([[3], [4]], columns=['letter', 'number'])
```

Combine DataFrame objects with overlapping columns and return everything. Columns outside the intersection will be filled with NaN values.

```python
>>> df3 = pd.DataFrame([[3, 'cat'], [4, 'dog']], columns=['letter', 'number', 'animal'])
```

Combine DataFrame objects horizontally along the x axis by passing in `axis=1`.
>>> df4 = pd.DataFrame([['bird', 'polly'], ['monkey', 'george']],
... columns=['animal', 'name'])
>>> pd.concat([df1, df4], axis=1)

<table>
<thead>
<tr>
<th>letter</th>
<th>number</th>
<th>animal</th>
<th>name</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>1</td>
<td>bird</td>
<td>polly</td>
</tr>
<tr>
<td>b</td>
<td>2</td>
<td>monkey</td>
<td>george</td>
</tr>
</tbody>
</table>

Prevent the result from including duplicate index values with the verify_integrity option.

>>> df5 = pd.DataFrame([1], index=['a'])
>>> df5
0       a 1
Name: a, dtype: int64

>>> df6 = pd.DataFrame([2], index=['a'])
>>> df6
0  a 2
Name: a, dtype: int64

>>> pd.concat([df5, df6], verify_integrity=True)
Traceback (most recent call last):
  ...
ValueError: Indexes have overlapping values: ['a']

pandas.get_dummies

pandas.get_dummies(data, prefix=None, prefix_sep='_', dummy_na=False, columns=None, sparse=False, drop_first=False, dtype=None)

Convert categorical variable into dummy/indicator variables.

Parameters

data [array-like, Series, or DataFrame] Data of which to get dummy indicators.

prefix [str, list of str, or dict of str, default None] String to append DataFrame column names. Pass a list with length equal to the number of columns when calling get_dummies on a DataFrame. Alternatively, prefix can be a dictionary mapping column names to prefixes.

prefix_sep [str, default '_'] If appending prefix, separator/delimiter to use. Or pass a list or dictionary as with prefix.

dummy_na [bool, default False] Add a column to indicate NaNs, if False NaNs are ignored.

columns [list-like, default None] Column names in the DataFrame to be encoded. If columns is None then all the columns with object or category dtype will be converted.

sparse [bool, default False] Whether the dummy-encoded columns should be backed by a SparseArray (True) or a regular NumPy array (False).

drop_first [bool, default False] Whether to get k-1 dummies out of k categorical levels by removing the first level.

dtype [dtype, default np.uint8] Data type for new columns. Only a single dtype is allowed. New in version 0.23.0.

Returns

DataFrame Dummy-coded data.

See also:

Series.str.get_dummies Convert Series to dummy codes.
Examples

```python
>>> s = pd.Series(list('abca'))

>>> pd.get_dummies(s)
   a  b  c
0  1  0  0
1  0  1  0
2  0  0  1
3  1  0  0

>>> sl = ['a', 'b', np.nan]

>>> pd.get_dummies(sl)
   a  b
0  1  0
1  0  1
2  0  0

>>> pd.get_dummies(sl, dummy_na=True)
   a  b  NaN
0  1  0  0
1  0  1  0
2  0  0  1

>>> df = pd.DataFrame({'A': ['a', 'b', 'a'], 'B': ['b', 'a', 'c'], ...
                    'C': [1, 2, 3]})

>>> pd.get_dummies(df, prefix=['col1', 'col2'])
   C  col1_a  col1_b  col2_a  col2_b  col2_c
0  1        1      0      0        1      0
1  2        0      1      1        0      0
2  3        1      0      0        0      1

>>> pd.get_dummies(pd.Series(list('abca')))  
   a  b  c
0  1  0  0
1  0  1  0
2  0  0  1
3  1  0  0
4  1  0  0

>>> pd.get_dummies(pd.Series(list('abca')), drop_first=True)
   b  c
0  0  0
1  1  0
2  0  1
3  0  0
4  0  0

>>> pd.get_dummies(pd.Series(list('abc')), dtype=float)
   a  b  c
0  1.0 0.0 0.0
```

(continues on next page)
pandas.factorize

```python
pandas.factorize(values, sort=False, na_sentinel=-1, size_hint=None, dropna=True)
```

Encode the object as an enumerated type or categorical variable.

This method is useful for obtaining a numeric representation of an array when all that matters is identifying distinct values. `factorize` is available as both a top-level function `pandas.factorize()`, and as a method `Series.factorize()` and `Index.factorize()`.

**Parameters**

- `values` [sequence] A 1-D sequence. Sequences that aren’t pandas objects are coerced to ndarrays before factorization.
- `sort` [bool, default False] Sort `uniques` and shuffle `codes` to maintain the relationship.
- `na_sentinel` [int, default -1] Value to mark “not found”.
- `size_hint` [int, optional] Hint to the hashtable sizer.

**Returns**

- `codes` [ndarray] An integer ndarray that’s an indexer into `uniques`. `uniques.take(codes)` will have the same values as `values`.
- `uniques` [ndarray, Index, or Categorical] The unique valid values. When `values` is Categorical, `uniques` is a Categorical. When `values` is some other pandas object, an `Index` is returned. Otherwise, a 1-D ndarray is returned.

**Note:** Even if there’s a missing value in `values`, `uniques` will *not* contain an entry for it.

**See also:**

- `cut` Discretize continuous-valued array.
- `unique` Find the unique value in an array.

**Examples**

These examples all show factorize as a top-level method like `pd.factorize(values)`. The results are identical for methods like `Series.factorize()`.

```python
>>> codes, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'])
>>> codes
array([0, 0, 1, 2, 0]...)
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

With `sort=True`, the `uniques` will be sorted, and `codes` will be shuffled so that the relationship is maintained.
pandas: powerful Python data analysis toolkit, Release 1.1.1

```python
>>> codes, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'], sort=True)
>>> codes
array([1, 1, 0, 2, 1]...)
>>> uniques
array(['a', 'b', 'c'], dtype=object)
```

Missing values are indicated in `codes` with `na_sentinel` (-1 by default). Note that missing values are never included in `uniques`.

```python
>>> codes, uniques = pd.factorize(['b', None, 'a', 'c', 'b'])
>>> codes
array([ 0, -1,  1,  2,  0]...)
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

Thus far, we’ve only factorized lists (which are internally coerced to NumPy arrays). When factorizing pandas objects, the type of `uniques` will differ. For Categoricals, a `Categorical` is returned.

```python
>>> cat = pd.Categorical(['a', 'a', 'c'], categories=['a', 'b', 'c'])
>>> codes, uniques = pd.factorize(cat)
>>> codes
array([0, 0, 1]...)
>>> uniques
['a', 'c']
Categories (3, object): ['a', 'b', 'c']
```

Notice that 'b' is in `uniques.categories`, despite not being present in `cat.values`.

For all other pandas objects, an Index of the appropriate type is returned.

```python
>>> cat = pd.Series(['a', 'a', 'c'])
>>> codes, uniques = pd.factorize(cat)
>>> codes
array([0, 0, 1]...)
>>> uniques
Index(['a', 'c'], dtype='object')
```

### pandas.unique

**pandas.unique(values)**

Hash table-based unique. Uniques are returned in order of appearance. This does NOT sort.

Significantly faster than `numpy.unique`. Includes NA values.

**Parameters**

- **values** [1d array-like]

**Returns**

- `numpy.ndarray` or `ExtensionArray` The return can be:
  - Index: when the input is an Index
  - Categorical: when the input is a Categorical dtype
  - ndarray: when the input is a Series/ndarray

Return `numpy.ndarray` or `ExtensionArray`. 

3.2. General functions 987
See also:

**Index.unique** Return unique values from an Index.

**Series.unique** Return unique values of Series object.

### Examples

```python
>>> pd.unique(pd.Series([2, 1, 3, 3]))
array([2, 1, 3])

>>> pd.unique(pd.Series([2] + [1] * 5))
array([2, 1])

>>> pd.unique(pd.Series([pd.Timestamp('20160101'), ...
    pd.Timestamp('20160101')]))
array(['2016-01-01T00:00:00.000000000'], dtype='datetime64[ns]')

>>> pd.unique(pd.Series([pd.Timestamp('20160101', tz='US/Eastern'), ...
    pd.Timestamp('20160101', tz='US/Eastern')]))
array([Timestamp('2016-01-01 00:00:00-0500', tz='US/Eastern')],
dtype=object)

>>> pd.unique(pd.Index([pd.Timestamp('20160101', tz='US/Eastern'), ...
    pd.Timestamp('20160101', tz='US/Eastern')]))
DatetimeIndex(['2016-01-01 00:00:00-05:00'],
... dtype='datetime64[ns, US/Eastern]', freq=None)

>>> pd.unique(list('baabc'))
array(['b', 'a', 'c'], dtype=object)
```

An unordered Categorical will return categories in the order of appearance.

```python
>>> pd.unique(pd.Series(pd.Categorical(list('baabc'))))
[b, a, c]
Categories (3, object): [b, a, c]

>>> pd.unique(pd.Series(pd.Categorical(list('baabc'), ...
    categories=list('abc'))))
[b, a, c]
Categories (3, object): [b, a, c]
```

An ordered Categorical preserves the category ordering.

```python
>>> pd.unique(pd.Series(pd.Categorical(list('baabc'), ...
    categories=list('abc'), ...
    ordered=True)))
[b, a, c]
Categories (3, object): [a < b < c]
```

An array of tuples

```python
>>> pd.unique([[('a', 'b'), ('b', 'a')], ('a', 'c'), ('b', 'a')])
array([[('a', 'b'), ('b', 'a'), ('a', 'c')],
... dtype=object])
```
pandas.wide_to_long

pandas.wide_to_long(df, stubnames, i, j, sep='', suffix='\d+')

Wide panel to long format. Less flexible but more user-friendly than melt.

With stubnames ['A', 'B'], this function expects to find one or more group of columns with format A-suffix1, A-suffix2,..., B-suffix1, B-suffix2,... You specify what you want to call this suffix in the resulting long format with j (for example j='year')

Each row of these wide variables are assumed to be uniquely identified by i (can be a single column name or a list of column names)

All remaining variables in the data frame are left intact.

**Parameters**

- **df** [DataFrame] The wide-format DataFrame.
- **stubnames** [str or list-like] The stub name(s). The wide format variables are assumed to start with the stub names.
- **i** [str or list-like] Column(s) to use as id variable(s).
- **j** [str] The name of the sub-observation variable. What you wish to name your suffix in the long format.
- **sep** [str, default ''] A character indicating the separation of the variable names in the wide format, to be stripped from the names in the long format. For example, if your column names are A-suffix1, A-suffix2, you can strip the hyphen by specifying sep='.'.
- **suffix** [str, default '\d+'] A regular expression capturing the wanted suffixes. '\d+' captures numeric suffixes. Suffixes with no numbers could be specified with the negated character class '\D+'. You can also further disambiguate suffixes, for example, if your wide variables are of the form A-one, B-two,..., and you have an unrelated column A-rating, you can ignore the last one by specifying suffix='(!?onetwo)'.

Changed in version 0.23.0: When all suffixes are numeric, they are cast to int64/float64.

**Returns**

DataFrame A DataFrame that contains each stub name as a variable, with new index (i, j).

**Notes**

All extra variables are left untouched. This simply uses pandas.melt under the hood, but is hard-coded to “do the right thing” in a typical case.

**Examples**

```python
>>> np.random.seed(123)
>>> df = pd.DataFrame({'A1970': {0: 'a', 1: 'b', 2: 'c'},
...                    'A1980': {0: 'd', 1: 'e', 2: 'f'},
...                    'B1970': {0: 2.5, 1: 1.2, 2: .7},
...                    'B1980': {0: 3.2, 1: 1.3, 2: .1},
...                    'X': dict(zip(range(3), np.random.randn(3)))
...                })
>>> df['id'] = df.index
>>> df
0     a      d     2.5    3.2  2.444640
1     b      e     1.2    1.3 -2.312113
2     c      f     0.7    0.1  0.836022
```

(continues on next page)
pandas: powerful Python data analysis toolkit, Release 1.1.1

(continued from previous page)

<p>| | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>a</td>
<td>d</td>
<td>2.5</td>
<td>3.2</td>
<td>-1.085631</td>
</tr>
<tr>
<td>1</td>
<td>b</td>
<td>e</td>
<td>1.2</td>
<td>1.3</td>
<td>0.997345</td>
</tr>
<tr>
<td>2</td>
<td>c</td>
<td>f</td>
<td>0.7</td>
<td>0.1</td>
<td>0.282978</td>
</tr>
</tbody>
</table>

```python
>>> pd.wide_to_long(df, ["A", "B"], i="id", j="year")

X  A  B
id year
0 1970 -1.085631 a 2.5
1 1970 0.997345 b 1.2
2 1970 0.282978 c 0.7
0 1980 -1.085631 d 3.2
1 1980 0.997345 e 1.3
2 1980 0.282978 f 0.1
```

With multiple id columns

```python
>>> df = pd.DataFrame({
...     'famid': [1, 1, 1, 2, 2, 2, 3, 3, 3],
...     'birth': [1, 2, 3, 1, 2, 3, 1, 2, 3],
...     'ht1': [2.8, 2.9, 2.2, 2.0, 1.8, 1.9, 2.2, 2.3, 2.1],
...     'ht2': [3.4, 3.8, 2.9, 3.2, 2.8, 2.4, 3.3, 3.4, 2.9]
... })
>>> df
famid  birth  ht1  ht2
0     1      1  2.8  3.4
1     1      2  2.9  3.8
2     1      3  2.2  2.9
3     2      1  2.0  3.2
4     2      2  1.8  2.8
5     2      3  1.9  2.4
6     3      1  2.2  3.3
7     3      2  2.3  3.4
8     3      3  2.1  2.9
```

```python
>>> l = pd.wide_to_long(df, stubnames='ht', i=['famid', 'birth'], j='age')
>>> l

ht
famid birth age
1   1   1  2.8
    2  3.4
2   1   2  2.9
    2  3.8
3   1   2  2.2
    2  2.9
2   1   1  2.0
    2  3.2
    2  1.8
    2  2.8
    2  1.9
    2  2.4
3   1   2  2.2
    2  3.3
2   1   2  2.3
    2  3.4
3   1   2  2.1
    2  2.9
```
Going from long back to wide just takes some creative use of `unstack`

```python
>>> w = l.unstack()
>>> w.columns = w.columns.map('{0[0]}{0[1]}'.format)
>>> w.reset_index()
   famid  birth  ht1  ht2
0      1     1   2.8  3.4
1      1     2   2.9  3.8
2      2     1   2.2  2.9
3      2     1   2.0  3.2
4      2     2   1.8  2.8
5      2     3   1.9  2.4
6      3     1   2.2  3.3
7      3     2   2.3  3.4
8      3     3   2.1  2.9
```

Less wieldy column names are also handled

```python
>>> np.random.seed(0)
>>> df = pd.DataFrame({'A(weekly)-2010': np.random.rand(3), ...
... 'A(weekly)-2011': np.random.rand(3), ...
... 'B(weekly)-2010': np.random.rand(3), ...
... 'B(weekly)-2011': np.random.rand(3), ...
... 'X' : np.random.randint(3, size=3)})
>>> df['id'] = df.index
>>> df
   A(weekly)-2010  A(weekly)-2011  B(weekly)-2010  B(weekly)-2011  X  id
0     0.548814     0.544883     0.437587     0.383442   0  0
1     0.715189     0.423655     0.891773     0.791725   1  1
2     0.602763     0.645894     0.963663     0.528895   1  2
```

```python
>>> pd.wide_to_long(df, ['A(weekly)', 'B(weekly)'], i='id', ...
... j='year', sep='-')
   X  A(weekly)  B(weekly)
id year
0  2010  0    0.548814  0.437587
1  2010  1    0.715189  0.891773
2  2010  1    0.602763  0.963663
0  2011  0    0.544883  0.383442
1  2011  1    0.423655  0.791725
2  2011  1    0.645894  0.528895
```

If we have many columns, we could also use a regex to find our stubnames and pass that list on to `wide_to_long`

```python
>>> stubnames = sorted...
... set([match[0] for match in df.columns.str.findall(r'[A-B]\(.*\)').values if match != []])
...}
>>> list(stubnames)
['A(weekly)', 'B(weekly)']
```

All of the above examples have integers as suffixes. It is possible to have non-integers as suffixes.

```python
>>> df = pd.DataFrame({...
... 'famid': [1, 1, 1, 2, 2, 2, 3, 3, 3],...
... 'birth': [1, 2, 3, 1, 2, 3, 1, 2, 3],...
... 'ht_one': [2.8, 2.9, 2.2, 2, 1.8, 1.9, 2.2, 2.3, 2.1],...
... (continues on next page)
```
...  'ht_two': [3.4, 3.8, 2.9, 3.2, 2.8, 2.4, 3.3, 3.4, 2.9]
... })

>>> df
famid  birth  ht_one  ht_two
0      1       1       2.8   3.4
1      1       2       2.9   3.8
2      1       3       2.2   2.9
3      2       1       2.0   3.2
4      2       2       1.8   2.8
5      2       3       1.9   2.4
6      3       1       2.2   3.3
7      3       2       2.3   3.4
8      3       3       2.1   2.9

>>> l = pd.wide_to_long(df, stubnames='ht', i=['famid', 'birth'], 
... j='age', sep='_', suffix='\w+)

>>> l

...  ht
famid  birth  age
1      1       one  2.8
      two     3.4
2      1       one  2.9
      two     3.8
3      1       one  2.2
      two     2.9
2      1       one  2.0
      two     3.2
2      2       one  1.8
      two     2.8
3      3       one  1.9
      two     2.4
3      1       one  2.2
      two     3.3
2      2       one  2.3
      two     3.4
3      3       one  2.1
      two     2.9

### 3.2.2 Top-level missing data

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>isna(obj)</code></td>
<td>Detect missing values for an array-like object.</td>
</tr>
<tr>
<td><code>isnull(obj)</code></td>
<td>Detect missing values for an array-like object.</td>
</tr>
<tr>
<td><code>notna(obj)</code></td>
<td>Detect non-missing values for an array-like object.</td>
</tr>
<tr>
<td><code>notnull(obj)</code></td>
<td>Detect non-missing values for an array-like object.</td>
</tr>
</tbody>
</table>
**pandas.isna**

**pandas.isna**(obj)

Detect missing values for an array-like object.

This function takes a scalar or array-like object and indicates whether values are missing (NaN in numeric arrays, None or NaN in object arrays, NaT in datetimelike).

**Parameters**

- **obj** [scalar or array-like] Object to check for null or missing values.

**Returns**

- **bool or array-like of bool** For scalar input, returns a scalar boolean. For array input, returns an array of boolean indicating whether each corresponding element is missing.

**See also:**

- **notna** Boolean inverse of pandas.isna.
- **Series.isna** Detect missing values in a Series.
- **DataFrame.isna** Detect missing values in a DataFrame.
- **Index.isna** Detect missing values in an Index.

**Examples**

Scalar arguments (including strings) result in a scalar boolean.

```
>>> pd.isna('dog')
False
```

```
>>> pd.isna(pd.NA)
True
```

```
>>> pd.isna(np.nan)
True
```

ndarrays result in an ndarray of booleans.

```
>>> array = np.array([[1, np.nan, 3], [4, 5, np.nan]])
```

```
>>> array
array([[ 1., nan, 3.],
       [ 4., 5., nan]])
```

```
>>> pd.isna(array)
array([[False, True, False],
       [False, False, True]])
```

For indexes, an ndarray of booleans is returned.

```
>>> index = pd.DatetimeIndex(['2017-07-05', '2017-07-06', None,
... '2017-07-08'])
```

```
>>> index
DatetimeIndex(['2017-07-05', '2017-07-06', 'NaT', '2017-07-08'],
              dtype='datetime64[ns]', freq=None)
```

```
>>> pd.isna(index)
array([[False, False, True, False]])
```
For Series and DataFrame, the same type is returned, containing booleans.

```python
>>> df = pd.DataFrame([[\'ant\', \'bee\', \'cat\'], [\'dog\', None, \'fly\']])
>>> df
   0    1   2
0  ant  bee  cat
1   dog None  fly
```

```python
>>> pd.isna(df)
   0   1   2
0 False False False
1 False  True False
```

```python
>>> pd.isna(df[1])
0 False
1  True
Name: 1, dtype: bool
```

**pandas.isnull**

The function `pandas.isnull` detects missing values for an array-like object.

- **Parameters**
  - *obj* [scalar or array-like] Object to check for null or missing values.

- **Returns**
  - bool or array-like of bool For scalar input, returns a scalar boolean. For array input, returns an array of boolean indicating whether each corresponding element is missing.

**See also:**

- `notna` Boolean inverse of pandas.isna.
- `Series.isna` Detect missing values in a Series.
- `DataFrame.isna` Detect missing values in a DataFrame.
- `Index.isna` Detect missing values in an Index.

**Examples**

Scalar arguments (including strings) result in a scalar boolean.

```python
>>> pd.isna('dog')
False
```

```python
>>> pd.isna(pd.NA)
True
```

```python
>>> pd.isna(np.nan)
True
```

ndarrays result in an ndarray of booleans.
array = np.array([[1, np.nan, 3], [4, 5, np.nan]])
array([[ 1., nan, 3.],
       [ 4., 5., nan]])
pd.isna(array)
array([[False, True, False],
       [False, False, True]])

For indexes, an ndarray of booleans is returned.

index = pd.DatetimeIndex(['2017-07-05', '2017-07-06', None,
                          '2017-07-08'])
index
DatetimeIndex(['2017-07-05', '2017-07-06', 'NaT', '2017-07-08'],
                dtype='datetime64[ns]', freq=None)
pd.isna(index)
array([False, False, True, False])

For Series and DataFrame, the same type is returned, containing booleans.

def = pd.DataFrame([[ant, bee, cat], [dog, None, fly]])
> df
     0  1  2
0  ant bee cat
1  dog None fly
pd.isna(df)
     0  1  2
0  False False False
1  False True False

pd.isna(df[1])
0  False
1  True
Name: 1, dtype: bool

pandas.notna

pandas.notna(obj)
Detect non-missing values for an array-like object.

This function takes a scalar or array-like object and indicates whether values are valid (not missing, which is NaN in numeric arrays, None or NaN in object arrays, NaT in datetimelike).

Parameters

obj [array-like or object value] Object to check for not null or non-missing values.

Returns

bool or array-like of bool For scalar input, returns a scalar boolean. For array input, returns an array of boolean indicating whether each corresponding element is valid.

See also:

isna Boolean inverse of pandas.notna.
Series.notna Detect valid values in a Series.
DataFrame.notna Detect valid values in a DataFrame.
Index.notna  Detect valid values in an Index.

Examples

Scalar arguments (including strings) result in a scalar boolean.

```python
>>> pd.notna('dog')
True
```

```python
>>> pd.notna(pd.NA)
False
```

```python
>>> pd.notna(np.nan)
False
```

Ndarrays result in an ndarray of booleans.

```python
>>> array = np.array([[1, np.nan, 3], [4, 5, np.nan]])
>>> pd.notna(array)
array([[ True, False, True],
       [ True, True, False]])
```

For indexes, an ndarray of booleans is returned.

```python
>>> index = pd.DatetimeIndex(['2017-07-05', '2017-07-06', 'NaT', '2017-07-08'])
>>> pd.notna(index)
array([ True, True, False, True])
```

For Series and DataFrame, the same type is returned, containing booleans.

```python
>>> df = pd.DataFrame([['ant', 'bee', 'cat'], ['dog', None, 'fly']])
>>> pd.notna(df)
   0   1   2
0   True   True   True
1   True   True   True
```

```python
>>> pd.notna(df[1])
0   True
1   False
Name: 1, dtype: bool
```
**pandasnonnull**

**pandas.notnull(obj)**
Detect non-missing values for an array-like object.

This function takes a scalar or array-like object and indicates whether values are valid (not missing, which is NaN in numeric arrays, None or NaN in object arrays, NaT in datetimelike).

**Parameters**

- **obj** [array-like or object value] Object to check for not null or non-missing values.

**Returns**

- **bool or array-like of bool** For scalar input, returns a scalar boolean. For array input, returns an array of boolean indicating whether each corresponding element is valid.

**See also:**

- **isna** Boolean inverse of pandas.notna.
- **Series.notna** Detect valid values in a Series.
- **DataFrame.notna** Detect valid values in a DataFrame.
- **Index.notna** Detect valid values in an Index.

**Examples**

Scalar arguments (including strings) result in a scalar boolean.

```
>>> pd.notna('dog')
True
```

```
>>> pd.notna(pd.NA)
False
```

```
>>> pd.notna(np.nan)
False
```

Ndarrays result in an ndarray of booleans.

```
>>> array = np.array([[1, np.nan, 3], [4, 5, np.nan]])
```

```
>>> pd.notna(array)
array([[ True, False, True],
       [ True, True, False]])
```

For indexes, an ndarray of booleans is returned.

```
>>> index = pd.DatetimeIndex(['2017-07-05', '2017-07-06', None, ...
... '2017-07-08'])
```

```
>>> pd.notna(index)
array([ True, True, False, True])
```
For Series and DataFrame, the same type is returned, containing booleans.

```python
df
0  1  2
ant bee cat
dog None fly
pd.notna(df)
0  1  2
True True True
True False True
pd.notna(df[1])
0  True
1  False
Name: 1, dtype: bool
```

### 3.2.3 Top-level conversions

**to_numeric**(arg, errors, downcast) Convert argument to a numeric type.

**pandas.to_numeric**

pandas.to_numeric(arg, errors=’raise’, downcast=None)

Convert argument to a numeric type.

The default return dtype is float64 or int64 depending on the data supplied. Use the downcast parameter to obtain other dtypes.

Please note that precision loss may occur if really large numbers are passed in. Due to the internal limitations of ndarray, if numbers smaller than -9223372036854775808 (np.iinfo(np.int64).min) or larger than 18446744073709551615 (np.iinfo(np.uint64).max) are passed in, it is very likely they will be converted to float so that they can be stored in an ndarray. These warnings apply similarly to Series since it internally leverages ndarray.

**Parameters**

- **arg** [scalar, list, tuple, 1-d array, or Series] Argument to be converted.
- **errors** [{‘ignore’, ‘raise’, ‘coerce’}, default ‘raise’]
  - If ‘raise’, then invalid parsing will raise an exception.
  - If ‘coerce’, then invalid parsing will be set as NaN.
  - If ‘ignore’, then invalid parsing will return the input.
- **downcast** [{‘integer’, ‘signed’, ‘unsigned’, ‘float’}, default None] If not None, and if the data has been successfully cast to a numerical dtype (or if the data was numeric to begin with), downcast that resulting data to the smallest numerical dtype possible according to the following rules:
  - ‘integer’ or ‘signed’: smallest signed int dtype (min.: np.int8)
  - ‘unsigned’: smallest unsigned int dtype (min.: np.uint8)
  - ‘float’: smallest float dtype (min.: np.float32)
As this behaviour is separate from the core conversion to numeric values, any errors raised during the downcasting will be surfaced regardless of the value of the 'errors' input.

In addition, downcasting will only occur if the size of the resulting data’s dtype is strictly larger than the dtype it is to be cast to, so if none of the dtypes checked satisfy that specification, no downcasting will be performed on the data.

**Returns**

ret Numeric if parsing succeeded. Return type depends on input. Series if Series, otherwise ndarray.

**See also:**

- `DataFrame.astype` Cast argument to a specified dtype.
- `to_datetime` Convert argument to datetime.
- `to_timedelta` Convert argument to timedelta.
- `numpy.ndarray.astype` Cast a numpy array to a specified type.
- `DataFrame.convert_dtypes` Convert dtypes.

### Examples

Take separate series and convert to numeric, coercing when told to

```python
>>> s = pd.Series(['1.0', '2', -3])
>>> pd.to_numeric(s)
0  1.0
1  2.0
2 -3.0
dtype: float64
>>> pd.to_numeric(s, downcast='float')
0  1.0
1  2.0
2 -3.0
dtype: float32
>>> pd.to_numeric(s, downcast='signed')
0   1
1   2
2  -3
dtype: int8
>>> s = pd.Series(['apple', '1.0', '2', -3])
>>> pd.to_numeric(s, errors='ignore')
0  apple
1   1.0
2   2
3   -3
dtype: object
>>> pd.to_numeric(s, errors='coerce')
0   NaN
1   1.0
2   2.0
3  -3.0
dtype: float64
```
### 3.2.4 Top-level dealing with datetimelike

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>to_datetime()</code></td>
<td>Convert argument to datetime.</td>
</tr>
<tr>
<td><code>to_timedelta(arg[, unit, errors])</code></td>
<td>Convert argument to timedelta.</td>
</tr>
<tr>
<td><code>date_range([start, end, periods, freq, tz, ...])</code></td>
<td>Return a fixed frequency DatetimeIndex.</td>
</tr>
<tr>
<td><code>bdate_range([start, end, periods, freq, tz, ...])</code></td>
<td>Return a fixed frequency DatetimeIndex, with business day as the default frequency.</td>
</tr>
<tr>
<td><code>period_range([start, end, periods, freq, name])</code></td>
<td>Return a fixed frequency PeriodIndex.</td>
</tr>
<tr>
<td><code>timedelta_range([start, end, periods, freq, ...])</code></td>
<td>Return a fixed frequency TimedeltaIndex, with day as the default frequency.</td>
</tr>
<tr>
<td><code>infer_freq(index[, warn])</code></td>
<td>Infer the most likely frequency given the input index.</td>
</tr>
</tbody>
</table>

#### pandas.to_datetime

**Convert argument to datetime.**

**Parameters**

- **arg** [int, float, str, datetime, list, tuple, 1-d array, Series, DataFrame/dict-like] The object to convert to a datetime.

- **errors** [{'ignore', ‘raise’, ‘coerce’}, default ‘raise’]
  - If ‘raise’, then invalid parsing will raise an exception.
  - If ‘coerce’, then invalid parsing will be set as NaT.
  - If ‘ignore’, then invalid parsing will return the input.

- **dayfirst** [bool, default False] Specify a date parse order if `arg` is str or its list-likes. If True, parses dates with the day first, eg 10/11/12 is parsed as 2012-11-10. Warning: dayfirst=True is not strict, but will prefer to parse with day first (this is a known bug, based on dateutil behavior).

- **yearfirst** [bool, default False] Specify a date parse order if `arg` is str or its list-likes.
  - If True parses dates with the year first, eg 10/11/12 is parsed as 2010-11-12.
  - If both dayfirst and yearfirst are True, yearfirst is preceded (same as dateutil).

- **utc** [bool, default None] Return UTC DatetimeIndex if True (converting any tz-aware date-time.datetime objects as well).
format [str, default None] The strftime to parse time, eg “%d/%m/%Y”, note that “%f” will parse all the way up to nanoseconds. See strftime documentation for more information on choices: https://docs.python.org/3/library/datetime.html#strftime-and-strptime-behavior.

exact [bool, True by default] Behaves as: - If True, require an exact format match. - If False, allow the format to match anywhere in the target string.

unit [str, default ‘ns’] The unit of the arg (D,s,ms,us,ns) denote the unit, which is an integer or float number. This will be based off the origin. Example, with unit=’ms’ and origin=’unix’ (the default), this would calculate the number of milliseconds to the unix epoch start.

infer_datetime_format [bool, default False] If True and no format is given, attempt to infer the format of the datetime strings based on the first non-NaN element, and if it can be inferred, switch to a faster method of parsing them. In some cases this can increase the parsing speed by ~5-10x.

origin [scalar, default ‘unix’] Define the reference date. The numeric values would be parsed as number of units (defined by unit) since this reference date.

- If ‘unix’ (or POSIX) time; origin is set to 1970-01-01.
- If ‘julian’, unit must be ‘D’, and origin is set to beginning of Julian Calendar. Julian day number 0 is assigned to the day starting at noon on January 1, 4713 BC.
- If Timestamp convertible, origin is set to Timestamp identified by origin.

cache [bool, default True] If True, use a cache of unique, converted dates to apply the datetime conversion. May produce significant speed-up when parsing duplicate date strings, especially ones with timezone offsets. The cache is only used when there are at least 50 values. The presence of out-of-bounds values will render the cache unusable and may slow down parsing.

New in version 0.23.0.

Changed in version 0.25.0: - changed default value from False to True.

Returns
datetime If parsing succeeded. Return type depends on input:

- list-like: DatetimeIndex
- Series: Series of datetime64 dtype
- scalar: Timestamp

In case when it is not possible to return designated types (e.g. when any element of input is before Timestamp.min or after Timestamp.max) return will have datetime.datetime type (or corresponding array/Series).

See also:

* DataFrame.astype Cast argument to a specified dtype.
* to_timedelta Convert argument to timedelta.
* convert_dtypes Convert dtypes.
Examples

Assembling a datetime from multiple columns of a DataFrame. The keys can be common abbreviations like ['year', 'month', 'day', 'minute', 'second', 'ms', 'us', 'ns']) or plurals of the same

```python
>>> df = pd.DataFrame({'year': [2015, 2016],
...                     'month': [2, 3],
...                     'day': [4, 5]})
>>> pd.to_datetime(df)
0  2015-02-04
1  2016-03-05
dtype: datetime64[ns]
```

If a date does not meet the timestamp limitations, passing errors='ignore' will return the original input instead of raising any exception.

Passing errors='coerce' will force an out-of-bounds date to NaT, in addition to forcing non-dates (or non-parseable dates) to NaT.

```python
>>> pd.to_datetime('13000101', format='%Y%m%d', errors='ignore')
datetime.datetime(1300, 1, 1, 0, 0)
>>> pd.to_datetime('13000101', format='%Y%m%d', errors='coerce')
NaT
```

Passing infer_datetime_format=True can often-times speedup a parsing if it's not an ISO8601 format exactly, but in a regular format.

```python
>>> s.head()
0  3/11/2000
1  3/12/2000
2  3/13/2000
3  3/11/2000
4  3/12/2000
```

```python
>>> %timeit pd.to_datetime(s, infer_datetime_format=True)
100 loops, best of 3: 10.4 ms per loop

>>> %timeit pd.to_datetime(s, infer_datetime_format=False)
1 loop, best of 3: 471 ms per loop
```

Using a unix epoch time

```python
>>> pd.to_datetime(1490195805, unit='s')
Timestamp('2017-03-22 15:16:45')
>>> pd.to_datetime(1490195805433502912, unit='ns')
Timestamp('2017-03-22 15:16:45.433502912')
```

**Warning:** For float arg, precision rounding might happen. To prevent unexpected behavior use a fixed-width exact type.

Using a non-unix epoch origin

```python
```
pandas.to_timedelta

**pandas.to_timedelta** *(arg, unit=None, errors='raise')*

Convert argument to timedelta.

Timedeltas are absolute differences in times, expressed in difference units (e.g. days, hours, minutes, seconds). This method converts an argument from a recognized timedelta format / value into a Timedelta type.

**Parameters**

- **arg** [str, timedelta, list-like or Series] The data to be converted to timedelta.
- **unit** [str, optional] Denotes the unit of the arg for numeric arg. Defaults to "ns".
  - Possible values:
    - ‘W’
    - ‘D’ / ‘days’ / ‘day’
    - ‘hours’ / ‘hour’ / ‘hr’ / ‘h’
    - ‘m’ / ‘minute’ / ‘min’ / ‘minutes’ / ‘T’
    - ‘S’ / ‘seconds’ / ‘sec’ / ‘second’
    - ‘ms’ / ‘milliseconds’ / ‘millisecond’ / ‘milli’ / ‘millis’ / ‘L’
    - ‘us’ / ‘microseconds’ / ‘microsecond’ / ‘micro’ / ‘micros’ / ‘U’
    - ‘ns’ / ‘nanoseconds’ / ‘nano’ / ‘nanos’ / ‘nanosecond’ / ‘N’

  Changed in version 1.1.0: Must not be specified when arg context strings and errors= "raise".

- **errors** [{‘ignore’, ‘raise’, ‘coerce’}, default ‘raise’]
  - If ‘raise’, then invalid parsing will raise an exception.
  - If ‘coerce’, then invalid parsing will be set as NaT.
  - If ‘ignore’, then invalid parsing will return the input.

**Returns**

timedelta64 or numpy.array of timedelta64 Output type returned if parsing succeeded.

**See also:**

- **DataFrame.astype** Cast argument to a specified dtype.
- **to_datetime** Convert argument to datetime.
- **convert_dtypes** Convert dtypes.
Examples

Parsing a single string to a Timedelta:

```python
>>> pd.to_timedelta('1 days 06:05:01.00003')
Timedelta('1 days 06:05:01.000030')
>>> pd.to_timedelta('15.5us')
Timedelta('0 days 00:00:00.000015500')
```

Parsing a list or array of strings:

```python
>>> pd.to_timedelta(['1 days 06:05:01.00003', '15.5us', 'nan'])
TimedeltaIndex(['1 days 06:05:01.000030', '0 days 00:00:00.000015500', NaT],
                dtype='timedelta64[ns]', freq=None)
```

Converting numbers by specifying the `unit` keyword argument:

```python
>>> pd.to_timedelta(np.arange(5), unit='s')
TimedeltaIndex(['0 days 00:00:00', '0 days 00:00:01', '0 days 00:00:02',
                '0 days 00:00:03', '0 days 00:00:04'],
                dtype='timedelta64[ns]', freq=None)
>>> pd.to_timedelta(np.arange(5), unit='d')
TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'],
                dtype='timedelta64[ns]', freq=None)
```

*pandas.date_range*

`pandas.date_range(start=None, end=None, periods=None, freq=None, tz=None, normalize=False, name=None, closed=None, **kwargs)`

Return a fixed frequency DatetimeIndex.

**Parameters**

- `start` [str or datetime-like, optional] Left bound for generating dates.
- `end` [str or datetime-like, optional] Right bound for generating dates.
- `periods` [int, optional] Number of periods to generate.
- `freq` [str or DateOffset, default ‘D’] Frequency strings can have multiples, e.g. ‘5H’. See [here](#) for a list of frequency aliases.
- `tz` [str or tzinfo, optional] Time zone name for returning localized DatetimeIndex, for example ‘Asia/Hong_Kong’. By default, the resulting DatetimeIndex is timezone-naive.
- `normalize` [bool, default False] Normalize start/end dates to midnight before generating date range.
- `name` [str, default None] Name of the resulting DatetimeIndex.
- `closed` [{None, ‘left’, ‘right’}, optional] Make the interval closed with respect to the given frequency to the ‘left’, ‘right’, or both sides (None, the default).

**kwargs For compatibility. Has no effect on the result.

**Returns**

- `rng` [DatetimeIndex]

See also:
**DatetimeIndex**  An immutable container for datetimes.

**timedelta_range**  Return a fixed frequency TimedeltaIndex.

**period_range**  Return a fixed frequency PeriodIndex.

**interval_range**  Return a fixed frequency IntervalIndex.

**Notes**

Of the four parameters `start, end, periods,` and `freq`, exactly three must be specified. If `freq` is omitted, the resulting DatetimeIndex will have `periods` linearly spaced elements between `start` and `end` (closed on both sides).

To learn more about the frequency strings, please see this link.

**Examples**

**Specifying the values**

The next four examples generate the same DatetimeIndex, but vary the combination of `start, end` and `periods`.

Specify `start` and `end`, with the default daily frequency.

```python
>>> pd.date_range(start='1/1/2018', end='1/08/2018')
```

Specify `start` and `periods`, the number of periods (days).

```python
>>> pd.date_range(start='1/1/2018', periods=8)
```

Specify `end` and `periods`, the number of periods (days).

```python
>>> pd.date_range(end='1/1/2018', periods=8)
DatetimeIndex(['2017-12-25', '2017-12-26', '2017-12-27', '2017-12-28', '2017-12-29', '2017-12-30', '2017-12-31', '2018-01-01'], dtype='datetime64[ns]', freq='D')
```

Specify `start`, `end`, and `periods`; the frequency is generated automatically (linearly spaced).

```python
>>> pd.date_range(start='2018-04-24', end='2018-04-27', periods=3)
DatetimeIndex(['2018-04-24 00:00:00', '2018-04-25 12:00:00', '2018-04-27 00:00:00'], dtype='datetime64[ns]', freq=None)
```

**Other Parameters**

Changed the `freq` (frequency) to 'M' (month end frequency).

```python
>>> pd.date_range(start='1/1/2018', periods=5, freq='M')
```
Multiples are allowed

```python
>>> pd.date_range(start='1/1/2018', periods=5, freq='3M')
               '2019-01-31'],
dtype='datetime64[ns]', freq='3M')
```

`freq` can also be specified as an Offset object.

```python
>>> pd.date_range(start='1/1/2018', periods=5, freq=pd.offsets.MonthEnd(3))
               '2019-01-31'],
dtype='datetime64[ns]', freq='3M')
```

Specify `tz` to set the timezone.

```python
>>> pd.date_range(start='1/1/2018', periods=5, tz='Asia/Tokyo')
DatetimeIndex(['2018-01-01 00:00:00+09:00', '2018-01-02 00:00:00+09:00',
               '2018-01-03 00:00:00+09:00', '2018-01-04 00:00:00+09:00',
               '2018-01-05 00:00:00+09:00'],
dtype='datetime64[ns, Asia/Tokyo]', freq='D')
```

closed controls whether to include `start` and `end` that are on the boundary. The default includes boundary points on either end.

```python
>>> pd.date_range(start='2017-01-01', end='2017-01-04', closed=None)
DatetimeIndex(['2017-01-01', '2017-01-02', '2017-01-03', '2017-01-04'],
dtype='datetime64[ns]', freq='D')
```

Use closed='left' to exclude `end` if it falls on the boundary.

```python
>>> pd.date_range(start='2017-01-01', end='2017-01-04', closed='left')
DatetimeIndex(['2017-01-01', '2017-01-02', '2017-01-03'],
dtype='datetime64[ns]', freq='D')
```

Use closed='right' to exclude `start` if it falls on the boundary.

```python
>>> pd.date_range(start='2017-01-01', end='2017-01-04', closed='right')
DatetimeIndex(['2017-01-02', '2017-01-03', '2017-01-04'],
dtype='datetime64[ns]', freq='D')
```

**pandas.bdate_range**

`pandas.bdate_range` is a function that returns a fixed frequency DatetimeIndex, with business day as the default frequency.

**Parameters**

- `start` [str or datetime-like, default None] Left bound for generating dates.
- `end` [str or datetime-like, default None] Right bound for generating dates.
- `periods` [int, default None] Number of periods to generate.
- `freq` [str or DateOffset, default ‘B’ (business daily)] Frequency strings can have multiples, e.g. ‘5H’.  

```python
>>> pd.date_range(start='1/1/2018', periods=5, freq='3M')
               '2019-01-31'],
dtype='datetime64[ns]', freq='3M')
```

`freq` can also be specified as an Offset object.

```python
>>> pd.date_range(start='1/1/2018', periods=5, freq=pd.offsets.MonthEnd(3))
               '2019-01-31'],
dtype='datetime64[ns]', freq='3M')
```

Specify `tz` to set the timezone.

```python
>>> pd.date_range(start='1/1/2018', periods=5, tz='Asia/Tokyo')
DatetimeIndex(['2018-01-01 00:00:00+09:00', '2018-01-02 00:00:00+09:00',
               '2018-01-03 00:00:00+09:00', '2018-01-04 00:00:00+09:00',
               '2018-01-05 00:00:00+09:00'],
dtype='datetime64[ns, Asia/Tokyo]', freq='D')
```

closed controls whether to include `start` and `end` that are on the boundary. The default includes boundary points on either end.

```python
>>> pd.date_range(start='2017-01-01', end='2017-01-04', closed=None)
DatetimeIndex(['2017-01-01', '2017-01-02', '2017-01-03', '2017-01-04'],
dtype='datetime64[ns]', freq='D')
```

Use closed='left' to exclude `end` if it falls on the boundary.

```python
>>> pd.date_range(start='2017-01-01', end='2017-01-04', closed='left')
DatetimeIndex(['2017-01-01', '2017-01-02', '2017-01-03'],
dtype='datetime64[ns]', freq='D')
```

Use closed='right' to exclude `start` if it falls on the boundary.

```python
>>> pd.date_range(start='2017-01-01', end='2017-01-04', closed='right')
DatetimeIndex(['2017-01-02', '2017-01-03', '2017-01-04'],
dtype='datetime64[ns]', freq='D')
```
tz [str or None] Time zone name for returning localized DatetimeIndex, for example Asia/Beijing.

normalize [bool, default False] Normalize start/end dates to midnight before generating date range.

name [str, default None] Name of the resulting DatetimeIndex.

weekmask [str or None, default None] Weekmask of valid business days, passed to numpy.busdaycalendar, only used when custom frequency strings are passed. The default value None is equivalent to ‘Mon Tue Wed Thu Fri’.

holidays [list-like or None, default None] Dates to exclude from the set of valid business days, passed to numpy.busdaycalendar, only used when custom frequency strings are passed.

closed [str, default None] Make the interval closed with respect to the given frequency to the ‘left’, ‘right’, or both sides (None).

**kwargs For compatibility. Has no effect on the result.

Returns

DatetimeIndex

Notes

Of the four parameters: start, end, periods, and freq, exactly three must be specified. Specifying freq is a requirement for bdate_range. Use date_range if specifying freq is not desired.

To learn more about the frequency strings, please see this link.

Examples

Note how the two weekend days are skipped in the result.

```python
>>> pd.bdate_range(start='1/1/2018', end='1/08/2018')
```

pandas.period_range

pandas.period_range (start=None, end=None, periods=None, freq=None, name=None)

Return a fixed frequency PeriodIndex.

The day (calendar) is the default frequency.

Parameters

start [str or period-like, default None] Left bound for generating periods.

date

end [str or period-like, default None] Right bound for generating periods.

periods [int, default None] Number of periods to generate.

freq [str or DateOffset, optional] Frequency alias. By default the freq is taken from start or end if those are Period objects. Otherwise, the default is "D" for daily frequency.

name [str, default None] Name of the resulting PeriodIndex.
Returns

PeriodIndex

Notes

Of the three parameters: start, end, and periods, exactly two must be specified.
To learn more about the frequency strings, please see this link.

Examples

```python
>>> pd.period_range(start='2017-01-01', end='2018-01-01', freq='M')
PeriodIndex(['2017-01', '2017-02', '2017-03', '2017-04', '2017-05', '2017-06',
             '2017-07', '2017-08', '2017-09', '2017-10', '2017-11', '2017-12',
             '2018-01'],
dtype='period[M]', freq='M')
```

If start or end are Period objects, they will be used as anchor endpoints for a PeriodIndex with frequency matching that of the period_range constructor.

```python
>>> pd.period_range(start=pd.Period('2017Q1', freq='Q'),
                   end=pd.Period('2017Q2', freq='Q'), freq='M')
PeriodIndex(['2017-03', '2017-04', '2017-05', '2017-06'],
dtype='period[M]', freq='M')
```

pandas.timedelta_range

pandas.timedelta_range(start=None, end=None, periods=None, freq=None, name=None, closed=None)

Return a fixed frequency TimedeltaIndex, with day as the default frequency.

Parameters

- **start** [str or timedelta-like, default None] Left bound for generating timedeltas.
- **end** [str or timedelta-like, default None] Right bound for generating timedeltas.
- **periods** [int, default None] Number of periods to generate.
- **freq** [str or DateOffset, default ‘D’] Frequency strings can have multiples, e.g. ‘5H’.
- **name** [str, default None] Name of the resulting TimedeltaIndex.
- **closed** [str, default None] Make the interval closed with respect to the given frequency to the ‘left’, ‘right’, or both sides (None).

Returns

- **rng** [TimedeltaIndex]
Notes

Of the four parameters `start`, `end`, `periods`, and `freq`, exactly three must be specified. If `freq` is omitted, the resulting `TimedeltaIndex` will have `periods` linearly spaced elements between `start` and `end` (closed on both sides).

To learn more about the frequency strings, please see this link.

Examples

```python
>>> pd.timedelta_range(start='1 day', periods=4)
TimedeltaIndex(['1 days', '2 days', '3 days', '4 days'],
               dtype='timedelta64[ns]', freq='D')
```

The `closed` parameter specifies which endpoint is included. The default behavior is to include both endpoints.

```python
>>> pd.timedelta_range(start='1 day', periods=4, closed='right')
TimedeltaIndex(['2 days', '3 days', '4 days'],
               dtype='timedelta64[ns]', freq='D')
```

The `freq` parameter specifies the frequency of the `TimedeltaIndex`. Only fixed frequencies can be passed, non-fixed frequencies such as 'M' (month end) will raise.

```python
>>> pd.timedelta_range(start='1 day', end='2 days', freq='6H')
TimedeltaIndex(['1 days 00:00:00', '1 days 06:00:00', '1 days 12:00:00',
                 '1 days 18:00:00', '2 days 00:00:00'],
                dtype='timedelta64[ns]', freq='6H')
```

Specify `start`, `end`, and `periods`; the frequency is generated automatically (linearly spaced).

```python
>>> pd.timedelta_range(start='1 day', end='5 days', periods=4)
TimedeltaIndex(['1 days 00:00:00', '2 days 08:00:00', '3 days 16:00:00',
                 '5 days 00:00:00'],
                dtype='timedelta64[ns]', freq='32H')
```

`pandas.infer_freq`

`pandas.infer_freq(index, warn=trye)`

Infer the most likely frequency given the input index. If the frequency is uncertain, a warning will be printed.

**Parameters**

- `index` [DatetimeIndex or TimedeltaIndex] If passed a Series will use the values of the series (NOT THE INDEX).
- `warn` [bool, default True]

**Returns**

- `str` or `None` None if no discernible frequency.

**Raises**

- `TypeError` If the index is not datetime-like.
- `ValueError` If there are fewer than three values.
3.2.5 Top-level dealing with intervals

\texttt{interval\_range([start, end, periods, freq, ...])} \quad \text{Return a fixed frequency IntervalIndex.}

\texttt{pandas.interval\_range} \quad \text{start=\text{None}, end=\text{None}, periods=\text{None}, freq=\text{None}, name=\text{None}, closed=\text{'right'}\} \quad \text{Return a fixed frequency IntervalIndex.}

\textbf{Parameters}

- \texttt{start} [numeric or datetime-like, default None] Left bound for generating intervals.
- \texttt{end} [numeric or datetime-like, default None] Right bound for generating intervals.
- \texttt{periods} [int, default None] Number of periods to generate.
- \texttt{freq} [numeric, str, or DateOffset, default None] The length of each interval. Must be consistent with the type of start and end, e.g. 2 for numeric, or ‘5H’ for datetime-like. Default is 1 for numeric and ‘D’ for datetime-like.
- \texttt{name} [str, default None] Name of the resulting IntervalIndex.
- \texttt{closed} [[‘left’, ‘right’, ‘both’, ‘neither’], default ‘right’] Whether the intervals are closed on the left-side, right-side, both or neither.

\textbf{Returns}

- IntervalIndex

\textbf{See also:}

- \texttt{IntervalIndex} An Index of intervals that are all closed on the same side.

\textbf{Notes}

Of the four parameters \texttt{start}, \texttt{end}, \texttt{periods}, and \texttt{freq}, exactly three must be specified. If \texttt{freq} is omitted, the resulting \texttt{IntervalIndex} will have \texttt{periods} linearly spaced elements between \texttt{start} and \texttt{end}, inclusively.

To learn more about datetime-like frequency strings, please see this link.

\textbf{Examples}

Numeric \texttt{start} and \texttt{end} is supported.

\begin{verbatim}
>>> pd.interval_range(start=0, end=5)
IntervalIndex([[0, 1], [1, 2], [2, 3], [3, 4], [4, 5]], closed='right', dtype='interval[int64]')
\end{verbatim}

Additionally, datetime-like input is also supported.

\begin{verbatim}
>>> pd.interval_range(start=pd.Timestamp('2017-01-01'),
... end=pd.Timestamp('2017-01-04'))
IntervalIndex([(2017-01-01, 2017-01-02), (2017-01-02, 2017-01-03),
(continues on next page)
The `freq` parameter specifies the frequency between the left and right endpoints of the individual intervals within the `IntervalIndex`. For numeric `start` and `end`, the frequency must also be numeric.

```python
>>> pd.interval_range(start=0, periods=4, freq=1.5)
IntervalIndex([(0.0, 1.5], (1.5, 3.0], (3.0, 4.5], (4.5, 6.0]],
closed='right', dtype='interval[datetime64[ns]]')
```

Similarly, for datetime-like `start` and `end`, the frequency must be convertible to a DateOffset.

```python
>>> pd.interval_range(start=pd.Timestamp('2017-01-01'),
... periods=3, freq='MS')
IntervalIndex([(2017-01-01, 2017-02-01], (2017-02-01, 2017-03-01],
(2017-03-01, 2017-04-01]],
closed='right', dtype='interval[datetime64[ns]]')
```

Specify `start`, `end`, and `periods`; the frequency is generated automatically (linearly spaced).

```python
>>> pd.interval_range(start=0, end=6, periods=4)
IntervalIndex([(0.0, 1.5], (1.5, 3.0], (3.0, 4.5], (4.5, 6.0]],
closed='right',
dtype='interval[float64]')
```

The `closed` parameter specifies which endpoints of the individual intervals within the `IntervalIndex` are closed.

```python
>>> pd.interval_range(end=5, periods=4, closed='both')
IntervalIndex([[1, 2], [2, 3], [3, 4], [4, 5]],
closed='both', dtype='interval[int64]')
```

### 3.2.6 Top-level evaluation

```
eval(expr[, parser, engine, truediv, ...])
```

Evaluate a Python expression as a string using various backends.

**pandas.eval**

```python
pandas.eval(expr, parser='pandas', engine=None, truediv=<object object>,
global_dict=None, local_dict=None, resolvers=(), level=0, target=None, inplace=False)
```

Evaluate a Python expression as a string using various backends.

The following arithmetic operations are supported: `+`, `-`, `*`, `/`, `**`, `%`, `//` (python engine only) along with the following boolean operations: `|` (or), `&` (and), and `~` (not). Additionally, the 'pandas' parser allows the use of `and`, `or`, and `not` with the same semantics as the corresponding bitwise operators. `Series` and `DataFrame` objects are supported and behave as they would with plain ol' Python evaluation.

**Parameters**

- `expr` [str] The expression to evaluate. This string cannot contain any Python statements, only Python expressions.
- `parser` `['pandas', 'python'], default 'pandas']` The parser to use to construct the syntax tree.

3.2. General functions 1011
from the expression. The default of `pandas` parses code slightly different than standard Python. Alternatively, you can parse an expression using the `python` parser to retain strict Python semantics. See the `enhancing performance` documentation for more details.

**engine** ['python', 'numexpr'] The engine used to evaluate the expression. Supported engines are

- None: tries to use numexpr, falls back to python
- 'numexpr': This default engine evaluates pandas objects using numexpr for large speed ups in complex expressions with large frames.
- 'python': Performs operations as if you had `eval`d in top level python. This engine is generally not that useful.

More backends may be available in the future.

**truediv** [bool, optional] Whether to use true division, like in Python >= 3. deprecated:: 1.0.0

**local_dict** [dict or None, optional] A dictionary of local variables, taken from locals() by default.

**global_dict** [dict or None, optional] A dictionary of global variables, taken from globals() by default.

**resolvers** [list of dict-like or None, optional] A list of objects implementing the `__getitem__` special method that you can use to inject an additional collection of namespaces to use for variable lookup. For example, this is used in the `query()` method to inject the `DataFrame.index` and `DataFrame.columns` variables that refer to their respective `DataFrame` instance attributes.

**level** [int, optional] The number of prior stack frames to traverse and add to the current scope. Most users will not need to change this parameter.

**target** [object, optional, default None] This is the target object for assignment. It is used when there is variable assignment in the expression. If so, then target must support item assignment with string keys, and if a copy is being returned, it must also support `.copy()`.

**inplace** [bool, default False] If target is provided, and the expression mutates target, whether to modify target inplace. Otherwise, return a copy of target with the mutation.

**Returns**

ndarray, numeric scalar, DataFrame, Series

**Raises**

**ValueError** There are many instances where such an error can be raised:

- `target=None`, but the expression is multiline.
- The expression is multiline, but not all them have item assignment. An example of such an arrangement is this:
  
  ```
  a = b + 1
  a + 2
  ```
  
  Here, there are expressions on different lines, making it multiline, but the last line has no variable assigned to the output of `a + 2`.

- `inplace=True`, but the expression is missing item assignment.
- Item assignment is provided, but the `target` does not support string item assignment.
- Item assignment is provided and `inplace=False`, but the `target` does not support the `.copy()` method.
See also:

**DataFrame.query** Evaluates a boolean expression to query the columns of a frame.

**DataFrame.eval** Evaluate a string describing operations on DataFrame columns.

**Notes**

The `dtype` of any objects involved in an arithmetic `%` operation are recursively cast to `float64`.

See the *enhancing performance* documentation for more details.

**Examples**

```python
>>> df = pd.DataFrame({"animal": ["dog", "pig"], "age": [10, 20]})
>>> df
animal   age
0   dog     10
1   pig     20
```

We can add a new column using `pd.eval`:

```python
>>> pd.eval("double_age = df.age * 2", target=df)
animal age double_age
0   dog   10       20
1   pig   20       40
```

### 3.2.7 Hashing

<table>
<thead>
<tr>
<th>util.hash_array(vals[, encoding, hash_key, ...])</th>
<th>Given a 1d array, return an array of deterministic integers.</th>
</tr>
</thead>
<tbody>
<tr>
<td>util.hash_pandas_object(obj[, index, ...])</td>
<td>Return a data hash of the Index/Series/DataFrame.</td>
</tr>
</tbody>
</table>

**pandas.util.hash_array**

Given a 1d array, return an array of deterministic integers.

**Parameters**

- **vals** [ndarray, Categorical]
- **encoding** [str, default ‘utf8’] Encoding for data & key when strings.
- **hash_key** [str, default _default_hash_key] Hash_key for string key to encode.
- **categorize** [bool, default True] Whether to first categorize object arrays before hashing. This is more efficient when the array contains duplicate values.

**Returns**

- 1d uint64 numpy array of hash values, same length as the vals
pandas: powerful Python data analysis toolkit, Release 1.1.1

**pandas.util.hash_pandas_object**

```python
pandas.util.hash_pandas_object(obj, index=True, encoding='utf8', hash_key='0123456789123456', categorize=True)
```

Return a data hash of the Index/Series/DataFrame.

**Parameters**

- `index` [bool, default True] Include the index in the hash (if Series/DataFrame).
- `encoding` [str, default 'utf8'] Encoding for data & key when strings.
- `hash_key` [str, default _default_hash_key] Hash_key for string key to encode.
- `categorize` [bool, default True] Whether to first categorize object arrays before hashing. This is more efficient when the array contains duplicate values.

**Returns**

Series of uint64, same length as the object

### 3.2.8 Testing

```python
test([extra_args])
```

**pandas.test**

```python
pandas.test(extra_args=None)
```

### 3.3 Series

#### 3.3.1 Constructor

```python
Series([data, index, dtype, name, copy, ...])  # One-dimensional ndarray with axis labels (including time series).
```

**pandas.Series**

```python
class pandas.Series(data=None, index=None, dtype=None, name=None, copy=False, fast-path=False)
```

One-dimensional ndarray with axis labels (including time series).

Labels need not be unique but must be a hashable type. The object supports both integer- and label-based indexing and provides a host of methods for performing operations involving the index. Statistical methods from ndarray have been overridden to automatically exclude missing data (currently represented as NaN).

Operations between Series (+, -, /, *) align values based on their associated index values— they need not be the same length. The result index will be the sorted union of the two indexes.

**Parameters**

- `data` [array-like, Iterable, dict, or scalar value] Contains data stored in Series.
Changed in version 0.23.0: If data is a dict, argument order is maintained for Python 3.6 and later.

**index** [array-like or Index (1d)] Values must be hashable and have the same length as data. Non-unique index values are allowed. Will default to RangelIndex (0, 1, 2, …, n) if not provided. If both a dict and index sequence are used, the index will override the keys found in the dict.

**dtype** [str, numpy.dtype, or ExtensionDtype, optional] Data type for the output Series. If not specified, this will be inferred from data. See the [user guide](#) for more usages.

**name** [str, optional] The name to give to the Series.

**copy** [bool, default False] Copy input data.

### Attributes

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>T</td>
<td>Return the transpose, which is by definition self.</td>
</tr>
<tr>
<td>array</td>
<td>The ExtensionArray of the data backing this Series or Index.</td>
</tr>
<tr>
<td>at</td>
<td>Access a single value for a row/column label pair.</td>
</tr>
<tr>
<td>attrs</td>
<td>Dictionary of global attributes on this object.</td>
</tr>
<tr>
<td>axes</td>
<td>Return a list of the row axis labels.</td>
</tr>
<tr>
<td>dtype</td>
<td>Return the dtype object of the underlying data.</td>
</tr>
<tr>
<td>dtypes</td>
<td>Return the dtype object of the underlying data.</td>
</tr>
<tr>
<td>hasnans</td>
<td>Return if I have any nans; enables various perf speedups.</td>
</tr>
<tr>
<td>iat</td>
<td>Access a single value for a row/column pair by integer position.</td>
</tr>
<tr>
<td>iloc</td>
<td>Purely integer-location based indexing for selection by position.</td>
</tr>
<tr>
<td>index</td>
<td>The index (axis labels) of the Series.</td>
</tr>
<tr>
<td>is_monotonic</td>
<td>Return boolean if values in the object are monotonic_increasing.</td>
</tr>
<tr>
<td>is_monotonic_decreasing</td>
<td>Return boolean if values in the object are monotonic_decreasing.</td>
</tr>
<tr>
<td>is_monotonic_increasing</td>
<td>Alias for is_monotonic.</td>
</tr>
<tr>
<td>is_unique</td>
<td>Return boolean if values in the object are unique.</td>
</tr>
<tr>
<td>loc</td>
<td>Access a group of rows and columns by label(s) or a boolean array.</td>
</tr>
<tr>
<td>name</td>
<td>Return the name of the Series.</td>
</tr>
<tr>
<td>nbytes</td>
<td>Return the number of bytes in the underlying data.</td>
</tr>
<tr>
<td>ndim</td>
<td>Number of dimensions of the underlying data, by definition 1.</td>
</tr>
<tr>
<td>shape</td>
<td>Return a tuple of the shape of the underlying data.</td>
</tr>
<tr>
<td>size</td>
<td>Return the number of elements in the underlying data.</td>
</tr>
<tr>
<td>values</td>
<td>Return Series as ndarray or ndarray-like depending on the dtype.</td>
</tr>
</tbody>
</table>
pandas.Series.T

**property** Series.T

Return the transpose, which is by definition self.

pandas.Series.array

**property** Series.array

The ExtensionArray of the data backing this Series or Index.

New in version 0.24.0.

Returns

ExtensionArray An ExtensionArray of the values stored within. For extension types, this is the actual array. For NumPy native types, this is a thin (no copy) wrapper around numpy.ndarray.

.array differs .values which may require converting the data to a different form.

See also:

*Index.to_numpy* Similar method that always returns a NumPy array.

*Series.to_numpy* Similar method that always returns a NumPy array.

Notes

This table lays out the different array types for each extension dtype within pandas.

<table>
<thead>
<tr>
<th>dtype</th>
<th>array type</th>
</tr>
</thead>
<tbody>
<tr>
<td>category</td>
<td>Categorical</td>
</tr>
<tr>
<td>period</td>
<td>PeriodArray</td>
</tr>
<tr>
<td>interval</td>
<td>IntervalArray</td>
</tr>
<tr>
<td>IntegerNA</td>
<td>IntegerArray</td>
</tr>
<tr>
<td>string</td>
<td>StringArray</td>
</tr>
<tr>
<td>boolean</td>
<td>BooleanArray</td>
</tr>
<tr>
<td>datetime64[ns, tz]</td>
<td>DatetimeArray</td>
</tr>
</tbody>
</table>

For any 3rd-party extension types, the array type will be an ExtensionArray.

For all remaining dtypes .array will be a arrays.NumpyExtensionArray wrapping the actual ndarray stored within. If you absolutely need a NumPy array (possibly with copying / coercing data), then use *Series.to_numpy()* instead.
Examples

For regular NumPy types like int, and float, a PandasArray is returned.

```python
>>> pd.Series([1, 2, 3]).array
<PandasArray>
[1, 2, 3]
Length: 3, dtype: int64
```

For extension types, like Categorical, the actual ExtensionArray is returned

```python
>>> ser = pd.Series(pd.Categorical(['a', 'b', 'a']))
>>> ser.array
['a', 'b', 'a']
Categories (2, object): ['a', 'b']
```

pandas.Series.at

**property** Series.at

Access a single value for a row/column label pair.

Similar to `loc`, in that both provide label-based lookups. Use `at` if you only need to get or set a single value in a DataFrame or Series.

**Raises**

**KeyError** If ‘label’ does not exist in DataFrame.

**See also:**

`DataFrame.iat` Access a single value for a row/column pair by integer position.

`DataFrame.loc` Access a group of rows and columns by label(s).

`Series.at` Access a single value using a label.

Examples

```python
>>> df = pd.DataFrame([[0, 2, 3], [0, 4, 1], [10, 20, 30]],
                    index=[4, 5, 6], columns=['A', 'B', 'C'])
>>> df
   A  B  C
4  0  2  3
5  0  4  1
6 10 20 30
>>> df.at[4, 'B']
2
>>> df.at[4, 'B'] = 10
>>> df.at[4, 'B']
10
```
Get value within a Series

```python
>>> df.loc[5].at['B']
4
```

`pandas.Series.attrs`

**property** `Series.attrs`  
Dictionary of global attributes on this object.

**Warning:** attrs is experimental and may change without warning.

`pandas.Series.axes`

**property** `Series.axes`  
Return a list of the row axis labels.

`pandas.Series.dtype`

**property** `Series.dtype`  
Return the dtype object of the underlying data.

`pandas.Series.dtypes`

**property** `Series.dtypes`  
Return the dtype object of the underlying data.

`pandas.Series.hasnans`

**property** `Series.hasnans`  
Return if I have any nans; enables various perf speedups.

`pandas.Series.iat`

**property** `Series.iat`  
Access a single value for a row/column pair by integer position.

Similar to `iloc`, in that both provide integer-based lookups. Use `iat` if you only need to get or set a single value in a DataFrame or Series.

**Raises**

`IndexError` When integer position is out of bounds.

**See also:**

`DataFrame.at` Access a single value for a row/column label pair.

`DataFrame.loc` Access a group of rows and columns by label(s).
DataFrame.iloc Access a group of rows and columns by integer position(s).

Examples

```python
>>> df = pd.DataFrame([[0, 2, 3], [0, 4, 1], [10, 20, 30]],
                      columns=['A', 'B', 'C'])
>>> df
      A  B  C
0     0  2  3
1     0  4  1
2    10 20 30
Get value at specified row/column pair

>>> df.iat[1, 2]
1
Set value at specified row/column pair

>>> df.iat[1, 2] = 10
>>> df.iat[1, 2]
10
Get value within a series

>>> df.loc[0].iat[1]
2
```

pandas.Series.iloc

property Series.iloc
Purely integer-location based indexing for selection by position.

.iloc[] is primarily integer position based (from 0 to length-1 of the axis), but may also be used with a boolean array.

Allowed inputs are:
- An integer, e.g. 5.
- A list or array of integers, e.g. [4, 3, 0].
- A slice object with ints, e.g. 1:7.
- A boolean array.
- A callable function with one argument (the calling Series or DataFrame) and that returns valid output for indexing (one of the above). This is useful in method chains, when you don’t have a reference to the calling object, but would like to base your selection on some value.

.iloc[] will raise IndexError if a requested indexer is out-of-bounds, except slice indexers which allow out-of-bounds indexing (this conforms with python/numpy slice semantics).

See more at Selection by Position.

See also:

.DataFrame.iat Fast integer location scalar accessor.
DataFrame.loc  Purely label-location based indexer for selection by label.
Series.iloc  Purely integer-location based indexing for selection by position.

Examples

```python
>>> mydict = [{'a': 1, 'b': 2, 'c': 3, 'd': 4},
            {'a': 100, 'b': 200, 'c': 300, 'd': 400},
            {'a': 1000, 'b': 2000, 'c': 3000, 'd': 4000}]

>>> df = pd.DataFrame(mydict)

>>> df
   a    b    c     d  
0  1    2    3     4  
1 100  200  300   400  
2 1000 2000 3000 4000

Indexing just the rows

With a scalar integer.

```python
>>> type(df.iloc[0])
<class 'pandas.core.series.Series'>
>>> df.iloc[0]
a    1
b    2
c    3
d    4
Name: 0, dtype: int64
```  

With a list of integers.

```python
>>> type(df.iloc[[0]])
<class 'pandas.core.frame.DataFrame'>
```  

With a slice object.

```python
>>> df.iloc[:3]  
   a    b    c     d  
0  1    2    3     4  
1 100  200  300   400  
2 1000 2000 3000 4000
```  

With a boolean mask the same length as the index.

```python
>>> df.iloc[[True, False, True]]  
   a    b    c     d  
0  1    2    3     4  
2 1000 2000 3000 4000
```
With a callable, useful in method chains. The `x` passed to the `lambda` is the DataFrame being sliced. This selects the rows whose index label even.

```python
>>> df.iloc[lambda x: x.index % 2 == 0]
a b c d
0 1 2 3 4
2 1000 2000 3000 4000
```

**Indexing both axes**

You can mix the indexer types for the index and columns. Use `:` to select the entire axis.

With scalar integers.

```python
>>> df.iloc[0, 1]
2
```

With lists of integers.

```python
>>> df.iloc[[0, 2], [1, 3]]
b d
0 2 4
2 2000 4000
```

With `slice` objects.

```python
>>> df.iloc[1:3, 0:3]
a b c
1 100 200 300
2 1000 2000 3000
```

With a boolean array whose length matches the columns.

```python
>>> df.iloc[:, [True, False, True, False]]
a c
0 1 3
1 100 300
2 1000 3000
```

With a callable function that expects the Series or DataFrame.

```python
>>> df.iloc[:, lambda df: [0, 2]]
a c
0 1 3
1 100 300
2 1000 3000
```

**pandas.Series.index**

`Series.index`: **Index**

The index (axis labels) of the Series.
pandas.Series.is_monotonic

**property** Series.is_monotonic

Return boolean if values in the object are monotonic_increasing.

Returns

bool

pandas.Series.is_monotonic_decreasing

**property** Series.is_monotonic_decreasing

Return boolean if values in the object are monotonic_decreasing.

Returns

bool

pandas.Series.is_monotonic_increasing

**property** Series.is_monotonic_increasing

Alias for is_monotonic.

pandas.Series.is_unique

**property** Series.is_unique

Return boolean if values in the object are unique.

Returns

bool

pandas.Series.loc

**property** Series.loc

Access a group of rows and columns by label(s) or a boolean array.

.loc[] is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

• A single label, e.g. 5 or 'a', (note that 5 is interpreted as a *label* of the index, and **never** as an integer position along the index).

• A list or array of labels, e.g. ['a', 'b', 'c'].

• A slice object with labels, e.g. 'a':'f'.

**Warning:** Note that contrary to usual python slices, **both** the start and the stop are included

• A boolean array of the same length as the axis being sliced, e.g. [True, False, True].

• A **callable** function with one argument (the calling Series or DataFrame) and that returns valid output for indexing (one of the above)
See more at Selection by Label

Raises

**KeyError** If any items are not found.

See also:

* **DataFrame.at** Access a single value for a row/column label pair.
* **DataFrame.iloc** Access group of rows and columns by integer position(s).
* **DataFrame.xs** Returns a cross-section (row(s) or column(s)) from the Series/DataFrame.
* **Series.loc** Access group of values using labels.

### Examples

#### Getting values

```python
>>> df = pd.DataFrame([[1, 2], [4, 5], [7, 8]],
                    index=['cobra', 'viper', 'sidewinder'],
                    columns=['max_speed', 'shield'])
>>> df
    max_speed shield
  cobra      1       2
  viper      4       5
  sidewinder 7       8
```

Single label. Note this returns the row as a Series.

```python
>>> df.loc['viper']
max_speed    4
shield       5
Name: viper, dtype: int64
```

List of labels. Note using `[]` returns a DataFrame.

```python
>>> df.loc[['viper', 'sidewinder']]
    max_speed shield
  viper       4       5
  sidewinder  7       8
```

Single label for row and column

```python
>>> df.loc['cobra', 'shield']
2
```

Slice with labels for row and single label for column. As mentioned above, note that both the start and stop of the slice are included.

```python
>>> df.loc['cobra': 'viper', 'max_speed']
cobra    1
viper    4
Name: max_speed, dtype: int64
```

Boolean list with the same length as the row axis
>>> df.loc[[False, False, True]]
  max_speed  shield
sidewinder    7  8

Conditional that returns a boolean Series

>>> df.loc[df['shield'] > 6]
  max_speed  shield
sidewinder    7  8

Conditional that returns a boolean Series with column labels specified

>>> df.loc[df['shield'] > 6, ['max_speed']]
  max_speed
sidewinder    7

Callable that returns a boolean Series

>>> df.loc[lambda df: df['shield'] == 8]
  max_speed  shield
sidewinder    7  8

Setting values

Set value for all items matching the list of labels

>>> df.loc[['viper', ' sidewinder'], ['shield']] = 50

Set value for an entire row

>>> df.loc['cobra'] = 10

Set value for an entire column

>>> df.loc[:, 'max_speed'] = 30

Set value for rows matching callable condition

>>> df.loc[df['shield'] > 35] = 0

(continues on next page)
Getting values on a DataFrame with an index that has integer labels

Another example using integers for the index

```python
>>> df = pd.DataFrame([[1, 2], [4, 5], [7, 8]],
                   index=[7, 8, 9], columns=['max_speed', 'shield'])
>>> df
    max_speed  shield
   7         1     2
   8         4     5
   9         7     8
```

Slice with integer labels for rows. As mentioned above, note that both the start and stop of the slice are included.

```python
>>> df.loc[7:9]
    max_speed  shield
   7         1     2
   8         4     5
   9         7     8
```

Getting values with a MultiIndex

A number of examples using a DataFrame with a MultiIndex

```python
tuples = [
    ('cobra', 'mark i'), ('cobra', 'mark ii'),
    ('sidewinder', 'mark i'), ('sidewinder', 'mark ii'),
    ('viper', 'mark ii'), ('viper', 'mark iii')
]

index = pd.MultiIndex.from_tuples(tuples)
values = [[12, 2], [0, 4], [10, 20],
          [1, 4], [7, 1], [16, 36]]

df = pd.DataFrame(values, columns=['max_speed', 'shield'], index=index)
>>> df
   max_speed  shield
    cobra          mark i     12     2
              mark ii      0     4
    sidewinder    mark i     10    20
              mark ii      1     4
    viper          mark ii     7     1
              mark iii    16    36
```

Single label. Note this returns a DataFrame with a single index.

```python
>>> df.loc['cobra']
   max_speed  shield
    mark i     12     2
    mark ii      0     4
```

Single index tuple. Note this returns a Series.

```python
>>> df.loc[('cobra', 'mark ii')]
   max_speed
    mark ii     0
```

(continues on next page)
Single label for row and column. Similar to passing in a tuple, this returns a Series.

```python
>>> df.loc['cobra', 'mark i']
max_speed 12
shield 2
Name: (cobra, mark i), dtype: int64
```

Single tuple. Note using [[]] returns a DataFrame.

```python
>>> df.loc[('cobra', 'mark ii')]
max_speed  shield
cobra mark ii 0 4
```

Single tuple for the index with a single label for the column

```python
>>> df.loc[('cobra', 'mark i'), 'shield']
2
```

Slice from index tuple to single label

```python
>>> df.loc[('cobra', 'mark i'): 'viper']
max_speed  shield
cobra mark i 12 2
mark ii 0 4
sidewinder mark i 10 20
mark ii 1 4
viper mark ii 7 1
mark iii 16 36
```

Slice from index tuple to index tuple

```python
>>> df.loc[('cobra', 'mark i'): ('viper', 'mark ii')]
max_speed  shield
cobra mark i 12 2
mark ii 0 4
sidewinder mark i 10 20
mark ii 1 4
viper mark ii 7 1
mark iii 16 36
```

```python
pandas.Series.name
```

**property Series.name**

Return the name of the Series.

The name of a Series becomes its index or column name if it is used to form a DataFrame. It is also used whenever displaying the Series using the interpreter.

**Returns**

- label (hashable object) The name of the Series, also the column name if part of a DataFrame.

**See also:**
**Series.rename** Sets the Series name when given a scalar input.

**Index.name** Corresponding Index property.

### Examples

The Series name can be set initially when calling the constructor.

```python
>>> s = pd.Series([1, 2, 3], dtype=np.int64, name='Numbers')
>>> s
0    1
1    2
2    3
Name: Numbers, dtype: int64
>>> s.name = "Integers"
>>> s
0    1
1    2
2    3
Name: Integers, dtype: int64
```

The name of a Series within a DataFrame is its column name.

```python
>>> df = pd.DataFrame([[1, 2], [3, 4], [5, 6]],
    columns=["Odd Numbers", "Even Numbers"])
>>> df
   Odd Numbers  Even Numbers
0          1        2
1          3        4
2          5        6
>>> df["Even Numbers"].name
'Even Numbers'
```

---

**pandas.Series.nbytes**

**property Series.nbytes**

Return the number of bytes in the underlying data.

**pandas.Series.ndim**

**property Series.ndim**

Number of dimensions of the underlying data, by definition 1.

**pandas.Series.shape**

**property Series.shape**

Return a tuple of the shape of the underlying data.
**pandas.Series.size**

**property Series.size**

Return the number of elements in the underlying data.

**pandas.Series.values**

**property Series.values**

Return Series as ndarray or ndarray-like depending on the dtype.

```
Warning: We recommend using Series.array or Series.to_numpy(), depending on whether you need a reference to the underlying data or a NumPy array.
```

Returns

```
numpy.ndarray or ndarray-like
```

See also:

*Series.array* Reference to the underlying data.

*Series.to_numpy* A NumPy array representing the underlying data.

**Examples**

```python
>>> pd.Series([1, 2, 3]).values
array([1, 2, 3])

>>> pd.Series(list('aabc')).values
array(['a', 'a', 'b', 'c'], dtype=object)

>>> pd.Series(list('aabc')).astype('category').values
['a', 'b', 'c']
Categories (3, object): ['a', 'b', 'c']
```

Timezone aware datetime data is converted to UTC:

```python
>>> pd.Series(pd.date_range('20130101', periods=3, tz='US/Eastern')).values
array(['2013-01-01T05:00:00.000000000',
       '2013-01-02T05:00:00.000000000',
       '2013-01-03T05:00:00.000000000'], dtype='datetime64[ns]')
```

(empty)
# Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>abs()</td>
<td>Return a Series/DataFrame with absolute numeric value of each element.</td>
</tr>
<tr>
<td>add(other[, level, fill_value, axis])</td>
<td>Return Addition of series and other, element-wise (binary operator add).</td>
</tr>
<tr>
<td>add_prefix(prefix)</td>
<td>Prefix labels with string prefix.</td>
</tr>
<tr>
<td>add_suffix(suffix)</td>
<td>Suffix labels with string suffix.</td>
</tr>
<tr>
<td>agg([func, axis])</td>
<td>Aggregate using one or more operations over the specified axis.</td>
</tr>
<tr>
<td>aggregate([func, axis])</td>
<td>Aggregate using one or more operations over the specified axis.</td>
</tr>
<tr>
<td>align(other[, join, axis, level, copy, ...])</td>
<td>Align two objects on their axes with the specified join method.</td>
</tr>
<tr>
<td>all([axis, bool_only, skipna, level])</td>
<td>Return whether all elements are True, potentially over an axis.</td>
</tr>
<tr>
<td>any([axis, bool_only, skipna, level])</td>
<td>Return whether any element is True, potentially over an axis.</td>
</tr>
<tr>
<td>append(to_append[, ignore_index, ...])</td>
<td>Concatenate two or more Series.</td>
</tr>
<tr>
<td>apply(func[, convert_dtype, args])</td>
<td>Invoke function on values of Series.</td>
</tr>
<tr>
<td>argmax([axis, skipna])</td>
<td>Return int position of the largest value in the Series.</td>
</tr>
<tr>
<td>argmin([axis, skipna])</td>
<td>Return int position of the smallest value in the Series.</td>
</tr>
<tr>
<td>argsort([axis, kind, order])</td>
<td>Return the integer indices that would sort the Series values.</td>
</tr>
<tr>
<td>asfreq(freq[, method, how, normalize, ...])</td>
<td>Convert TimeSeries to specified frequency.</td>
</tr>
<tr>
<td>asof(where[, subset])</td>
<td>Return the last row(s) without any NaNs before where.</td>
</tr>
<tr>
<td>astype(dtype[, copy, errors])</td>
<td>Cast a pandas object to a specified dtype dtype.</td>
</tr>
<tr>
<td>at_time(time[, asof, axis])</td>
<td>Select values at particular time of day (e.g., 9:30AM).</td>
</tr>
<tr>
<td>autocorr([lag])</td>
<td>Compute the lag-N autocorrelation.</td>
</tr>
<tr>
<td>backfill([axis, inplace, limit, downcast])</td>
<td>Synonym for DataFrame.fillna() with method='bfill'.</td>
</tr>
<tr>
<td>between(left, right[, inclusive])</td>
<td>Return boolean Series equivalent to left &lt;= series &lt;= right.</td>
</tr>
<tr>
<td>between_time(start_time, end_time[, ...])</td>
<td>Select values between particular times of the day (e.g., 9:00-9:30 AM).</td>
</tr>
<tr>
<td>bfill([axis, inplace, limit, downcast])</td>
<td>Synonym for DataFrame.fillna() with method='bfill'.</td>
</tr>
<tr>
<td>bool()</td>
<td>Return the bool of a single element Series or DataFrame.</td>
</tr>
<tr>
<td>cat</td>
<td>alias of pandas.core.arrays.categorical.CategoricalAccessor</td>
</tr>
<tr>
<td>clip([lower, upper, axis, inplace])</td>
<td>Trim values at input threshold(s).</td>
</tr>
<tr>
<td>combine(other, func[, fill_value])</td>
<td>Combine the Series with a Series or scalar according to func.</td>
</tr>
<tr>
<td>combine_first(other)</td>
<td>Combine Series values, choosing the calling Series's values first.</td>
</tr>
<tr>
<td>compare(other[, align_axis, keep_shape, ...])</td>
<td>Compare to another Series and show the differences.</td>
</tr>
<tr>
<td>convert_dtypes([infer_objects, ...])</td>
<td>Convert columns to best possible dtypes using dtypes supporting pd.NA.</td>
</tr>
</tbody>
</table>

continues on next page
Table 29 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>copy([deep])</code></td>
<td>Make a copy of this object’s indices and data.</td>
</tr>
<tr>
<td><code>corr(other[, method, min_periods])</code></td>
<td>Compute correlation with other Series, excluding missing values.</td>
</tr>
<tr>
<td><code>count([level])</code></td>
<td>Return number of non-NA/null observations in the Series.</td>
</tr>
<tr>
<td><code>cov(other[, min_periods, ddof])</code></td>
<td>Compute covariance with Series, excluding missing values.</td>
</tr>
<tr>
<td><code>cummax([axis, skipna])</code></td>
<td>Return cumulative maximum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td><code>cummin([axis, skipna])</code></td>
<td>Return cumulative minimum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td><code>cumprod([axis, skipna])</code></td>
<td>Return cumulative product over a DataFrame or Series axis.</td>
</tr>
<tr>
<td><code>cumsum([axis, skipna])</code></td>
<td>Return cumulative sum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td><code>describe([percentiles, include, exclude, ...])</code></td>
<td>Generate descriptive statistics.</td>
</tr>
<tr>
<td><code>diff([periods])</code></td>
<td>First discrete difference of element.</td>
</tr>
<tr>
<td><code>div(other[, level, fill_value, axis])</code></td>
<td>Return Floating division of series and other, element-wise (binary operator <code>truediv</code>).</td>
</tr>
<tr>
<td><code>divide(other[, level, fill_value, axis])</code></td>
<td>Return Floating division of series and other, element-wise (binary operator <code>truediv</code>).</td>
</tr>
<tr>
<td><code>divmod(other[, level, fill_value, axis])</code></td>
<td>Return Integer division and modulo of series and other, element-wise (binary operator <code>divmod</code>).</td>
</tr>
<tr>
<td><code>dot(other)</code></td>
<td>Compute the dot product between the Series and the columns of other.</td>
</tr>
<tr>
<td><code>drop([labels, axis, index, columns, level, ...])</code></td>
<td>Return Series with specified index labels removed.</td>
</tr>
<tr>
<td><code>drop_duplicates([keep, inplace])</code></td>
<td>Return Series with duplicate values removed.</td>
</tr>
<tr>
<td><code>droplevel(level[, axis])</code></td>
<td>Return DataFrame with requested index / column level(s) removed.</td>
</tr>
<tr>
<td><code>dropna([axis, inplace, how])</code></td>
<td>Return a new Series with missing values removed.</td>
</tr>
</tbody>
</table>
| `dt` | alias of `pandas.coreindexes.accessors`.
  CombinedDatetimelikeProperties |
| `duplicated([keep])` | Indicate duplicate Series values. |
| `eq(other[, level, fill_value, axis])` | Return Equal to of series and other, element-wise (binary operator `eq`). |
| `equals(other)` | Test whether two objects contain the same elements. |
| `ewm([com, span, halflife, alpha, ...])` | Provide exponential weighted (EW) functions. |
| `expanding([min_periods, center, axis])` | Provide expanding transformations. |
| `explode([ignore_index])` | Transform each element of a list-like to a row. |
| `factorize([sort, na_sentinel])` | Encode the object as an enumerated type or categorical variable. |
| `ffill([axis, inplace, limit, downcast])` | Synonym for `DataFrame.fillna()` with method='ffill'. |
| `fillna([value, method, axis, inplace, ...])` | Fill NA/NaN values using the specified method. |
| `filter([items, like, regex, axis])` | Subset the dataframe rows or columns according to the specified index labels. |
| `first(offset)` | Select initial periods of time series data based on a date offset. |
| `first_valid_index()` | Return index for first non-NA/null value. |

continues on next page
Table 29 – continued from previous page

floordiv(other[, level, fill_value, axis]) Return Integer division of series and other, element-wise (binary operator floordiv).

ge(other[, level, fill_value, axis]) Return Greater than or equal to of series and other, element-wise (binary operator ge).

gt(other[, level, fill_value, axis]) Return Greater than of series and other, element-wise (binary operator gt).

head([n]) Return the first \( n \) rows.

hist([by, ax, grid, xlabelsize, xrot, . . .]) Draw histogram of the input series using matplotlib.

idxmax([axis, skipna]) Return the row label of the maximum value.

idxmin([axis, skipna]) Return the row label of the minimum value.

infer_objects() Attempt to infer better dtypes for object columns.

interpolate([method, limit, inplace, . . .]) Please note that only method='linear' is supported for DataFrame/Series with a MultiIndex.

isin(values) Whether elements in Series are contained in values.

isna() Detect missing values.

isnull() Detect missing values.

item() Return the first element of the underlying data as a python scalar.

items() Lazily iterate over (index, value) tuples.

iteritems() Lazily iterate over (index, value) tuples.

keys() Return alias for index.

kurt([axis, skipna, level, numeric_only]) Return unbiased kurtosis over requested axis.

kurtosis([axis, skipna, level, numeric_only]) Return unbiased kurtosis over requested axis.

last[offset] Select final periods of time series data based on a date offset.

last_valid_index() Return index for last non-NA/null value.

le(other[, level, fill_value, axis]) Return Less than or equal to of series and other, element-wise (binary operator le).

lt(other[, level, fill_value, axis]) Return Less than of series and other, element-wise (binary operator lt).

mad([axis, skipna, level]) Return the mean absolute deviation of the values for the requested axis.

map(arg[, na_action]) Map values of Series according to input correspondence.

mask(cond[, other, inplace, axis, . . .]) Replace values where the condition is True.

max([axis, skipna, level, numeric_only]) Return the maximum of the values for the requested axis.

mean([axis, skipna, level, numeric_only]) Return the mean of the values for the requested axis.

median([axis, skipna, level, numeric_only]) Return the median of the values for the requested axis.

memory_usage([index, deep]) Return the memory usage of the Series.

min([axis, skipna, level, numeric_only]) Return the minimum of the values for the requested axis.

mod(other[, level, fill_value, axis]) Return Modulo of series and other, element-wise (binary operator mod).

mode([dropna]) Return the mode(s) of the dataset.

continues on next page
<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>mul</code></td>
<td>Return Multiplication of series and other, element-wise (binary operator <code>mul</code>).</td>
</tr>
<tr>
<td><code>multiply</code></td>
<td>Return Multiplication of series and other, element-wise (binary operator <code>mul</code>).</td>
</tr>
<tr>
<td><code>ne</code></td>
<td>Return Not equal to of series and other, element-wise (binary operator <code>ne</code>).</td>
</tr>
<tr>
<td><code>nlargest</code></td>
<td>Return the largest <code>n</code> elements.</td>
</tr>
<tr>
<td><code>notna</code></td>
<td>Detect existing (non-missing) values.</td>
</tr>
<tr>
<td><code>notnull</code></td>
<td>Detect existing (non-missing) values.</td>
</tr>
<tr>
<td><code>nsmallest</code></td>
<td>Return the smallest <code>n</code> elements.</td>
</tr>
<tr>
<td><code>nlargest</code></td>
<td>Return the largest <code>n</code> elements.</td>
</tr>
<tr>
<td><code>nsmallest</code></td>
<td>Return the smallest <code>n</code> elements.</td>
</tr>
<tr>
<td><code>pad</code></td>
<td>Synonym for <code>DataFrame.fillna()</code> with method='ffill'.</td>
</tr>
<tr>
<td><code>pct_change</code></td>
<td>Percentage change between the current and a prior element.</td>
</tr>
<tr>
<td><code>pipe</code></td>
<td>Apply <code>func(self, *args, **kwargs)</code>.</td>
</tr>
<tr>
<td><code>plot</code></td>
<td>Alias of <code>pandas.plotting._core.PlotAccessor</code>.</td>
</tr>
<tr>
<td><code>pop</code></td>
<td>Return item and drops from series.</td>
</tr>
<tr>
<td><code>pow</code></td>
<td>Return Exponential power of series and other, element-wise (binary operator <code>pow</code>).</td>
</tr>
<tr>
<td><code>prod</code></td>
<td>Return the product of the values for the requested axis.</td>
</tr>
<tr>
<td><code>product</code></td>
<td>Return the product of the values for the requested axis.</td>
</tr>
<tr>
<td><code>quantile</code></td>
<td>Return value at the given quantile.</td>
</tr>
<tr>
<td><code>radd</code></td>
<td>Return Addition of series and other, element-wise (binary operator <code>radd</code>).</td>
</tr>
<tr>
<td><code>rank</code></td>
<td>Compute numerical data ranks (1 through n) along axis.</td>
</tr>
<tr>
<td><code>ravel</code></td>
<td>Return the flattened underlying data as an ndarray.</td>
</tr>
<tr>
<td><code>rdiv</code></td>
<td>Return Floating division of series and other, element-wise (binary operator <code>rtruediv</code>).</td>
</tr>
<tr>
<td><code>rdivmod</code></td>
<td>Return Integer division and modulo of series and other, element-wise (binary operator <code>rdivmod</code>).</td>
</tr>
<tr>
<td><code>reindex</code></td>
<td>Conform Series to new index with optional filling logic.</td>
</tr>
<tr>
<td><code>reindex_like</code></td>
<td>Return an object with matching indices as other object.</td>
</tr>
<tr>
<td><code>rename</code></td>
<td>Alter Series index labels or name.</td>
</tr>
<tr>
<td><code>rename_axis</code></td>
<td>Set the name of the axis for the index or columns.</td>
</tr>
<tr>
<td><code>reorder_levels</code></td>
<td>Rearrange index levels using input order.</td>
</tr>
<tr>
<td><code>repeat</code></td>
<td>Repeat elements of a Series.</td>
</tr>
<tr>
<td><code>replace</code></td>
<td>Replace values given in <code>to_replace</code> with <code>value</code>.</td>
</tr>
<tr>
<td><code>resample</code></td>
<td>Resample time-series data.</td>
</tr>
<tr>
<td><code>reset_index</code></td>
<td>Generate a new DataFrame or Series with the index reset.</td>
</tr>
<tr>
<td><code>rfloordiv</code></td>
<td>Return Integer division of series and other, element-wise (binary operator <code>rfloordiv</code>).</td>
</tr>
<tr>
<td><code>rmod</code></td>
<td>Return Modulo of series and other, element-wise (binary operator <code>rmod</code>).</td>
</tr>
</tbody>
</table>
Table 29 – continued from previous page

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>rmul</code></td>
<td>Return Multiplication of series and other, element-wise (binary operator <code>rmul</code>).</td>
</tr>
<tr>
<td><code>rolling</code></td>
<td>Provide rolling window calculations.</td>
</tr>
<tr>
<td><code>round</code></td>
<td>Round each value in a Series to the given number of decimals.</td>
</tr>
<tr>
<td><code>rpow</code></td>
<td>Return Exponential power of series and other, element-wise (binary operator <code>rpow</code>).</td>
</tr>
<tr>
<td><code>rsub</code></td>
<td>Return Subtraction of series and other, element-wise (binary operator <code>rsub</code>).</td>
</tr>
<tr>
<td><code>rtruediv</code></td>
<td>Return Floating division of series and other, element-wise (binary operator <code>rtruediv</code>).</td>
</tr>
<tr>
<td><code>sample</code></td>
<td>Return a random sample of items from an axis of object.</td>
</tr>
<tr>
<td><code>searchsorted</code></td>
<td>Find indices where elements should be inserted to maintain order.</td>
</tr>
<tr>
<td><code>sem</code></td>
<td>Return unbiased standard error of the mean over requested axis.</td>
</tr>
<tr>
<td><code>set_axis</code></td>
<td>Assign desired index to given axis.</td>
</tr>
<tr>
<td><code>shift</code></td>
<td>Shift index by desired number of periods with an optional time <code>freq</code>.</td>
</tr>
<tr>
<td><code>skew</code></td>
<td>Return unbiased skew over requested axis.</td>
</tr>
<tr>
<td><code>slice_shift</code></td>
<td>Equivalent to <code>shift</code> without copying data.</td>
</tr>
<tr>
<td><code>sort_index</code></td>
<td>Sort Series by index labels.</td>
</tr>
<tr>
<td><code>sort_values</code></td>
<td>Sort by the values.</td>
</tr>
<tr>
<td><code>squeeze</code></td>
<td>Squeeze 1 dimensional axis objects into scalars.</td>
</tr>
<tr>
<td><code>std</code></td>
<td>Return sample standard deviation over requested axis.</td>
</tr>
<tr>
<td><code>str</code></td>
<td>Alias of <code>pandas.core.strings.StringMethods</code>.</td>
</tr>
<tr>
<td><code>sub</code></td>
<td>Return Subtraction of series and other, element-wise (binary operator <code>sub</code>).</td>
</tr>
<tr>
<td><code>subtract</code></td>
<td>Return Subtraction of series and other, element-wise (binary operator <code>sub</code>).</td>
</tr>
<tr>
<td><code>sum</code></td>
<td>Return the sum of the values for the requested axis.</td>
</tr>
<tr>
<td><code>swapaxes</code></td>
<td>Interchange axes and swap values axes appropriately.</td>
</tr>
<tr>
<td><code>swaplevel</code></td>
<td>Swap levels i and j in a <code>MultiIndex</code>.</td>
</tr>
<tr>
<td><code>tail</code></td>
<td>Return the last n rows.</td>
</tr>
<tr>
<td><code>take</code></td>
<td>Return the elements in the given positional indices along an axis.</td>
</tr>
<tr>
<td><code>to_clipboard</code></td>
<td>Copy object to the system clipboard.</td>
</tr>
<tr>
<td><code>to_csv</code></td>
<td>Write object to a comma-separated values (csv) file.</td>
</tr>
<tr>
<td><code>to_dict</code></td>
<td>Convert Series to <code>{label -&gt; value}</code> dict or dict-like object.</td>
</tr>
<tr>
<td><code>to_excel</code></td>
<td>Write object to an Excel sheet.</td>
</tr>
<tr>
<td><code>to_frame</code></td>
<td>Convert Series to DataFrame.</td>
</tr>
<tr>
<td><code>to_hdf</code></td>
<td>Write the contained data to an HDF5 file using HDF-Store.</td>
</tr>
<tr>
<td><code>to_json</code></td>
<td>Convert the object to a JSON string.</td>
</tr>
</tbody>
</table>

continues on next page
Table 29 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>to_latex()</code></td>
<td>Render object to a LaTeX tabular, longtable, or nested table/tabular.</td>
</tr>
<tr>
<td><code>to_list()</code></td>
<td>Return a list of the values.</td>
</tr>
<tr>
<td><code>to_markdown()</code></td>
<td>Print Series in Markdown-friendly format.</td>
</tr>
<tr>
<td><code>to_numpy()</code></td>
<td>A NumPy ndarray representing the values in this Series or Index.</td>
</tr>
<tr>
<td><code>to_period()</code></td>
<td>Convert Series from DatetimeIndex to PeriodIndex.</td>
</tr>
<tr>
<td><code>to_pickle()</code></td>
<td>Pickle (serialize) object to file.</td>
</tr>
<tr>
<td><code>to_sql()</code></td>
<td>Write records stored in a DataFrame to a SQL database.</td>
</tr>
<tr>
<td><code>to_string()</code></td>
<td>Render a string representation of the Series.</td>
</tr>
<tr>
<td><code>to_timestamp()</code></td>
<td>Cast to DatetimeIndex of Timestamps, at beginning of period.</td>
</tr>
<tr>
<td><code>to_xarray()</code></td>
<td>Return an xarray object from the pandas object.</td>
</tr>
<tr>
<td><code>tolist()</code></td>
<td>Return a list of the values.</td>
</tr>
<tr>
<td><code>transform(func[, axis])</code></td>
<td>Call <code>func</code> on self producing a Series with transformed values.</td>
</tr>
<tr>
<td><code>transpose(*args, **kwargs)</code></td>
<td>Return the transpose, which is by definition self.</td>
</tr>
<tr>
<td><code>truediv(other[, level, fill_value, axis])</code></td>
<td>Return Floating division of series and other, element-wise (binary operator <code>truediv</code>).</td>
</tr>
<tr>
<td><code>truncate(before, after, axis, copy)</code></td>
<td>Truncate a Series or DataFrame before and after some index value.</td>
</tr>
<tr>
<td><code>tshift([periods, freq, axis])</code></td>
<td>(DEPRECATED) Shift the time index, using the index’s frequency if available.</td>
</tr>
<tr>
<td><code>tz_convert(tz[, axis, level, copy])</code></td>
<td>Convert tz-aware axis to target time zone.</td>
</tr>
<tr>
<td><code>tz_localize(tz[, axis, level, copy, ...])</code></td>
<td>Localize tz-naive index of a Series or DataFrame to target time zone.</td>
</tr>
<tr>
<td><code>unique()</code></td>
<td>Return unique values of Series object.</td>
</tr>
<tr>
<td><code>unstack([level, fill_value])</code></td>
<td>Unstack, also known as pivot, Series with MultiIndex to produce DataFrame.</td>
</tr>
<tr>
<td><code>update(other)</code></td>
<td>Modify Series in place using values from passed Series.</td>
</tr>
<tr>
<td><code>value_counts([normalize, sort, ascending, ...])</code></td>
<td>Return a Series containing counts of unique values.</td>
</tr>
<tr>
<td><code>var(axis, skipna, level, ddof, numeric_only)</code></td>
<td>Return unbiased variance over requested axis.</td>
</tr>
<tr>
<td><code>view([dtype])</code></td>
<td>Create a new view of the Series.</td>
</tr>
<tr>
<td><code>where(cond[, other, inplace, axis, level, ...])</code></td>
<td>Replace values where the condition is False.</td>
</tr>
<tr>
<td><code>xs(key[, axis, level, drop_level])</code></td>
<td>Return cross-section from the Series/DataFrame.</td>
</tr>
</tbody>
</table>

**pandas.Series.abs**

Series.abs()

Return a Series/DataFrame with absolute numeric value of each element.

This function only applies to elements that are all numeric.

**Returns**

abs  Series/DataFrame containing the absolute value of each element.

**See also:**

numpy.abs  Calculate the absolute value element-wise.
Notes

For complex inputs, $1.2 + 1j$, the absolute value is $\sqrt{a^2 + b^2}$.

Examples

Absolute numeric values in a Series.

```python
g = pd.Series([-1.10, 2, -3.33, 4])
g.abs()
```

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1.10</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>2.00</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>3.33</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>4.00</td>
<td></td>
</tr>
<tr>
<td>dtype: float64</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Absolute numeric values in a Series with complex numbers.

```python
g = pd.Series([1.2 + 1j])
g.abs()
```

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1.56205</td>
</tr>
<tr>
<td>dtype: float64</td>
<td></td>
</tr>
</tbody>
</table>

Absolute numeric values in a Series with a Timedelta element.

```python
g = pd.Series([pd.Timedelta('1 days')])
g.abs()
```

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1 days</td>
</tr>
<tr>
<td>dtype: timedelta64[ns]</td>
<td></td>
</tr>
</tbody>
</table>

Select rows with data closest to certain value using argsort (from StackOverflow).

```python
df = pd.DataFrame({'a': [4, 5, 6, 7], 'b': [10, 20, 30, 40], 'c': [100, 50, -30, -50]})
df
```

```
   a  b   c
0  4 10 100
1  5 20  50
2  6 30 -30
3  7 40 -50
```

```python
df.loc[(df.c - 43).abs().argsort()]
```

```
   a  b   c
1  5 20  50
0  4 10 100
2  6 30 -30
3  7 40 -50
```
pandas.Series.add

Series.add(other, level=None, fill_value=None, axis=0)

Return Addition of series and other, element-wise (binary operator add).

Equivalent to series + other, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

Series.radd Reverse of the Addition operator, see Python documentation for more details.

Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d   NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b   NaN
d    1.0
e   NaN
dtype: float64
>>> a.add(b, fill_value=0)
a    2.0
b    1.0
c    1.0
d    1.0
e   NaN
dtype: float64
```
pandas.Series.add_prefix

Series.add_prefix(prefix)

Prefix labels with string prefix.

For Series, the row labels are prefixed. For DataFrame, the column labels are prefixed.

Parameters

prefix [str] The string to add before each label.

Returns

Series or DataFrame New Series or DataFrame with updated labels.

See also:

Series.add_suffix Suffix row labels with string suffix.

DataFrame.add_suffix Suffix column labels with string suffix.

Examples

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s
0    1
1    2
2    3
3    4
dtype: int64

>>> s.add_prefix('item_')
item_0  1
item_1  2
item_2  3
item_3  4
dtype: int64

>>> df = pd.DataFrame({'A': [1, 2, 3, 4], 'B': [3, 4, 5, 6]})
>>> df
   A  B
0  1  3
1  2  4
2  3  5
3  4  6

>>> df.add_prefix('col_')
   col_A  col_B
0    1    3
1    2    4
2    3    5
3    4    6
```
pandas.Series.add_suffix

Series.add_suffix(suffix)

Suffix labels with string suffix.

For Series, the row labels are suffixed. For DataFrame, the column labels are suffixed.

Parameters

suffix [str] The string to add after each label.

Returns

Series or DataFrame New Series or DataFrame with updated labels.

See also:

Series.add_prefix Prefix row labels with string prefix.

DataFrame.add_prefix Prefix column labels with string prefix.

Examples

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s
0    1
1    2
2    3
3    4
dtype: int64

>>> s.add_suffix('_item')
0_item    1
1_item    2
2_item    3
3_item    4
dtype: int64

>>> df = pd.DataFrame({'A': [1, 2, 3, 4], 'B': [3, 4, 5, 6]})
>>> df
   A  B
0  1  3
1  2  4
2  3  5
3  4  6

>>> df.add_suffix('_col')
   A_col  B_col
0      1    3
1      2    4
2      3    5
3      4    6
```
pandas.Series.agg

Series.agg(func=None, axis=0, *args, **kwargs)

Aggregate using one or more operations over the specified axis.

New in version 0.20.0.

Parameters

- **func** [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a Series or when passed to Series.apply.
  - Accepted combinations are:
    - function
    - string function name
    - list of functions and/or function names, e.g. [np.sum, 'mean']
    - dict of axis labels -> functions, function names or list of such.

- **axis** [[0 or ‘index’]] Parameter needed for compatibility with DataFrame.

- **args** Positional arguments to pass to func.

- **kwargs** Keyword arguments to pass to func.

Returns

- scalar, Series or DataFrame The return can be:
  - scalar : when Series.agg is called with single function
  - Series : when DataFrame.agg is called with a single function
  - DataFrame : when DataFrame.agg is called with several functions

Return scalar, Series or DataFrame.

See also:

- **Series.apply** Invoke function on a Series.
- **Series.transform** Transform function producing a Series with like indexes.

Notes

agg is an alias for aggregate. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

Examples

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s
0  1
1  2
2  3
3  4
dtype: int64
```
pandas.Series.aggregate

Series.aggregate (func=None, axis=0, *args, **kwargs)
Aggregate using one or more operations over the specified axis.
New in version 0.20.0.

Parameters

  func  [function, str, list or dict] Function to use for aggregating the data. If a function, must
either work when passed a Series or when passed to Series.apply.
  Accepted combinations are:
  • function
  • string function name
  • list of functions and/or function names, e.g. [np.sum, 'mean']
  • dict of axis labels -> functions, function names or list of such.

  axis  [[0 or ‘index’]] Parameter needed for compatibility with DataFrame.

  *args  Positional arguments to pass to func.

  **kwargs  Keyword arguments to pass to func.

Returns

  scalar, Series or DataFrame  The return can be:
  • scalar : when Series.agg is called with single function
  • Series : when DataFrame.agg is called with a single function
  • DataFrame : when DataFrame.agg is called with several functions

Return scalar, Series or DataFrame.

See also:

  Series.apply  Invoke function on a Series.

  Series.transform  Transform function producing a Series with like indexes.
Notes

`agg` is an alias for `aggregate`. Use the alias.
A passed user-defined-function will be passed a Series for evaluation.

Examples

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s
0 1
1 2
2 3
3 4
dtype: int64

>>> s.agg('min')
1

>>> s.agg(['min', 'max'])
min 1
max 4
dtype: int64
```

`pandas.Series.align`

Series.align(other, join='outer', axis=None, level=None, copy=True, fill_value=None, method=None, limit=None, fill_axis=0, broadcast_axis=None)
Align two objects on their axes with the specified join method.

Join method is specified for each axis Index.

Parameters

- `other` [DataFrame or Series]
- `join` ['outer', 'inner', 'left', 'right'], default 'outer'
- `axis` [allowed axis of the other object, default None] Align on index (0), columns (1), or both (None).
- `level` [int or level name, default None] Broadcast across a level, matching Index values on the passed MultiIndex level.
- `copy` [bool, default True] Always returns new objects. If copy=False and no reindexing is required then original objects are returned.
- `fill_value` [scalar, default np.NaN] Value to use for missing values. Defaults to NaN, but can be any “compatible” value.
- `method` ['backfill', 'bfill', 'pad', 'ffill', None], default None] Method to use for filling holes in reindexed Series:
  - pad / ffill: propagate last valid observation forward to next valid.
  - backfill / bfill: use NEXT valid observation to fill gap.
limit [int, default None] If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled. Must be greater than 0 if not None.

fill_axis [0 or ‘index’], default 0] Filling axis, method and limit.

broadcast_axis [{0 or ‘index’}, default None] Broadcast values along this axis, if aligning two objects of different dimensions.

Returns

(left, right) [(Series, type of other)] Aligned objects.

**pandas.Series.all**

Series.all (axis=0, bool_only=None, skipna=True, level=None, **kwargs)

Return whether all elements are True, potentially over an axis.

Returns True unless there at least one element within a series or along a Dataframe axis that is False or equivalent (e.g. zero or empty).

Parameters

axis [{0 or ‘index’, 1 or ‘columns’, None}, default 0] Indicate which axis or axes should be reduced.

- 0 / ‘index’ : reduce the index, return a Series whose index is the original column labels.
- 1 / ‘columns’ : reduce the columns, return a Series whose index is the original index.
- None : reduce all axes, return a scalar.

bool_only [bool, default None] Include only boolean columns. If None, will attempt to use everything, then use only boolean data. Not implemented for Series.

skipna [bool, default True] Exclude NA/null values. If the entire row/column is NA and skipna is True, then the result will be True, as for an empty row/column. If skipna is False, then NA are treated as True, because these are not equal to zero.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

**kwargs [any, default None] Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

scalar or Series If level is specified, then, Series is returned; otherwise, scalar is returned.

See also:

Series.all Return True if all elements are True.

DataFrame.any Return True if one (or more) elements are True.
Examples

Series

```python
>>> pd.Series([True, True]).all()
True
>>> pd.Series([True, False]).all()
False
>>> pd.Series([]).all()
True
>>> pd.Series([np.nan]).all()
True
>>> pd.Series([np.nan]).all(skipna=False)
True
```

DataFrames

Create a dataframe from a dictionary.

```python
>>> df = pd.DataFrame({'col1': [True, True], 'col2': [True, False]})
```

Default behaviour checks if column-wise values all return True.

```python
>>> df.all()
col1    True
col2    False
dtype: bool
```

Specify `axis='columns'` to check if row-wise values all return True.

```python
>>> df.all(axis='columns')
0   True
1   False
dtype: bool
```

Or `axis=None` for whether every value is True.

```python
>>> df.all(axis=None)
False
```

pandas.Series.any

Series.any (axis=0, bool_only=None, skipna=True, level=None, **kwargs)

Return whether any element is True, potentially over an axis.

Returns False unless there at least one element within a series or along a Dataframe axis that is True or equivalent (e.g. non-zero or non-empty).

Parameters

- **axis** [{0 or ‘index’, 1 or ‘columns’, None}, default 0] Indicate which axis or axes should be reduced.
  - 0 / ‘index’: reduce the index, return a Series whose index is the original column labels.
1 / ‘columns’ : reduce the columns, return a Series whose index is the original index.

• None : reduce all axes, return a scalar.

bool_only [bool, default None] Include only boolean columns. If None, will attempt to use everything, then use only boolean data. Not implemented for Series.

skipna [bool, default True] Exclude NA/null values. If the entire row/column is NA and skipna is True, then the result will be False, as for an empty row/column. If skipna is False, then NA are treated as True, because these are not equal to zero.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

**kwargs [any, default None] Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

scalar or Series  If level is specified, then, Series is returned; otherwise, scalar is returned.

See also:

numpy.any  Numpy version of this method.
Series.any  Return whether any element is True.
Series.all  Return whether all elements are True.
DataFrame.any  Return whether any element is True over requested axis.
DataFrame.all  Return whether all elements are True over requested axis.

Examples

Series

For Series input, the output is a scalar indicating whether any element is True.

```python
>>> pd.Series([False, False]).any()
False
>>> pd.Series([True, False]).any()
True
>>> pd.Series([]).any()
False
>>> pd.Series([np.nan]).any()
False
>>> pd.Series([np.nan]).any(skipna=False)
True
```

DataFrame

Whether each column contains at least one True element (the default).

```python
>>> df = pd.DataFrame({"A": [1, 2], "B": [0, 2], "C": [0, 0]})
>>> df
   A  B  C
0  1  0  0
1  2  2  0
```
Aggregating over the columns.

```python
>>> df = pd.DataFrame({'A': [True, False], 'B': [1, 2]})
>>> df
   A  B
0  True 1
1 False 2
```

```python
>>> df.any(axis='columns')
0  True
1  True
```

Aggregating over the entire DataFrame with `axis=None`.

```python
>>> df.any(axis=None)
True
```

`any` for an empty DataFrame is an empty Series.

```python
>>> pd.DataFrame([]).any()
Series([], dtype: bool)
```

**pandas.Series.append**

Series .append (to_append, ignore_index=False, verify_integrity=False)  
Concatenate two or more Series.

**Parameters**

- to_append [Series or list/tuple of Series] Series to append with self.
- ignore_index [bool, default False] If True, the resulting axis will be labeled 0, 1, ..., n - 1.
- verify_integrity [bool, default False] If True, raise Exception on creating index with duplicates.

**Returns**

Series Concatenated Series.
See also:

`concat` General function to concatenate DataFrame or Series objects.

Notes

Iteratively appending to a Series can be more computationally intensive than a single concatenate. A better solution is to append values to a list and then concatenate the list with the original Series all at once.

Examples

```python
>>> s1 = pd.Series([1, 2, 3])
>>> s2 = pd.Series([4, 5, 6])
>>> s3 = pd.Series([4, 5, 6], index=[3, 4, 5])
>>> s1.append(s2)
0 1
1 2
2 3
0 4
1 5
2 6
dtype: int64
```

```python
>>> s1.append(s3)
0 1
1 2
2 3
3 4
4 5
5 6
dtype: int64
```

With `ignore_index` set to True:

```python
>>> s1.append(s2, ignore_index=True)
0 1
1 2
2 3
3 4
4 5
5 6
dtype: int64
```

With `verify_integrity` set to True:

```python
>>> s1.append(s2, verify_integrity=True)
Traceback (most recent call last):
 ... 
ValueError: Indexes have overlapping values: [0, 1, 2]
```
**pandas.Series.apply**

`Series.apply(func, convert_dtypes=True, args=(), **kwds)`

Invoke function on values of Series.

Can be ufunc (a NumPy function that applies to the entire Series) or a Python function that only works on single values.

**Parameters**

- `func` [function] Python function or NumPy ufunc to apply.
- `convert_dtypes` [bool, default True] Try to find better dtype for elementwise function results. If False, leave as dtype=object.
- `args` [tuple] Positional arguments passed to func after the series value.
- `**kwds` Additional keyword arguments passed to func.

**Returns**

- `Series or DataFrame` If func returns a Series object the result will be a DataFrame.

**See also:**

- `Series.map` For element-wise operations.
- `Series.agg` Only perform aggregating type operations.
- `Series.transform` Only perform transforming type operations.

**Examples**

Create a series with typical summer temperatures for each city.

```python
>>> s = pd.Series([20, 21, 12],
                 index=['London', 'New York', 'Helsinki'])
>>> s
London    20
New York  21
Helsinki  12
dtype: int64
```

Square the values by defining a function and passing it as an argument to apply().

```python
>>> def square(x):
...     return x ** 2
... s.apply(square)
London    400
New York  441
Helsinki  144
dtype: int64
```

Square the values by passing an anonymous function as an argument to apply().

```python
>>> s.apply(lambda x: x ** 2)
London    400
New York  441
Helsinki  144
dtype: int64
```
Define a custom function that needs additional positional arguments and pass these additional arguments using the `args` keyword.

```python
>>> def subtract_custom_value(x, custom_value):
...     return x - custom_value

>>> s.apply(subtract_custom_value, args=(5,))
London   15
New York 16
Helsinki  7
dtype: int64
```

Define a custom function that takes keyword arguments and pass these arguments to `apply`.

```python
>>> def add_custom_values(x, **kwargs):
...     for month in kwargs:
...         x += kwargs[month]
...     return x

>>> s.apply(add_custom_values, june=30, july=20, august=25)
London   95
New York 96
Helsinki 87
dtype: int64
```

Use a function from the Numpy library.

```python
>>> s.apply(np.log)
London  2.995732
New York 3.044522
Helsinki 2.484907
dtype: float64
```

### `pandas.Series.argmax`

`Series.argmax` *(axis=None, skipna=True, *args, **kwargs)*

Return int position of the largest value in the Series.

If the maximum is achieved in multiple locations, the first row position is returned.

**Parameters**

- `axis` *[None]* Dummy argument for consistency with Series.
- `skipna` [bool, default True] Exclude NA/null values when showing the result.
- `*args`, `**kwargs` Additional arguments and keywords for compatibility with NumPy.

**Returns**

- `int` Row position of the maximum value.

**See also:**

- `Series.argmax` Return position of the maximum value.
- `Series.argmin` Return position of the minimum value.
- `numpy.ndarray.argmax` Equivalent method for numpy arrays.
Series.idxmax  Return index label of the maximum values.
Series.idxmin  Return index label of the minimum values.

Examples

Consider dataset containing cereal calories

```python
>>> s = pd.Series({'Corn Flakes': 100.0, 'Almond Delight': 110.0,  
                 'Cinnamon Toast Crunch': 120.0, 'Cocoa Puff': 110.0})
>>> s
Corn Flakes          100.0
Almond Delight       110.0
Cinnamon Toast Crunch 120.0
Cocoa Puff           110.0
dtype: float64
```

```python
>>> s.argmax()
2
>>> s.argmin()
0
```

The maximum cereal calories is the third element and the minimum cereal calories is the first element, since series is zero-indexed.

pandas.Series.argmin

Series.argmin(axis=None, skipna=True, *args, **kwargs)

Return int position of the smallest value in the Series.

If the minimum is achieved in multiple locations, the first row position is returned.

Parameters

axis  [{None}] Dummy argument for consistency with Series.
skipna  [bool, default True] Exclude NA/null values when showing the result.
*args, **kwargs  Additional arguments and keywords for compatibility with NumPy.

Returns

int  Row position of the minimum value.

See also:

Series.argmin  Return position of the minimum value.
Series.argmax  Return position of the maximum value.
numpy.ndarray.argmin  Equivalent method for numpy arrays.
Series.idxmax  Return index label of the maximum values.
Series.idxmin  Return index label of the minimum values.
Examples

Consider dataset containing cereal calories

```python
>>> s = pd.Series({'Corn Flakes': 100.0, 'Almond Delight': 110.0,
...                 'Cinnamon Toast Crunch': 120.0, 'Cocoa Puff': 110.0})
>>> s
Corn Flakes    100.0
Almond Delight 110.0
Cinnamon Toast Crunch 120.0
Cocoa Puff     110.0
dtype: float64

>>> s.argmax()
2
>>> s.argmin()
0
```

The maximum cereal calories is the third element and the minimum cereal calories is the first element, since series is zero-indexed.

**pandas.Series.argsort**

- **Series.argsort** (axis=0, kind='quicksort', order=None)
  - Return the integer indices that would sort the Series values.
  - Override ndarray.argsort. Argsorts the value, omitting NA/null values, and places the result in the same locations as the non-NA values.

  **Parameters**

  - **axis** [{0 or "index"}] Has no effect but is accepted for compatibility with numpy.
  - **kind** [{"mergesort", ‘quicksort’, ‘heapsort’}, default ‘quicksort’] Choice of sorting algorithm. See np.sort for more information. ‘mergesort’ is the only stable algorithm.
  - **order** [None] Has no effect but is accepted for compatibility with numpy.

  **Returns**

  - **Series** Positions of values within the sort order with -1 indicating nan values.

  **See also:**

  - `numpy.ndarray.argsort` Returns the indices that would sort this array.

**pandas.Series.asfreq**

- **Series.asfreq** (freq, method=None, how=None, normalize=False, fill_value=None)
  - Convert TimeSeries to specified frequency.
  - Optionally provide filling method to pad/backfill missing values.

  Returns the original data conformed to a new index with the specified frequency. resample is more appropriate if an operation, such as summarization, is necessary to represent the data at the new frequency.

  **Parameters**

  - **freq** [DateOffset or str] Frequency DateOffset or string.
method [[‘backfill’ / ‘bfill’, ‘pad’ / ’ffill’], default None] Method to use for filling holes in reindexed Series (note this does not fill NaNs that already were present):

- ‘pad’ / ‘fill’: propagate last valid observation forward to next valid
- ‘backfill’ / ‘bfill’: use NEXT valid observation to fill.

how [[‘start’, ‘end’], default end] For PeriodIndex only (see PeriodIndex.asfreq).

normalize [bool, default False] Whether to reset output index to midnight.

fill_value [scalar, optional] Value to use for missing values, applied during upsampling (note this does not fill NaNs that already were present).

Returns

Same type as caller  Object converted to the specified frequency.

See also:

reindex  Conform DataFrame to new index with optional filling logic.

Notes

To learn more about the frequency strings, please see this link.

Examples

Start by creating a series with 4 one minute timestamps.

```python
>>> index = pd.date_range('1/1/2000', periods=4, freq='T')
>>> series = pd.Series([0.0, None, 2.0, 3.0], index=index)
>>> df = pd.DataFrame({'s':series})
>>> df
  s
2000-01-01 00:00:00  0.0
2000-01-01 00:01:00  NaN
2000-01-01 00:02:00  2.0
2000-01-01 00:03:00  3.0
```

Upsample the series into 30 second bins.

```python
>>> df.asfreq(freq='30S')
  s
2000-01-01 00:00:00  0.0
2000-01-01 00:00:30  NaN
2000-01-01 00:01:00  NaN
2000-01-01 00:01:30  NaN
2000-01-01 00:02:00  2.0
2000-01-01 00:02:30  NaN
2000-01-01 00:03:00  3.0
```

Upsample again, providing a fill value.

```python
>>> df.asfreq(freq='30S', fill_value=9.0)
  s
2000-01-01 00:00:00  0.0
2000-01-01 00:00:30  9.0
```

(continues on next page)
Upsample again, providing a method.

```python
>>> df.asfreq(freq='30S', method='bfill')
S
2000-01-01 00:00:00  0.0
2000-01-01 00:00:30  NaN
2000-01-01 00:01:00  NaN
2000-01-01 00:01:30  2.0
2000-01-01 00:02:00  2.0
2000-01-01 00:02:30  3.0
2000-01-01 00:03:00  3.0
```

**pandas.Series.asof**

`Series.asof(where, subset=None)`

Return the last row(s) without any NaNs before `where`.

The last row (for each element in `where`, if list) without any NaN is taken. In case of a `DataFrame`, the last row without NaN considering only the subset of columns (if not `None`).

If there is no good value, NaN is returned for a Series or a Series of NaN values for a DataFrame.

**Parameters**

- `where` [date or array-like of dates] Date(s) before which the last row(s) are returned.
- `subset` [str or array-like of str, default `None`] For DataFrame, if not `None`, only use these columns to check for NaNs.

**Returns**

- scalar, Series, or DataFrame The return can be:
  - scalar: when `self` is a Series and `where` is a scalar
  - Series: when `self` is a Series and `where` is an array-like, or when `self` is a DataFrame and `where` is a scalar
  - DataFrame: when `self` is a DataFrame and `where` is an array-like

Return scalar, Series, or DataFrame.

**See also:**

- `merge_asof` Perform an asof merge. Similar to left join.
Notes

Dates are assumed to be sorted. Raises if this is not the case.

Examples

A Series and a scalar where.

```python
>>> s = pd.Series([1, 2, np.nan, 4], index=[10, 20, 30, 40])
>>> s
10 1.0
20 2.0
30 NaN
40 4.0
dtype: float64

>>> s.asof(20)
2.0
```

For a sequence where, a Series is returned. The first value is NaN, because the first element of where is before the first index value.

```python
>>> s.asof([5, 20])
5 NaN
20 2.0
dtype: float64
```

Missing values are not considered. The following is 2.0, not NaN, even though NaN is at the index location for 30.

```python
>>> s.asof(30)
2.0
```

Take all columns into consideration

```python
>>> df = pd.DataFrame({'a': [10, 20, 30, 40, 50],
...                   'b': [None, None, None, None, 500],
...                   'datetime': pd.DatetimeIndex(['2018-02-27 09:01:00',
...                                                 '2018-02-27 09:02:00',
...                                                 '2018-02-27 09:03:00',
...                                                 '2018-02-27 09:04:00',
...                                                 '2018-02-27 09:05:00']))
>>> df.asof(pd.DatetimeIndex(['2018-02-27 09:03:30',
...                             '2018-02-27 09:04:30']))
   a    b
2018-02-27 09:03:30 NaN NaN
2018-02-27 09:04:30 NaN NaN
```

Take a single column into consideration

```python
>>> df.asof(pd.DatetimeIndex(['2018-02-27 09:03:30',
...                             '2018-02-27 09:04:30']),
...          subset=['a'])
   a    b
2018-02-27 09:03:30 30.0 NaN
2018-02-27 09:04:30 40.0 NaN
```
pandas.Series.astype

Series.astype (dtype, copy= True, errors='raise')

Cast a pandas object to a specified dtype dtype.

Parameters

dtype [data type, or dict of column name -> data type] Use a numpy.dtype or Python type to cast entire pandas object to the same type. Alternatively, use {col: dtype, ...}, where col is a column label and dtype is a numpy.dtype or Python type to cast one or more of the DataFrame's columns to column-specific types.

copy [bool, default True] Return a copy when copy=True (be very careful setting copy=False as changes to values then may propagate to other pandas objects).

errors [{'raise', 'ignore'}, default 'raise'] Control raising of exceptions on invalid data for provided dtype.
  • raise: allow exceptions to be raised
  • ignore: suppress exceptions. On error return original object.

Returns

casted [same type as caller]

See also:

to_datetime Convert argument to datetime.
to_timedelta Convert argument to timedelta.
to_numeric Convert argument to a numeric type.
numpy.ndarray.astype Cast a numpy array to a specified type.

Examples

Create a DataFrame:

```python
>>> d = {'col1': [1, 2], 'col2': [3, 4]}
>>> df = pd.DataFrame(data=d)
>>> df.dtypes
   col1 int64
   col2 int64
   dtype: object
```

Cast all columns to int32:

```python
>>> df.astype('int32').dtypes
   col1 int32
   col2 int32
   dtype: object
```

Cast col1 to int32 using a dictionary:

```python
>>> df.astype({'col1': 'int32'}).dtypes
   col1 int32
   col2 int64
   dtype: object
```
Create a series:

```python
>>> ser = pd.Series([1, 2], dtype='int32')
>>> ser
0    1
1    2
dtype: int32
```
```python
>>> ser.astype('int64')
0    1
1    2
dtype: int64
```

Convert to categorical type:

```python
>>> ser.astype('category')
0    1
1    2
dtype: category
Categories (2, int64): [1, 2]
```

Convert to ordered categorical type with custom ordering:

```python
>>> cat_dtype = pd.api.types.CategoricalDtype(
...     categories=[2, 1], ordered=True)
>>> ser.astype(cat_dtype)
0    1
1    2
dtype: category
Categories (2, int64): [2 < 1]
```

Note that using `copy=False` and changing data on a new pandas object may propagate changes:

```python
>>> s1 = pd.Series([1, 2])
>>> s2 = s1.astype('int64', copy=False)
>>> s2[0] = 10
>>> s1 # note that s1[0] has changed too
0    10
1    2
dtype: int64
```

Create a series of dates:

```python
>>> ser_date = pd.Series(pd.date_range('20200101', periods=3))
>>> ser_date
0   2020-01-01
1   2020-01-02
2   2020-01-03
dtype: datetime64[ns]
```

Datetimnes are localized to UTC first before converting to the specified timezone:

```python
>>> ser_date.astype('datetime64[ns, US/Eastern]')
0   2019-12-31 19:00:00-05:00
1   2020-01-01 19:00:00-05:00
2   2020-01-02 19:00:00-05:00
dtype: datetime64[ns, US/Eastern]
```
**pandas.Series.at_time**

Series.at_time (time, asof=False, axis=None)
Select values at particular time of day (e.g., 9:30AM).

Parameters
- **time** [datetime.time or str]
- **axis** [{0 or 'index', 1 or 'columns'}, default 0] New in version 0.24.0.

Returns
- Series or DataFrame

Raises
- **TypeError** If the index is not a DatetimeIndex

See also:
- between_time Select values between particular times of the day.
- first Select initial periods of time series based on a date offset.
- last Select final periods of time series based on a date offset.
- DatetimeIndex.indexer_at_time Get just the index locations for values at particular time of the day.

**Examples**

```python
>>> i = pd.date_range('2018-04-09', periods=4, freq='12H')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
   A
2018-04-09 00:00:00 1
2018-04-09 12:00:00 2
2018-04-10 00:00:00 3
2018-04-10 12:00:00 4
>>> ts.at_time('12:00')
    A
2018-04-09 12:00:00 2
2018-04-10 12:00:00 4
```

**pandas.Series.autocorr**

Series.autocorr (lag=1)
Compute the lag-N autocorrelation.

This method computes the Pearson correlation between the Series and its shifted self.

Parameters
- **lag** [int, default 1] Number of lags to apply before performing autocorrelation.

Returns
- **float** The Pearson correlation between self and self.shift(lag).
See also:

- **Series.corr** Compute the correlation between two Series.
- **Series.shift** Shift index by desired number of periods.
- **DataFrame.corr** Compute pairwise correlation of columns.
- **DataFrame.corrwith** Compute pairwise correlation between rows or columns of two DataFrame objects.

Notes

If the Pearson correlation is not well defined return ‘NaN’.

Examples

```python
>>> s = pd.Series([0.25, 0.5, 0.2, -0.05])
>>> s.autocorr()
0.10355...
>>> s.autocorr(lag=2)
-0.99999...
```

If the Pearson correlation is not well defined, then ‘NaN’ is returned.

```python
>>> s = pd.Series([1, 0, 0, 0])
>>> s.autocorr()
nan
```

**pandas.Series.backfill**

Series.backfill(*axis=None, inplace=False, limit=None, downcast=None*)

Synonym for DataFrame.fillna() with method='bfill'.

Returns

{klass} or None Object with missing values filled or None if inplace=True.

**pandas.Series.between**

Series.between(*left, right, inclusive=True*)

Return boolean Series equivalent to left <= series <= right.

This function returns a boolean vector containing True wherever the corresponding Series element is between the boundary values left and right. NA values are treated as False.

Parameters

- left [scalar or list-like] Left boundary.
- right [scalar or list-like] Right boundary.
- inclusive [bool, default True] Include boundaries.

Returns

Series Series representing whether each element is between left and right (inclusive).
See also:

Series.gt Greater than of series and other.
Series.lt Less than of series and other.

Notes

This function is equivalent to (left <= ser) & (ser <= right)

Examples

```python
def s = pd.Series([2, 0, 4, 8, np.nan])

Boundary values are included by default:
```n
```python
s.between(1, 4)
0   True
1   False
2   True
3   False
4   False
dtype: bool
```

With inclusive set to False boundary values are excluded:
```python
s.between(1, 4, inclusive=False)
0   True
1   False
2   False
3   False
4   False
dtype: bool
```

left and right can be any scalar value:
```python
s = pd.Series(['Alice', 'Bob', 'Carol', 'Eve'])
s.between('Anna', 'Daniel')
```
```python
0   False
1   True
2   True
3   False
dtype: bool
```

**pandas.Series.between_time**

Series.between_time(start_time, end_time, include_start=True, include_end=True, axis=None)

Select values between particular times of the day (e.g., 9:00-9:30 AM).

By setting start_time to be later than end_time, you can get the times that are not between the two times.

**Parameters**

start_time [datetime.time or str] Initial time as a time filter limit.
**end_time** [datetime.time or str] End time as a time filter limit.

**include_start** [bool, default True] Whether the start time needs to be included in the result.

**include_end** [bool, default True] Whether the end time needs to be included in the result.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] Determine range time on index or columns value.

    New in version 0.24.0.

**Returns**

    Series or DataFrame  Data from the original object filtered to the specified dates range.

**Raises**

    TypeError  If the index is not a DatetimeIndex

**See also:**

    at_time  Select values at a particular time of the day.

    first  Select initial periods of time series based on a date offset.

    last  Select final periods of time series based on a date offset.

    DatetimeIndex.indexer_between_time  Get just the index locations for values between particular times of the day.

**Examples**

```python
>>> i = pd.date_range('2018-04-09', periods=4, freq='1D20min')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
      A
2018-04-09 00:00:00  1
2018-04-10 00:20:00  2
2018-04-11 00:40:00  3
2018-04-12 01:00:00  4

>>> ts.between_time('0:15', '0:45')
      A
2018-04-10 00:20:00  2
2018-04-11 00:40:00  3

You get the times that are not between two times by setting start_time later than end_time:

```python
>>> ts.between_time('0:45', '0:15')
      A
2018-04-09 00:00:00  1
2018-04-12 01:00:00  4
```
pandas.Series.bfill

Series.bfill (axis=None, inplace=False, limit=None, downcast=None)

Synonym for DataFrame.fillna() with method='bfill'.

Returns

klass or None  Object with missing values filled or None if inplace=True.

pandas.Series.bool

Series.bool()

Return the bool of a single element Series or DataFrame.

This must be a boolean scalar value, either True or False. It will raise a ValueError if the Series or DataFrame does not have exactly 1 element, or that element is not boolean (integer values 0 and 1 will also raise an exception).

Returns

bool  The value in the Series or DataFrame.

See also:

Series.astype  Change the data type of a Series, including to boolean.

DataFrame.astype  Change the data type of a DataFrame, including to boolean.

numpy.bool_  NumPy boolean data type, used by pandas for boolean values.

Examples

The method will only work for single element objects with a boolean value:

```python
>>> pd.Series([True]).bool()
True
>>> pd.Series([False]).bool()
False
```

```python
>>> pd.DataFrame({'col': [True]}).bool()
True
>>> pd.DataFrame({'col': [False]}).bool()
False
```

pandas.Series.cat

Series.cat()

Accessor object for categorical properties of the Series values.

Be aware that assigning to categories is a inplace operation, while all methods return new categorical data per default (but can be called with inplace=True).

Parameters

data  [Series or CategoricalIndex]
### Examples

```python
>>> s = pd.Series(list("abbccc")).astype("category")

0  a
1  b
2  b
3  c
4  c
5  c
dtype: category
Categories (3, object): ['a', 'b', 'c']

```

```python
>>> s.cat.categories
Index(['a', 'b', 'c'], dtype='object')
```

```python
>>> s.cat.rename_categories(list("cba"))
0  c
1  b
2  b
3  a
4  a
5  a
dtype: category
Categories (3, object): ['c', 'b', 'a']
```

```python
>>> s.cat.reorder_categories(list("cba"))
0  a
1  b
2  b
3  c
4  c
5  c
dtype: category
Categories (3, object): ['c', 'b', 'a']
```

```python
>>> s.cat.add_categories(
    ["d", "e"]
)
0  a
1  b
2  b
3  c
4  c
5  c
dtype: category
Categories (5, object): ['a', 'b', 'c', 'd', 'e']
```

```python
>>> s.cat.remove_categories(["a", "c"])
0  NaN
1  b
2  b
3  NaN
4  NaN
5  NaN
dtype: category
Categories (1, object): ['b']
```

---

3.3. Series  1061
```python
>>> s1 = s.cat.add_categories(["d", "e"])
0   a
1   b
2   b
3   c
4   c
5   c
dtype: category
Categories (3, object): ['a', 'b', 'c']
```

```python
>>> s.cat.set_categories(list("abcde"))
0   a
1   b
2   b
3   c
4   c
5   c
dtype: category
Categories (5, object): ['a', 'b', 'c', 'd', 'e']
```

```python
>>> s.cat.as_ordered()
0   a
1   b
2   b
3   c
4   c
5   c
dtype: category
Categories (3, object): ['a' < 'b' < 'c']
```

```python
>>> s.cat.as_unordered()
0   a
1   b
2   b
3   c
4   c
5   c
dtype: category
Categories (3, object): ['a', 'b', 'c']
```

**pandas.Series.clip**

`Series.clip(lower=None, upper=None, axis=None, inplace=False, *args, **kwargs)`

Trim values at input threshold(s).

Assigns values outside boundary to boundary values. Thresholds can be singular values or array like, and in the latter case the clipping is performed element-wise in the specified axis.

**Parameters**

- `lower` [float or array_like, default None] Minimum threshold value. All values below this threshold will be set to it.

- `upper` [float or array_like, default None] Maximum threshold value. All values above this threshold will be set to it.
**axis**  [int or str axis name, optional] Align object with lower and upper along the given axis.

**inplace**  [bool, default False] Whether to perform the operation in place on the data.

**args, **kwargs**  Additional keywords have no effect but might be accepted for compatibility with numpy.

**Returns**

Series or DataFrame  Same type as calling object with the values outside the clip boundaries replaced.

**See also:**

- **Series.clip**  Trim values at input threshold in series.
- **DataFrame.clip**  Trim values at input threshold in dataframe.
- **numpy.clip**  Clip (limit) the values in an array.

**Examples**

```python
>>> data = {'col_0': [9, -3, 0, -1, 5], 'col_1': [-2, -7, 6, 8, -5]
>>> df = pd.DataFrame(data)
>>> df
  col_0  col_1
0      9   -2
1     -3   -7
2      0    6
3     -1    8
4      5   -5
```

Clips per column using lower and upper thresholds:

```python
>>> df.clip(-4, 6)
   col_0  col_1
0     6   -2
1    -3   -4
2     0    6
3    -1    6
4     5   -4
```

Clips using specific lower and upper thresholds per column element:

```python
>>> t = pd.Series([2, -4, -1, 6, 3])
>>> t
0    2
1   -4
2   -1
3    6
4    3
dtype: int64
```

```python
>>> df.clip(t, t + 4, axis=0)
   col_0  col_1
0     6    2
1    -3   -4
2     0    3
```

(continues on next page)
pandas.Series.combine

Series.combine(other, func, fill_value=None)
Combine the Series with a Series or scalar according to func.

Combine the Series and other using func to perform elementwise selection for combined Series. fill_value is assumed when value is missing at some index from one of the two objects being combined.

Parameters

other [Series or scalar] The value(s) to be combined with the Series.
func [function] Function that takes two scalars as inputs and returns an element.
fill_value [scalar, optional] The value to assume when an index is missing from one Series or the other. The default specifies to use the appropriate NaN value for the underlying dtype of the Series.

Returns

Series The result of combining the Series with the other object.

See also:

Series.combine_first Combine Series values, choosing the calling Series’ values first.

Examples

Consider 2 Datasets s1 and s2 containing highest clocked speeds of different birds.

```python
>>> s1 = pd.Series({'falcon': 330.0, 'eagle': 160.0})
>>> s1
falcon 330.0
eagle 160.0
dtype: float64
>>> s2 = pd.Series({'falcon': 345.0, 'eagle': 200.0, 'duck': 30.0})
>>> s2
falcon 345.0
eagle 200.0
duck 30.0
dtype: float64
```

Now, to combine the two datasets and view the highest speeds of the birds across the two datasets

```python
>>> s1.combine(s2, max)
        duck   NaN
falcon  345.0
eagle  200.0
dtype: float64
```

In the previous example, the resulting value for duck is missing, because the maximum of a NaN and a float is a NaN. So, in the example, we set fill_value=0, so the maximum value returned will be the value from some dataset.
```python
>>> s1.combine(s2, max, fill_value=0)
duck    30.0
eagle   200.0
falcon  345.0
dtype: float64
```

### pandas.Series.combine_first

`Series.combine_first(other)`

Combine Series values, choosing the calling Series’s values first.

**Parameters**

- `other` [Series] The value(s) to be combined with the `Series`.

**Returns**

- `Series` The result of combining the Series with the other object.

**See also:**

- `Series.combine` Perform elementwise operation on two Series using a given function.

**Notes**

Result index will be the union of the two indexes.

**Examples**

```python
>>> s1 = pd.Series([1, np.nan])
>>> s2 = pd.Series([3, 4])
>>> s1.combine_first(s2)
0  1.0
1  4.0
dtype: float64
```

### pandas.Series.compare

`Series.compare(other, align_axis=1, keep_shape=False, keep_equal=False)`

Compare to another Series and show the differences.

New in version 1.1.0.

**Parameters**

- `other` [Series] Object to compare with.

- `align_axis` [0 or ‘index’, 1 or ‘columns’], default 1 Determine which axis to align the comparison on.

  - 0, or ‘index’ [Resulting differences are stacked vertically] with rows drawn alternately from self and other.

  - 1, or ‘columns’ [Resulting differences are aligned horizontally] with columns drawn alternately from self and other.
**keep_shape**  [bool, default False] If true, all rows and columns are kept. Otherwise, only the ones with different values are kept.

**keep_equal**  [bool, default False] If true, the result keeps values that are equal. Otherwise, equal values are shown as NaNs.

**Returns**

**Series or DataFrame**  If axis is 0 or ‘index’ the result will be a Series. The resulting index will be a MultiIndex with ‘self’ and ‘other’ stacked alternately at the inner level.

If axis is 1 or ‘columns’ the result will be a DataFrame. It will have two columns namely ‘self’ and ‘other’.

**See also:**

*DataFrame.compare*  Compare with another DataFrame and show differences.

**Notes**

Matching NaNs will not appear as a difference.

**Examples**

```python
>>> s1 = pd.Series(['a', 'b', 'c', 'd', 'e'])
>>> s2 = pd.Series(['a', 'a', 'c', 'b', 'e'])

Align the differences on columns

```python
>>> s1.compare(s2)
    self  other
     1    b    a
     3    d    b
```

Stack the differences on indices

```python
>>> s1.compare(s2, align_axis=0)
       self  other
       1      b  NaN
      other  a    NaN
     3      d    a
    other  b    NaN
dtype: object
```

Keep all original rows

```python
>>> s1.compare(s2, keep_shape=True)
     self  other
     0  NaN    NaN
     1    b    a
     2  NaN    NaN
     3    d    b
     4  NaN    NaN
```

Keep all original rows and also all original values
pandas.Series.convert_dtypes

Series.convert_dtypes(infer_objects=True, convert_string=True, convert_integer=True, convert_boolean=True)

Convert columns to best possible dtypes using dtypes supporting pd.NA.

New in version 1.0.0.

Parameters

    infer_objects [bool, default True] Whether object dtypes should be converted to the best possible types.
    convert_string [bool, default True] Whether object dtypes should be converted to StringDtype().
    convert_integer [bool, default True] Whether, if possible, conversion can be done to integer extension types.
    convert_boolean [bool, defaults True] Whether object dtypes should be converted to BooleanDtype().

Returns

Series or DataFrame Copy of input object with new dtype.

See also:

infer_objects Infer dtypes of objects.
to_datetime Convert argument to datetime.
to_timedelta Convert argument to timedelta.
to_numeric Convert argument to a numeric type.

Notes

By default, convert_dtypes will attempt to convert a Series (or each Series in a DataFrame) to dtypes that support pd.NA. By using the options convert_string, convert_integer, and convert_boolean, it is possible to turn off individual conversions to StringDtype, the integer extension types or BooleanDtype, respectively.

For object-dtyped columns, if infer_objects is True, use the inference rules as during normal Series/DataFrame construction. Then, if possible, convert to StringDtype, BooleanDtype or an appropriate integer extension type, otherwise leave as object.

If the dtype is integer, convert to an appropriate integer extension type.

If the dtype is numeric, and consists of all integers, convert to an appropriate integer extension type.
In the future, as new dtypes are added that support `pd.NA`, the results of this method will change to support those new dtypes.

**Examples**

```python
>>> df = pd.DataFrame(
...     {
...         "a": pd.Series([1, 2, 3], dtype=np.dtype("int32")),
...         "b": pd.Series(["x", "y", "z"], dtype=np.dtype("O")),
...         "c": pd.Series([True, False, np.nan], dtype=np.dtype("O")),
...         "d": pd.Series(["h", "i", np.nan], dtype=np.dtype("O")),
...         "e": pd.Series([10, np.nan, 20], dtype=np.dtype("float")),
...         "f": pd.Series([np.nan, 100.5, 200], dtype=np.dtype("float")),
...     }
... )
```

Start with a DataFrame with default dtypes.

```python
>>> df
   a  b   c     d   e   f
0  1  x  True  h  10.0 NaN
1  2  y False i  NaN  100.5
2  3  z  NaN  NaN  20.0  200.0
```

```python
>>> df.dtypes
a    int32
b     object
c    object
d     object
e   float64
f   float64
dtype: object
```

Convert the DataFrame to use best possible dtypes.

```python
>>> dfn = df.convert_dtypes()
>>> dfn
   a   b   c   d   e   f
0  1  x  True  h  10.0 NaN
1  2  y False i  NaN  100.5
2  3  z  NaN  NaN  20.0  200.0
```

```python
>>> dfn.dtypes
a    Int32
b    string
c   boolean
d    string
e    Int64
f   float64
dtype: object
```

Start with a Series of strings and missing data represented by `np.nan`.

```python
>>> s = pd.Series(["a", "b", np.nan])
>>> s
```

(continues on next page)
Obtain a Series with dtype `StringDtype`.

```python
>>> s.convert_dtypes()
0   a
1   b
2  <NA>
dtype: string
```

**pandas.Series.copy**

Method `copy` *(deep=True)*

Make a copy of this object’s indices and data.

- When `deep=True` (default), a new object will be created with a copy of the calling object’s data and indices. Modifications to the data or indices of the copy will not be reflected in the original object (see notes below).
- When `deep=False`, a new object will be created without copying the calling object’s data or index (only references to the data and index are copied). Any changes to the data of the original will be reflected in the shallow copy (and vice versa).

**Parameters**

- `deep` [bool, default True] Make a deep copy, including a copy of the data and the indices. With `deep=False` neither the indices nor the data are copied.

**Returns**

- `copy` [Series or DataFrame] Object type matches caller.

**Notes**

- When `deep=True`, data is copied but actual Python objects will not be copied recursively, only the reference to the object. This is in contrast to `copy.deepcopy` in the Standard Library, which recursively copies object data (see examples below).
- While `Index` objects are copied when `deep=True`, the underlying numpy array is not copied for performance reasons. Since `Index` is immutable, the underlying data can be safely shared and a copy is not needed.
Examples

```python
>>> s = pd.Series([1, 2], index=['a', 'b'])
>>> s
a 1
b 2
dtype: int64

>>> s_copy = s.copy()
>>> s_copy
a 1
b 2
dtype: int64

Shallow copy versus default (deep) copy:

```python
>>> s = pd.Series([1, 2], index=['a', 'b'])
>>> deep = s.copy()
>>> shallow = s.copy(deep=False)

Shallow copy shares data and index with original.

```python
>>> s is shallow
False
>>> s.values is shallow.values and s.index is shallow.index
True

Deep copy has own copy of data and index.

```python
>>> s is deep
False
>>> s.values is deep.values or s.index is deep.index
False

Updates to the data shared by shallow copy and original is reflected in both; deep copy remains unchanged.

```python
>>> s[0] = 3
>>> shallow[1] = 4
>>> s
a 3
b 4
dtype: int64

```python
>>> shallow
a 3
b 4
dtype: int64

```python
>>> deep
a 1
b 2
dtype: int64

```python
Note that when copying an object containing Python objects, a deep copy will copy the data, but will not do so recursively. Updating a nested data object will be reflected in the deep copy.

```python
>>> s = pd.Series([[1, 2], [3, 4]])
>>> deep = s.copy()
>>> s[0][0] = 10
```
pandas.Series.corr

Series.corr(other, method='pearson', min_periods=None)
Compute correlation with other Series, excluding missing values.

Parameters

other [Series] Series with which to compute the correlation.

method [{‘pearson’, ‘kendall’, ‘spearman’} or callable] Method used to compute correlation:
• pearson : Standard correlation coefficient
• kendall : Kendall Tau correlation coefficient
• spearman : Spearman rank correlation
• callable: Callable with input two 1d ndarrays and returning a float.

New in version 0.24.0: Note that the returned matrix from corr will have 1 along the diagonals and will be symmetric regardless of the callable’s behavior.

min_periods [int, optional] Minimum number of observations needed to have a valid result.

Returns

float Correlation with other.

See also:

DataFrame.corr Compute pairwise correlation between columns.
DataFrame.corrwith Compute pairwise correlation with another DataFrame or Series.

Examples

```python
>>> def histogram_intersection(a, b):
...     v = np.minimum(a, b).sum().round(decimals=1)
...     return v
>>> s1 = pd.Series([.2, .0, .6, .2])
>>> s2 = pd.Series([.3, .6, .0, .1])
>>> s1.corr(s2, method=histogram_intersection)
0.3
```
**pandas.Series.count**

Series.count(level=None)

Return number of non-NA/null observations in the Series.

**Parameters**

- **level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a smaller Series.

**Returns**

- **int or Series (if level specified)** Number of non-null values in the Series.

**See also:**

- **DataFrame.count** Count non-NA cells for each column or row.

**Examples**

```python
>>> s = pd.Series([0.0, 1.0, np.nan])
>>> s.count()
2
```

**pandas.Series.cov**

Series.cov(other, min_periods=None, ddof=1)

Compute covariance with Series, excluding missing values.

**Parameters**

- **other** [Series] Series with which to compute the covariance.

- **min_periods** [int, optional] Minimum number of observations needed to have a valid result.

- **ddof** [int, default 1] Delta degrees of freedom. The divisor used in calculations is \( N - ddof \), where \( N \) represents the number of elements.

**Returns**

- **float** Covariance between Series and other normalized by N-1 (unbiased estimator).

**See also:**

- **DataFrame.cov** Compute pairwise covariance of columns.
Examples

```python
>>> s1 = pd.Series([0.90010907, 0.13484424, 0.62036035])
>>> s2 = pd.Series([0.12528585, 0.26962463, 0.51111198])
>>> s1.cov(s2)
-0.01685762652715874
```

**pandas.Series.cummax**

`Series.cummax(axis=None, skipna=True, *args, **kwargs)`

Return cumulative maximum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative maximum.

**Parameters**

- `axis` [0 or ‘index’, 1 or ‘columns’], default 0] The index or the name of the axis. 0 is equivalent to None or ‘index’.
- `skipna` [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.
- `*args, **kwargs` Additional keywords have no effect but might be accepted for compatibility with NumPy.

**Returns**

 scalar or Series  Return cumulative maximum of scalar or Series.

**See also:**

- `core.window.Expanding.max` Similar functionality but ignores NaN values.
- `Series.max` Return the maximum over Series axis.
- `Series.cummax` Return cumulative maximum over Series axis.
- `Series.cummin` Return cumulative minimum over Series axis.
- `Series.cumsum` Return cumulative sum over Series axis.
- `Series.cumprod` Return cumulative product over Series axis.

**Examples**

**Series**

```python
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1    NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.
To include NA values in the operation, use **skipna=False**

```python
>>> s.cummax(skipna=False)
0  2.0
1  NaN
2  NaN
3  NaN
4  NaN
dtype: float64
```

**DataFrame**

```python
>>> df = pd.DataFrame([[2.0, 1.0],
                      ...                    [3.0, np.nan],
                      ...                    [1.0, 0.0]],
                      ...                   columns=list('AB'))
>>> df
   A  B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the maximum in each column. This is equivalent to **axis=None** or **axis='index'**.

```python
>>> df.cummax()
   A  B
0  2.0  1.0
1  3.0  NaN
2  3.0  1.0
```

To iterate over columns and find the maximum in each row, use **axis=1**

```python
>>> df.cummax(axis=1)
   A  B
0  2.0  2.0
1  3.0  NaN
2  1.0  1.0
```
pandas.Series.cummin

Series.cummin(axis=None, skipna=True, *args, **kwargs)

Return cumulative minimum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative minimum.

Parameters

axis [{0 or ‘index’, 1 or ‘columns’}, default 0] The index or the name of the axis. 0 is equivalent to None or ‘index’.

skipna [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

*args, **kwargs Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

scalar or Series Return cumulative minimum of scalar or Series.

See also:

core.window.Expanding.min Similar functionality but ignores NaN values.

Series.min Return the minimum over Series axis.

Series.cummax Return cumulative maximum over Series axis.

Series.cummin Return cumulative minimum over Series axis.

Series.cumsum Return cumulative sum over Series axis.

Series.cumprod Return cumulative product over Series axis.

Examples

Series

```python
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1    NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.

```python
>>> s.cummin()
0    2.0
1    NaN
2    2.0
3   -1.0
4   -1.0
dtype: float64
```

To include NA values in the operation, use skipna=False
>>> s.cummin(skipna=False)
0   2.0
1   NaN
2   NaN
3   NaN
4   NaN
dtype: float64

DataFrame

>>> df = pd.DataFrame([[2.0, 1.0],
...                     [3.0, np.nan],
...                     [1.0, 0.0]],
...                    columns=list('AB'))

>>> df
A   B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0

By default, iterates over rows and finds the minimum in each column. This is equivalent to `axis=None` or `axis='index'`.

>>> df.cummin()
     A   B
0  2.0  1.0
1  2.0  NaN
2  1.0  0.0

To iterate over columns and find the minimum in each row, use `axis=1`

>>> df.cummin(axis=1)
     A   B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0

**pandas.Series.cumprod**

Series.cumprod axis=None, skipna=True, *args, **kwargs

Return cumulative product over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative product.

**Parameters**

- **axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] The index or the name of the axis. 0 is equivalent to None or ‘index’.
- **skipna** [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.
- **args, **kwargs** Additional keywords have no effect but might be accepted for compatibility with NumPy.

**Returns**

- **scalar or Series** Return cumulative product of scalar or Series.
See also:

`core.window.Expanding.prod` Similar functionality but ignores NaN values.

`Series.prod` Return the product over Series axis.

`Series.cummax` Return cumulative maximum over Series axis.

`Series.cummin` Return cumulative minimum over Series axis.

`Series.cumsum` Return cumulative sum over Series axis.

`Series.cumprod` Return cumulative product over Series axis.

Examples

Series

```python
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1    NaN
2    5.0
3   -1.0
4     0.0
dtype: float64
```

By default, NA values are ignored.

```python
>>> s.cumprod()
0    2.0
1    NaN
2   10.0
3  -10.0
4   -0.0
dtype: float64
```

To include NA values in the operation, use `skipna=False`

```python
>>> s.cumprod(skipna=False)
0    2.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64
```

Dataframe

```python
>>> df = pd.DataFrame([[2.0, 1.0],
...                     [3.0, np.nan],
...                     [1.0, 0.0]],
...                    columns=list('AB'))
>>> df
   A  B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```
By default, iterates over rows and finds the product in each column. This is equivalent to `axis=None` or `axis='index'`.

```python
>>> df.cumprod()
     A   B
0  2.0  1.0
1  6.0  NaN
2  6.0  0.0
```

To iterate over columns and find the product in each row, use `axis=1`

```python
>>> df.cumprod(axis=1)
     A  B
0  2.0  2.0
1  3.0  NaN
2  1.0  0.0
```

**pandas.Series.cumsum**

`Series.cumsum(axis=None, skipna=True, *args, **kwargs)`

Return cumulative sum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative sum.

**Parameters**

- `axis` ([0 or ‘index’, 1 or ‘columns’], default 0) The index or the name of the axis. 0 is equivalent to None or ‘index’.
- `skipna` [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.
- `*args, **kwargs` Additional keywords have no effect but might be accepted for compatibility with NumPy.

**Returns**

- `scalar or Series` Return cumulative sum of scalar or Series.

**See also:**

- `core.window.Expanding.sum` Similar functionality but ignores NaN values.
- `Series.sum` Return the sum over Series axis.
- `Series.cummax` Return cumulative maximum over Series axis.
- `Series.cummin` Return cumulative minimum over Series axis.
- `Series.cumsum` Return cumulative sum over Series axis.
- `Series.cumprod` Return cumulative product over Series axis.
Examples

Series

```python
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1   NaN
2     5.0
3    -1.0
4     0.0
dtype: float64
```

By default, NA values are ignored.

```python
>>> s.cumsum()
0 2.0
1 NaN
2 7.0
3 6.0
4 6.0
dtype: float64
```

To include NA values in the operation, use `skipna=False`

```python
>>> s.cumsum(skipna=False)
0 2.0
1 NaN
2 NaN
3 NaN
4 NaN
dtype: float64
```

Dataframe

```python
>>> df = pd.DataFrame([[2.0, 1.0],
...                     [3.0, np.nan],
...                     [1.0, 0.0]],
...                   columns=list('AB'))
>>> df
     A  B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the sum in each column. This is equivalent to `axis=None` or `axis='index'`.

```python
>>> df.cumsum()
       A  B
0  2.00  1.0
1  5.00  NaN
2  6.00  1.0
```

To iterate over columns and find the sum in each row, use `axis=1`

```python
>>> df.cumsum(axis=1)
     A  B
0  2.0  1.0
1  5.0  NaN
2  6.0  1.0
```
pandas.Series.describe

Series.describe(percentiles=None, include=None, exclude=None, datetime_is_numeric=False)

Generate descriptive statistics.

Descriptive statistics include those that summarize the central tendency, dispersion and shape of a dataset’s distribution, excluding NaN values.

Analyzes both numeric and object series, as well as DataFrame column sets of mixed data types. The output will vary depending on what is provided. Refer to the notes below for more detail.

Parameters

percentiles [list-like of numbers, optional] The percentiles to include in the output. All should fall between 0 and 1. The default is [.25, .5, .75], which returns the 25th, 50th, and 75th percentiles.

include ['all', list-like of dtypes or None (default), optional] A white list of data types to include in the result. Ignored for Series. Here are the options:

• ‘all’ : All columns of the input will be included in the output.

• A list-like of dtypes : Limits the results to the provided data types. To limit the result to numeric types submit numpy.number. To limit it instead to object columns submit the numpy.object data type. Strings can also be used in the style of select_dtypes (e.g. df.describe(include=['O'])). To select pandas categorical columns, use 'category'

• None (default) : The result will include all numeric columns.

exclude [list-like of dtypes or None (default), optional,] A black list of data types to omit from the result. Ignored for Series. Here are the options:

• A list-like of dtypes : Excludes the provided data types from the result. To exclude numeric types submit numpy.number. To exclude object columns submit the data type numpy.object. Strings can also be used in the style of select_dtypes (e.g. df.describe(include=['O'])). To exclude pandas categorical columns, use 'category'

• None (default) : The result will exclude nothing.

datetime_is_numeric [bool, default False] Whether to treat datetime dtypes as numeric. This affects statistics calculated for the column. For DataFrame input, this also controls whether datetime columns are included by default.

New in version 1.1.0.

Returns

Series or DataFrame Summary statistics of the Series or DataFrame provided.

See also:

DataFrame.count Count number of non-NA/null observations.

DataFrame.max Maximum of the values in the object.
**DataFrame.min** Minimum of the values in the object.

**DataFrame.mean** Mean of the values.

**DataFrame.std** Standard deviation of the observations.

**DataFrame.select_dtypes** Subset of a DataFrame including/excluding columns based on their dtype.

**Notes**

For numeric data, the result’s index will include `count`, `mean`, `std`, `min`, `max` as well as lower, 50 and upper percentiles. By default the lower percentile is 25 and the upper percentile is 75. The 50 percentile is the same as the median.

For object data (e.g. strings or timestamps), the result’s index will include `count`, `unique`, `top`, and `freq`. The `top` is the most common value. The `freq` is the most common value’s frequency. Timestamps also include the `first` and `last` items.

If multiple object values have the highest count, then the `count` and `top` results will be arbitrarily chosen from among those with the highest count.

For mixed data types provided via a DataFrame, the default is to return only an analysis of numeric columns. If the data frame consists only of object and categorical data without any numeric columns, the default is to return an analysis of both the object and categorical columns. If include='all' is provided as an option, the result will include a union of attributes of each type.

The `include` and `exclude` parameters can be used to limit which columns in a DataFrame are analyzed for the output. The parameters are ignored when analyzing a Series.

**Examples**

Describing a numeric Series.

```python
>>> s = pd.Series([1, 2, 3])
>>> s.describe()
count  3.0  
mean   2.0  
std    1.0  
min    1.0  
25%    1.5  
50%    2.0  
75%    2.5  
max    3.0  
dtype: float64
```

Describing a categorical Series.

```python
>>> s = pd.Series(['a', 'a', 'b', 'c'])
>>> s.describe()
count  4  
unique 3  
top    a  
freq   2  
dtype: object
```

Describing a timestamp Series.
>>> s = pd.Series([...
... np.datetime64("2000-01-01"),
... np.datetime64("2010-01-01"),
... np.datetime64("2010-01-01")
... ])  
>>> s.describe(datetime_is_numeric=True)
count 3  
mean 2006-09-01 08:00:00  
min 2000-01-01 00:00:00  
25% 2004-12-31 12:00:00  
50% 2010-01-01 00:00:00  
75% 2010-01-01 00:00:00  
max 2010-01-01 00:00:00  
dtype: object

Describing a DataFrame. By default only numeric fields are returned.

```python
>>> df = pd.DataFrame({'categorical': pd.Categorical(['d','e','f']),
...                     'numeric': [1, 2, 3],
...                     'object': ['a', 'b', 'c']})
```

```python
>>> df.describe()  
numeric  
count 3.0  
mean 2.0  
std 1.0  
min 1.0  
25% 1.5  
50% 2.0  
75% 2.5  
max 3.0
```

Describing all columns of a DataFrame regardless of data type.

```python
>>> df.describe(include='all')  
categorical numeric object  
count 3 3.0 3  
unique 3 NaN 3  
top f NaN a  
freq 1 NaN 1  
mean NaN 2.0 NaN  
std NaN 1.0 NaN  
min NaN 1.0 NaN  
25% NaN 1.5 NaN  
50% NaN 2.0 NaN  
75% NaN 2.5 NaN  
max NaN 3.0 NaN
```

Describing a column from a DataFrame by accessing it as an attribute.

```python
>>> df.numeric.describe()  
count 3.0  
mean 2.0  
std 1.0  
min 1.0  
25% 1.5  
50% 2.0
```

(continues on next page)
Including only numeric columns in a DataFrame description.

```python
>>> df.describe(include=[np.number])
numeric
count  3.0
mean   2.0
std    1.0
min    1.0
25%    1.5
50%    2.0
75%    2.5
max    3.0
```

Including only string columns in a DataFrame description.

```python
>>> df.describe(include=[object])
object
count  3
unique 3
top   a
freq   1
```

Including only categorical columns from a DataFrame description.

```python
>>> df.describe(include=['category'])
categorical
count  3
unique 3
top   f
freq   1
```

Excluding numeric columns from a DataFrame description.

```python
>>> df.describe(exclude=[np.number])
categorical  object
count  3  3
unique 3  3
top   f  a
freq   1  1
```

Excluding object columns from a DataFrame description.

```python
>>> df.describe(exclude=[object])
categorical  numeric
count  3  3.0
unique 3  NaN
top    f  NaN
freq   1  NaN
mean   NaN  2.0
std    NaN  1.0
min    NaN  1.0
25%    NaN  1.5
```
pandas.Series.diff

Series.diff(periods=1)

First discrete difference of element.

Calculates the difference of a Series element compared with another element in the Series (default is element in previous row).

Parameters

periods [int, default 1] Periods to shift for calculating difference, accepts negative values.

Returns

Series First differences of the Series.

See also:

Series.pct_change Percent change over given number of periods.
Series.shift Shift index by desired number of periods with an optional time freq.
DataFrame.diff First discrete difference of object.

Notes

For boolean dtypes, this uses operator.xor() rather than operator.sub(). The result is calculated according to current dtype in Series, however dtype of the result is always float64.

Examples

Difference with previous row

```python
>>> s = pd.Series([1, 1, 2, 3, 5, 8])
>>> s.diff()  
0   NaN
1   0.0
2   1.0
3   1.0
4   2.0
5   3.0
dtype: float64
```

Difference with 3rd previous row

```python
>>> s.diff(periods=3) 
0   NaN
1   NaN
2   NaN
3   2.0
4   4.0
```
5  6.0
dtype: float64

Difference with following row

```python
>>> s.diff(periods=-1)
0   0.0
1  -1.0
2  -1.0
3  -2.0
4  -3.0
5   NaN
dtype: float64
```

Overflow in input dtype

```python
>>> s = pd.Series([1, 0], dtype=np.uint8)
>>> s.diff()
0   NaN
1  255.0
dtype: float64
```

**pandas.Series.div**

Series `div` \[other, level=None, fill_value=None, axis=0\]

Return Floating division of series and other, element-wise (binary operator `truediv`).

Equivalent to `series / other`, but with support to substitute a `fill_value` for missing data in either one of the inputs.

**Parameters**

- **other** [Series or scalar value]

- **fill_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

- **level** [int or name] Broadcast across a level, matching Index values on the passed Multi-Index level.

**Returns**

Series The result of the operation.

**See also:**

- **Series.rtruediv** Reverse of the Floating division operator, see Python documentation for more details.
Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a 1.0
b 1.0
c 1.0
d NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a 1.0
b NaN
d 1.0
e NaN
dtype: float64
>>> a.divide(b, fill_value=0)
a 1.0
b inf
c inf
d 0.0
e NaN
dtype: float64
```

pandas.Series.divide

Series.divide (other, level=None, fill_value=None, axis=0)

Return Floating division of series and other, element-wise (binary operator truediv).

Equivalent to `series / other`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

Series.rtruediv Reverse of the Floating division operator, see Python documentation for more details.
Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a 1.0
b 1.0
c 1.0
d NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a 1.0
b NaN
d 1.0
e NaN
dtype: float64
```

```python
>>> a.divide(b, fill_value=0)
a 1.0
b inf
c inf
d 0.0
e NaN
dtype: float64
```

**pandas.Series.divmod**

Series.divmod(other, level=None, fill_value=None, axis=0)

Return integer division and modulo of series and other, element-wise (binary operator divmod).

Equivalent to series divmod other, but with support to substitute a fill_value for missing data in either one of the inputs.

**Parameters**

- **other** [Series or scalar value]
- **fill_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.
- **level** [int or name] Broadcast across a level, matching Index values on the passed Multi-Index level.

**Returns**

- **2-Tuple of Series** The result of the operation.

**See also:**

- **Series.rdivmod** Reverse of the Integer division and modulo operator, see Python documentation for more details.
**pandas.Series.dot**

*Series.dot(other)*

Compute the dot product between the Series and the columns of other.

This method computes the dot product between the Series and another one, or the Series and each columns of a DataFrame, or the Series and each columns of an array.

It can also be called using `self @ other` in Python >= 3.5.

**Parameters**

- **other** [Series, DataFrame or array-like] The other object to compute the dot product with its columns.

**Returns**

- **scalar, Series or numpy.ndarray** Return the dot product of the Series and other if other is a Series, the Series of the dot product of Series and each rows of other if other is a DataFrame or a numpy.ndarray between the Series and each columns of the numpy array.

**See also:**

- **DataFrame.dot** Compute the matrix product with the DataFrame.
- **Series.mul** Multiplication of series and other, element-wise.

**Notes**

The Series and other has to share the same index if other is a Series or a DataFrame.

**Examples**

```python
>>> s = pd.Series([0, 1, 2, 3])
>>> other = pd.Series([-1, 2, -3, 4])
>>> s.dot(other)
8
>>> s @ other
8
>>> df = pd.DataFrame([[0, 1], [-2, 3], [4, -5], [6, 7]])
>>> s.dot(df)
0   24
1   14
dtype: int64
>>> arr = np.array([[0, 1], [-2, 3], [4, -5], [6, 7]])
>>> s.dot(arr)
array([24, 14])
```
pandas.Series.drop

Series.drop(labels=None, axis=0, index=None, columns=None, level=None, inplace=False, errors='raise')

Return Series with specified index labels removed.

Remove elements of a Series based on specifying the index labels. When using a multi-index, labels on different levels can be removed by specifying the level.

Parameters

- **labels** [single label or list-like] Index labels to drop.
- **axis** [0, default 0] Redundant for application on Series.
- **index** [single label or list-like] Redundant for application on Series, but ‘index’ can be used instead of ‘labels’.
- **columns** [single label or list-like] No change is made to the Series; use ‘index’ or ‘labels’ instead.
- **level** [int or level name, optional] For MultiIndex, level for which the labels will be removed.
- **inplace** [bool, default False] If True, do operation inplace and return None.
- **errors** [{'ignore', 'raise'}, default 'raise'] If 'ignore', suppress error and only existing labels are dropped.

Returns

- **Series** Series with specified index labels removed.

Raises

- **KeyError** If none of the labels are found in the index.

See also:

- **Series.reindex** Return only specified index labels of Series.
- **Series.dropna** Return series without null values.
- **Series.drop_duplicates** Return Series with duplicate values removed.
- **DataFrame.drop** Drop specified labels from rows or columns.

Examples

```python
>>> s = pd.Series(data=np.arange(3), index=['A', 'B', 'C'])
>>> s
A 0
B 1
C 2
dtype: int64

Drop labels B en C

>>> s.drop(labels=['B', 'C'])
A 0
dtype: int64
```
Drop 2nd level label in MultiIndex Series

```python
>>> midx = pd.MultiIndex(levels=[['lama', 'cow', 'falcon'],
... ['speed', 'weight', 'length']],
... codes=[[0, 0, 0, 1, 1, 1, 2, 2, 2],
... [0, 1, 2, 0, 1, 2, 0, 1, 2]])
>>> s = pd.Series([45, 200, 1.2, 30, 250, 1.5, 320, 1, 0.3],
... index=midx)
```

```bash
>>> s
lama speed 45.0
weight 200.0
length 1.2
cow speed 30.0
weight 250.0
length 1.5
falcon speed 320.0
weight 1.0
length 0.3
dtype: float64
```

```bash
>>> s.drop(labels='weight', level=1)
lama speed 45.0
length 1.2
cow speed 30.0
length 1.5
falcon speed 320.0
length 0.3
dtype: float64
```

**pandas.Series.drop_duplicates**

Series.drop_duplicates(keep='first', inplace=False)

Return Series with duplicate values removed.

**Parameters**

keep [‘first’, ‘last’, False], default ‘first’ Method to handle dropping duplicates:
- ‘first’ : Drop duplicates except for the first occurrence.
- ‘last’ : Drop duplicates except for the last occurrence.
- False : Drop all duplicates.

inplace [bool, default False] If True, performs operation inplace and returns None.

**Returns**

Series Series with duplicates dropped.

**See also:**

Index.drop_duplicates Equivalent method on Index.

DataFrame.drop_duplicates Equivalent method on DataFrame.

Series.duplicated Related method on Series, indicating duplicate Series values.
Examples

Generate a Series with duplicated entries.

```python
>>> s = pd.Series(['lama', 'cow', 'lama', 'beetle', 'lama', 'hippo'],
                   name='animal')
>>> s
0  lama
1  cow
2  lama
3  beetle
4  lama
5  hippo
Name: animal, dtype: object
```

With the ‘keep’ parameter, the selection behaviour of duplicated values can be changed. The value ‘first’ keeps the first occurrence for each set of duplicated entries. The default value of keep is ‘first’.

```python
>>> s.drop_duplicates()
0  lama
1  cow
3  beetle
5  hippo
Name: animal, dtype: object
```

The value ‘last’ for parameter ‘keep’ keeps the last occurrence for each set of duplicated entries.

```python
>>> s.drop_duplicates(keep='last')
1  cow
3  beetle
4  lama
5  hippo
Name: animal, dtype: object
```

The value False for parameter ‘keep’ discards all sets of duplicated entries. Setting the value of ‘inplace’ to True performs the operation inplace and returns None.

```python
>>> s.drop_duplicates(keep=False, inplace=True)
>>> s
1  cow
3  beetle
5  hippo
Name: animal, dtype: object
```

**pandas.Series.droplevel**

*Series.droplevel* (*level, axis=0*)

Return DataFrame with requested index / column level(s) removed.

New in version 0.24.0.

**Parameters**

- **level** (*int, str, or list-like*) If a string is given, must be the name of a level If list-like, elements must be names or positional indexes of levels.

- **axis** (*[0 or 'index', 1 or 'columns'], default 0*) Axis along which the level(s) is removed:
• 0 or ‘index’: remove level(s) in column.
• 1 or ‘columns’: remove level(s) in row.

**Returns**

**DataFrame** DataFrame with requested index / column level(s) removed.

**Examples**

```python
>>> df = pd.DataFrame([...
...      [1, 2, 3, 4],
...      [5, 6, 7, 8],
...      [9, 10, 11, 12]
... ]).set_index([0, 1]).rename_axis(['a', 'b'])
```

```python
>>> df.columns = pd.MultiIndex.from_tuples([...
...       ('c', 'e'), ('d', 'f')
... ], names=['level_1', 'level_2'])
```

```python
>>> df
level_1 c d
level_2 e f
a b
1 2 3 4
5 6 7 8
9 10 11 12
```

```python
>>> df.droplevel('a')
level_1 c d
level_2 e f
b
2 3 4
6 7 8
10 11 12
```

```python
>>> df.droplevel('level_2', axis=1)
level_1 c d
a b
1 2 3 4
5 6 7 8
9 10 11 12
```

**pandas.Series.dropna**

**Series.dropna**(axis=0, inplace=False, how=None)

Return a new Series with missing values removed.

See the [User Guide](User Guide) for more on which values are considered missing, and how to work with missing data.

**Parameters**

- **axis** [{0 or ‘index’}, default 0] There is only one axis to drop values from.
- **inplace** [bool, default False] If True, do operation inplace and return None.
Returns

Series  Series with NA entries dropped from it.

See also:

Series.isna  Indicate missing values.
Series.notna  Indicate existing (non-missing) values.
Series.fillna  Replace missing values.
DataFrame.dropna  Drop rows or columns which contain NA values.
Index.dropna  Drop missing indices.

Examples

```python
>>> ser = pd.Series([1., 2., np.nan])
>>> ser
0    1.0
1    2.0
2  NaN
dtype: float64

Drop NA values from a Series.

```python
>>> ser.dropna()
0    1.0
1    2.0
dtype: float64
```

Keep the Series with valid entries in the same variable.

```python
>>> ser.dropna(inplace=True)
>>> ser
0    1.0
1    2.0
dtype: float64
```

Empty strings are not considered NA values. None is considered an NA value.

```python
>>> ser = pd.Series([np.NaN, 2, pd.NaT, '', None, 'I stay'])
>>> ser
0 NaN
1    2
2  NaT
3
4  None
5    I stay
dtype: object
>>> ser.dropna()
1    2
3
5    I stay
dtype: object
```
pandas.Series.dt

Series.dt()
Accessor object for datetimelike properties of the Series values.

Examples

```python
>>> seconds_series = pd.Series(pd.date_range("2000-01-01", periods=3, freq="s"))
>>> seconds_series
0 2000-01-01 00:00:00
1 2000-01-01 00:00:01
2 2000-01-01 00:00:02
dtype: datetime64[ns]
>>> seconds_series.dt.second
0 0
1 1
2 2
dtype: int64

>>> hours_series = pd.Series(pd.date_range("2000-01-01", periods=3, freq="h"))
>>> hours_series
0 2000-01-01 00:00:00
1 2000-01-01 01:00:00
2 2000-01-01 02:00:00
dtype: datetime64[ns]
>>> hours_series.dt.hour
0 0
1 1
2 2
dtype: int64

>>> quarters_series = pd.Series(pd.date_range("2000-01-01", periods=3, freq="q"))
>>> quarters_series
0 2000-03-31
1 2000-06-30
2 2000-09-30
dtype: datetime64[ns]
>>> quarters_series.dt.quarter
0 1
1 2
2 3
dtype: int64
```

Returns a Series indexed like the original Series. Raises TypeError if the Series does not contain datetimelike values.
pandas.Series.duplicated

Series.duplicated(keep='first')
Indicate duplicate Series values.

Duplicated values are indicated as True values in the resulting Series. Either all duplicates, all except the first or all except the last occurrence of duplicates can be indicated.

Parameters

keep [{'first', 'last', False}, default 'first'] Method to handle dropping duplicates:
  • 'first': Mark duplicates as True except for the first occurrence.
  • 'last': Mark duplicates as True except for the last occurrence.
  • False: Mark all duplicates as True.

Returns

Series Series indicating whether each value has occurred in the preceding values.

See also:

Index.duplicated Equivalent method on pandas.Index.
DataFrame.duplicated Equivalent method on pandas.DataFrame.
Series.drop_duplicates Remove duplicate values from Series.

Examples

By default, for each set of duplicated values, the first occurrence is set on False and all others on True:

```python
>>> animals = pd.Series(['lama', 'cow', 'lama', 'beetle', 'lama'])
>>> animals.duplicated()  
0   False
1   False
2    True
3   False
4    True
dtype: bool
```

which is equivalent to

```python
>>> animals.duplicated(keep='first')
0   False
1   False
2    True
3   False
4    True
dtype: bool
```

By using 'last', the last occurrence of each set of duplicated values is set on False and all others on True:

```python
>>> animals.duplicated(keep='last')
0    True
1   False
2    True
3   False
```

(continues on next page)
By setting keep on False, all duplicates are True:

```python
>>> animals.duplicated(keep=False)
0   True
1  False
2   True
3  False
4   True
dtype: bool
```

### pandas.Series.eq

**Series.eq** *(other, level=None, fill_value=None, axis=0)*

Return Equal to of series and other, element-wise (binary operator `eq`).

Equivalent to `series == other`, but with support to substitute a `fill_value` for missing data in either one of the inputs.

**Parameters**

- **other** [Series or scalar value]
- **fill_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.
- **level** [int or name] Broadcast across a level, matching Index values on the passed Multi-Index level.

**Returns**

- **Series** The result of the operation.

**Examples**

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d   NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b   NaN
d    1.0
e   NaN
dtype: float64
>>> a.eq(b, fill_value=0)
a    True
Name: a, dtype: bool
```
pandas.Series.equals

Series.equals(other)
Test whether two objects contain the same elements.

This function allows two Series or DataFrames to be compared against each other to see if they have the same shape and elements. NaNs in the same location are considered equal. The column headers do not need to have the same type, but the elements within the columns must be the same dtype.

Parameters

other [Series or DataFrame] The other Series or DataFrame to be compared with the first.

Returns

bool True if all elements are the same in both objects, False otherwise.

See also:

Series.eq Compare two Series objects of the same length and return a Series where each element is True if the element in each Series is equal, False otherwise.

Dataframe.eq Compare two DataFrame objects of the same shape and return a DataFrame where each element is True if the respective element in each DataFrame is equal, False otherwise.

testing.assert_series_equal Raises an AssertionError if left and right are not equal. Provides an easy interface to ignore inequality in dtypes, indexes and precision among others.

testing.assert_frame_equal Like assert_series_equal, but targets DataFrames.
numpy.array_equal Return True if two arrays have the same shape and elements, False otherwise.

Notes

This function requires that the elements have the same dtype as their respective elements in the other Series or DataFrame. However, the column labels do not need to have the same type, as long as they are still considered equal.

Examples

```python
>>> df = pd.DataFrame({1: [10], 2: [20]})
>>> df
     0  1  2
0 10 10 20
```

DataFrames df and exactly_equal have the same types and values for their elements and column labels, which will return True.
>>> exactly_equal = pd.DataFrame({1: [10], 2: [20]})
>>> exactly_equal
   1  2
0 10 20

>>> df.equals(exactly_equal)
True

DataFrames df and different_column_type have the same element types and values, but have different types for the column labels, which will still return True.

>>> different_column_type = pd.DataFrame({1.0: [10], 2.0: [20]})
>>> different_column_type
   1.0  2.0
0   10   20

>>> df.equals(different_column_type)
True

DataFrames df and different_data_type have different types for the same values for their elements, and will return False even though their column labels are the same values and types.

>>> different_data_type = pd.DataFrame({1: [10.0], 2: [20.0]})
>>> different_data_type
   1  2
0 10.0 20.0

>>> df.equals(different_data_type)
False

**pandas.Series.ewm**

Series.ewm (com=None, span=None, halflife=None, alpha=None, min_periods=0, adjust=True, ignore_na=False, axis=0, times=None)

Provide exponential weighted (EW) functions.

Available EW functions: mean(), var(), std(), corr(), cov().

Exactly one parameter: com, span, halflife, or alpha must be provided.

**Parameters**

- **com** [float, optional] Specify decay in terms of center of mass, \( \alpha = 1/(1 + \text{com}) \), for \( \text{com} \geq 0 \).

- **span** [float, optional] Specify decay in terms of span, \( \alpha = 2/(\text{span} + 1) \), for \( \text{span} \geq 1 \).

- **halflife** [float, str, timedelta, optional] Specify decay in terms of half-life, \( \alpha = 1 - \exp(-\ln(2)/\text{halflife}) \), for \( \text{halflife} > 0 \).

  If **times** is specified, the time unit (str or timedelta) over which an observation decays to half its value. Only applicable to **mean()** and halflife value will not apply to the other functions.

  New in version 1.1.0.

- **alpha** [float, optional] Specify smoothing factor \( \alpha \) directly, \( 0 < \alpha \leq 1 \).

- **min_periods** [int, default 0] Minimum number of observations in window required to have a value (otherwise result is NA).

- **adjust** [bool, default True] Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average).
When adjust=True (default), the EW function is calculated using weights \( w_i = (1 - \alpha)^i \). For example, the EW moving average of the series \([x_0, x_1, \ldots, x_t]\) would be:

\[
y_t = \frac{x_t + (1 - \alpha)x_{t-1} + (1 - \alpha)^2x_{t-2} + \ldots + (1 - \alpha)^t x_0}{1 + (1 - \alpha) + (1 - \alpha)^2 + \ldots + (1 - \alpha)^t}
\]

When adjust=False, the exponentially weighted function is calculated recursively:

\[
y_0 = x_0 \\
y_t = (1 - \alpha)y_{t-1} + \alpha x_t,
\]

ignore_na [bool, default False] Ignore missing values when calculating weights; specify True to reproduce pre-0.15.0 behavior.

• When ignore_na=False (default), weights are based on absolute positions. For example, the weights of \(x_0\) and \(x_2\) used in calculating the final weighted average of \([x_0, None, x_2]\) are \((1 - \alpha)^2\) and 1 if adjust=True, and \((1 - \alpha)^2\) and \(\alpha\) if adjust=False.

• When ignore_na=True (reproducing pre-0.15.0 behavior), weights are based on relative positions. For example, the weights of \(x_0\) and \(x_2\) used in calculating the final weighted average of \([x_0, None, x_2]\) are \(1 - \alpha\) and 1 if adjust=True, and \(1 - \alpha\) and \(\alpha\) if adjust=False.

axis [{0, 1}, default 0] The axis to use. The value 0 identifies the rows, and 1 identifies the columns.

times [str, np.ndarray, Series, default None] New in version 1.1.0. Times corresponding to the observations. Must be monotonically increasing and datetime64[ns] dtype.

If str, the name of the column in the DataFrame representing the times.

If 1-D array like, a sequence with the same shape as the observations.

Only applicable to mean().

Returns

DataFrame A Window sub-classed for the particular operation.

See also:

rolling Provides rolling window calculations.

expanding Provides expanding transformations.

Notes

More details can be found at: Exponentially weighted windows.
Examples

```python
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]})
>>> df
   B
0  0
1  1
2  2
3  NaN
4  4

>>> df.ewm(com=0.5).mean()
   B
0  0.000000
1  0.750000
2  1.615385
3  1.615385
4  3.670213

Specifying times with a timedelta halflife when computing mean.

```python
>>> times = ['2020-01-01', '2020-01-03', '2020-01-10', '2020-01-15', '2020-01-17']
>>> df.ewm(halflife='4 days', times=pd.DatetimeIndex(times)).mean()
   B
0  0.000000
1  0.585786
2  1.523889
3  1.523889
4  3.233686
```

pandas.Series.expanding

Series.expanding(min_periods=1, center=None, axis=0)

Provide expanding transformations.

Parameters

- **min_periods** [int, default 1] Minimum number of observations in window required to have a value (otherwise result is NA).
- **center** [bool, default False] Set the labels at the center of the window.
- **axis** [int or str, default 0]

Returns

a Window sub-classed for the particular operation

See also:

- **rolling** Provides rolling window calculations.
- **ewm** Provides exponential weighted functions.
pandas: powerful Python data analysis toolkit, Release 1.1.1

Notes
By default, the result is set to the right edge of the window. This can be changed to the center of the
window by setting center=True.
Examples
>>> df = pd.DataFrame({"B": [0, 1, 2, np.nan, 4]})
>>> df
B
0 0.0
1 1.0
2 2.0
3 NaN
4 4.0
>>> df.expanding(2).sum()
B
0 NaN
1 1.0
2 3.0
3 3.0
4 7.0

pandas.Series.explode
Series.explode(ignore_index=False)
Transform each element of a list-like to a row.
New in version 0.25.0.
Parameters
ignore_index [bool, default False] If True, the resulting index will be labeled 0, 1, . . . , n
- 1.
New in version 1.1.0.
Returns
Series Exploded lists to rows; index will be duplicated for these rows.
See also:
Series.str.split Split string values on specified separator.
Series.unstack Unstack, a.k.a. pivot, Series with MultiIndex to produce DataFrame.
DataFrame.melt Unpivot a DataFrame from wide format to long format.
DataFrame.explode Explode a DataFrame from list-like columns to long format.

3.3. Series

1101


Notes

This routine will explode list-likes including lists, tuples, Series, and np.ndarray. The result dtype of the subset rows will be object. Scalars will be returned unchanged. Empty list-likes will result in a np.nan for that row.

Examples

```python
>>> s = pd.Series([[1, 2, 3], 'foo', [], [3, 4]])
>>> s
0 [1, 2, 3]
1 ['foo']
2 []
3 [3, 4]
dtype: object

>>> s.explode()
0 1
0 2
0 3
1 ['foo']
2 [NaNaN]
3 3
3 4
dtype: object
```

pandas.Series.factorize

Series.factorize(sort=False, na_sentinel=-1)

Encode the object as an enumerated type or categorical variable.

This method is useful for obtaining a numeric representation of an array when all that matters is identifying distinct values. factorize is available as both a top-level function pandas.factorize(), and as a method Series.factorize() and Index.factorize().

Parameters

- **sort** [bool, default False] Sort uniques and shuffle codes to maintain the relationship.
- **na_sentinel** [int, default -1] Value to mark “not found”.

Returns

- **codes** [ndarray] An integer ndarray that’s an indexer into uniques. uniques.take(codes) will have the same values as values.
- **uniques** [ndarray, Index, or Categorical] The unique valid values. When values is Categorical, uniques is a Categorical. When values is some other pandas object, an Index is returned. Otherwise, a 1-D ndarray is returned.

Note: Even if there’s a missing value in values, uniques will not contain an entry for it.

See also:
cut  Discretize continuous-valued array.
unique  Find the unique value in an array.

Examples

These examples all show factorize as a top-level method like `pd.factorize(values)`. The results are identical for methods like `Series.factorize()`.

```python
>>> codes, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'])
>>> codes
array([0, 0, 1, 2, 0]...)
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

With `sort=True`, the `uniques` will be sorted, and `codes` will be shuffled so that the relationship is maintained.

```python
>>> codes, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'], sort=True)
>>> codes
array([1, 1, 0, 2, 1]...)
>>> uniques
array(['a', 'b', 'c'], dtype=object)
```

Missing values are indicated in `codes` with `na_sentinel` (−1 by default). Note that missing values are never included in `uniques`.

```python
>>> codes, uniques = pd.factorize(['b', None, 'a', 'c', 'b'])
>>> codes
array([ 0, -1, 1, 2, 0]...)
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

Thus far, we’ve only factorized lists (which are internally coerced to NumPy arrays). When factorizing pandas objects, the type of `uniques` will differ. For Categoricals, a `Categorical` is returned.

```python
>>> cat = pd.Categorical(['a', 'a', 'c'], categories=['a', 'b', 'c'])
>>> codes, uniques = pd.factorize(cat)
>>> codes
array([0, 0, 1]...)
>>> uniques
['a', 'c']
Categories (3, object): ['a', 'b', 'c']
```

Notice that 'b' is in `uniques.categories`, despite not being present in `cat.values`.

For all other pandas objects, an Index of the appropriate type is returned.

```python
>>> cat = pd.Series(['a', 'a', 'c'])
>>> codes, uniques = pd.factorize(cat)
>>> codes
array([0, 0, 1]...)
>>> uniques
Index(['a', 'c'], dtype='object')
```
pandas.Series.ffill

**Series.ffill**(axis=None, inplace=False, limit=None, downcast=None)

Synonym for *DataFrame.fillna()* with method='ffill'.

**Returns**

{klass} or None  Object with missing values filled or None if inplace=True.

pandas.Series.fillna

**Series.fillna**(value=None, method=None, axis=None, inplace=False, limit=None, downcast=None)

Fill NA/NaN values using the specified method.

**Parameters**

- **value** [scalar, dict, Series, or DataFrame] Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). Values not in the dict/Series/DataFrame will not be filled. This value cannot be a list.


- **axis** [0 or ‘index’] Axis along which to fill missing values.

- **inplace** [bool, default False] If True, fill in-place. Note: this will modify any other views on this object (e.g., a no-copy slice for a column in a DataFrame).

- **limit** [int, default None] If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled. Must be greater than 0 if not None.

- **downcast** [dict, default is None] A dict of item->dtype of what to downcast if possible, or the string ‘infer’ which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible).

**Returns**

Series or None  Object with missing values filled or None if inplace=True.

See also:

- **interpolate** Fill NaN values using interpolation.
- **reindex** Conform object to new index.
- **asfreq** Convert TimeSeries to specified frequency.
Examples

```python
def = pd.DataFrame([[np.nan, 2, np.nan, 0],
                    [3, 4, np.nan, 1],
                    [np.nan, np.nan, np.nan, 5],
                    [np.nan, 3, np.nan, 4]],
                   columns=list('ABCD'))
def
A  B  C  D
0  NaN 2.0  NaN  0
1  3.0 4.0  NaN  1
2  NaN NaN  NaN  5
3  NaN 3.0  NaN  4
Replace all NaN elements with 0s.
```  
```python
def.fillna(0)
A  B  C  D
0  0.0 2.0  0.0  0
1  3.0 4.0  0.0  1
2  0.0 0.0  0.0  5
3  0.0 3.0  0.0  4
We can also propagate non-null values forward or backward.
```  
```python
def.fillna(method='ffill')
A  B  C  D
0  NaN 2.0  NaN  0
1  3.0 4.0  NaN  1
2  3.0 4.0  NaN  5
3  3.0 3.0  NaN  4
Replace all NaN elements in column ‘A’, ‘B’, ‘C’, and ‘D’, with 0, 1, 2, and 3 respectively.
```  
```python
values = {'A': 0, 'B': 1, 'C': 2, 'D': 3}
def.fillna(value=values)
A  B  C  D
0  0.0 2.0  2.0  0
1  3.0 4.0  2.0  1
2  0.0 1.0  2.0  5
3  0.0 3.0  2.0  4
Only replace the first NaN element.
```  
```python
def.fillna(value=values, limit=1)
A  B  C  D
0  0.0 2.0  2.0  0
1  3.0 4.0  NaN  1
2  NaN 1.0  NaN  5
3  NaN 3.0  NaN  4
```
pandas.Series.filter

Series.filter(items=None, like=None, regex=None, axis=None)

Subset the dataframe rows or columns according to the specified index labels.

Note that this routine does not filter a dataframe on its contents. The filter is applied to the labels of the index.

Parameters

- **items** [list-like] Keep labels from axis which are in items.
- **like** [str] Keep labels from axis for which “like in label == True”.
- **regex** [str (regular expression)] Keep labels from axis for which re.search(regex, label) == True.
- **axis** [{0 or ‘index’, 1 or ‘columns’, None}, default None] The axis to filter on, expressed either as an index (int) or axis name (str). By default this is the info axis, ‘index’ for Series, ‘columns’ for DataFrame.

Returns

- same type as input object

See also:

**DataFrame.loc** Access a group of rows and columns by label(s) or a boolean array.

Notes

The items, like, and regex parameters are enforced to be mutually exclusive.

axis defaults to the info axis that is used when indexing with [].

Examples

```python
def = pd.DataFrame(np.array(([[1, 2, 3], [4, 5, 6]])),
                   index=['mouse', 'rabbit'],
                   columns=['one', 'two', 'three'])
def
one    two    three
mouse  1.0    2.0    3.0
rabbit 4.0    5.0    6.0

# select columns by name
def.filter(items=['one', 'three'])
one    three
mouse  1.0    3.0
rabbit 4.0    6.0

# select columns by regular expression
def.filter(regex='e$', axis=1)
one    three
mouse  1.0    3.0
rabbit 4.0    6.0
```
### pandas.Series.first

**Series.first(offset)**
Select initial periods of time series data based on a date offset.

When having a DataFrame with dates as index, this function can select the first few rows based on a date offset.

**Parameters**
- *offset* [str, DateOffset or dateutil.relativedelta] The offset length of the data that will be selected. For instance, ‘1M’ will display all the rows having their index within the first month.

**Returns**
- Series or DataFrame A subset of the caller.

**Raises**
- TypeError If the index is not a `DatetimeIndex`

See also:
- `last` Select final periods of time series based on a date offset.
- `at_time` Select values at a particular time of the day.
- `between_time` Select values between particular times of the day.

**Examples**

```python
>>> i = pd.date_range('2018-04-09', periods=4, freq='2D')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
   A
2018-04-09  1
2018-04-11  2
2018-04-13  3
2018-04-15  4

Get the rows for the first 3 days:

```python
code
```python
>>> ts.first('3D')
   A
2018-04-09  1
2018-04-11  2
```

Notice the data for 3 first calendar days were returned, not the first 3 days observed in the dataset, and therefore data for 2018-04-13 was not returned.
pandas.Series.first_valid_index

`Series.first_valid_index()`
Return index for first non-NA/null value.

Returns

scalar [type of index]

Notes

If all elements are non-NA/null, returns None. Also returns None for empty Series/DataFrame.

pandas.Series.floordiv

`Series.floordiv(other=None, level=None, fill_value=None, axis=0)`
Return Integer division of series and other, element-wise (binary operator `floordiv`). Equivalent to `series // other`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]
fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.
level [int or name] Broadcast across a level, matching Index values on the passed Multi-Index level.

Returns

Series The result of the operation.

See also:

`Series.rfloordiv` Reverse of the Integer division operator, see Python documentation for more details.

Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a   1.0
b   1.0
c   1.0
d   NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a   1.0
b   NaN
d   1.0
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

(continued from previous page)

e NaN
dtype: float64
>>> a.floordiv(b, fill_value=0)
a 1.0
b NaN
c NaN
d 0.0
e NaN
dtype: float64

pandas.Series.ge

Series.ge(other, level=None, fill_value=None, axis=0)
Return Greater than or equal to of series and other, element-wise (binary operator ge).

Equivalent to series >= other, but with support to substitute a fill_value for missing data in either
one of the inputs.

Parameters

other [Series or scalar value]
fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values,
and any new element needed for successful Series alignment, with this value before
computation. If data in both corresponding Series locations is missing the result of
filling (at that location) will be missing.
level [int or name] Broadcast across a level, matching Index values on the passed Multi-
Index level.

Returns

Series The result of the operation.

Examples

>>> a = pd.Series([1, 1, 1, np.nan, 1], index=['a', 'b', 'c', 'd', 'e'])
>>> a
a 1.0
b 1.0
c 1.0
d NaN
e 1.0
dtype: float64
>>> b = pd.Series([0, 1, 2, np.nan, 1], index=['a', 'b', 'c', 'd', 'f'])
>>> b
a 0.0
b 1.0
c 2.0
d NaN
f 1.0
dtype: float64
>>> a.ge(b, fill_value=0)
a True
b True
### pandas.Series.get

**Series.get**(key, default=None)

Get item from object for given key (ex: DataFrame column).

Returns default value if not found.

**Parameters**

- **key** [object]

**Returns**

- **value** [same type as items contained in object]

### pandas.Series.groupby

**Series.groupby**(by=None, axis=0, level=None, as_index=True, sort=True, group_keys=True, squeeze=<object object>, observed=False, dropna=True)

Group Series using a mapper or by a Series of columns.

A groupby operation involves some combination of splitting the object, applying a function, and combining the results. This can be used to group large amounts of data and compute operations on these groups.

**Parameters**

- **by** [mapping, function, label, or list of labels] Used to determine the groups for the groupby. If by is a function, it’s called on each value of the object’s index. If a dict or Series is passed, the Series or dict VALUES will be used to determine the groups (the Series’ values are first aligned; see .align() method). If an ndarray is passed, the values are used as-is determine the groups. A label or list of labels may be passed to group by the columns in self. Notice that a tuple is interpreted as a (single) key.

- **axis** [(0 or ‘index’, 1 or ‘columns’), default 0] Split along rows (0) or columns (1).

- **level** [int, level name, or sequence of such, default None] If the axis is a MultiIndex (hierarchical), group by a particular level or levels.

- **as_index** [bool, default True] For aggregated output, return object with group labels as the index. Only relevant for DataFrame input. as_index=False is effectively “SQL-style” grouped output.

- **sort** [bool, default True] Sort group keys. Get better performance by turning this off. Note this does not influence the order of observations within each group. Groupby preserves the order of rows within each group.

- **group_keys** [bool, default True] When calling apply, add group keys to index to identify pieces.
squeeze [bool, default False] Reduce the dimensionality of the return type if possible, otherwise return a consistent type.

Deprecated since version 1.1.0.

observed [bool, default False] This only applies if any of the groupers are Categoricals. If True: only show observed values for categorical groupers. If False: show all values for categorical groupers.

New in version 0.23.0.

dropna [bool, default True] If True, and if group keys contain NA values, NA values together with row/column will be dropped. If False, NA values will also be treated as the key in groups

New in version 1.1.0.

Returns

SeriesGroupBy Returns a groupby object that contains information about the groups.

See also:

resample Convenience method for frequency conversion and resampling of time series.

Notes

See the user guide for more.

Examples

```python
grouped_by_index = ser.groupby(ser > 100).mean()
grouped_by_index = ser.groupby(level=0).mean()
grouped_by_index = ser.groupby('a').mean()
grouped_by_index = ser.groupby('b').mean()
grouped_by_index = ser.groupby(level=0).mean()
grouped_by_index = ser.groupby(level=1).mean()
```

Grouping by Indexes

We can groupby different levels of a hierarchical index using the level parameter:
We can also choose to include NA in group keys or not by defining *dropna* parameter, the default setting is *True*:

```python
>>> ser = pd.Series([1, 2, 3, 3], index=['a', 'a', 'b', np.nan])
>>> ser.groupby(level=0).sum()
a 3
b 3
dtype: int64

>>> ser.groupby(level=0, dropna=False).sum()
a 3
b 3
NaN 3
dtype: int64
```
pandas.Series.gt

Series.gt(other, level=None, fill_value=None, axis=0)
Return Greater than of series and other, element-wise (binary operator gt).
Equivalent to series > other, but with support to substitute a fill_value for missing data in either
one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values,
and any new element needed for successful Series alignment, with this value before
computation. If data in both corresponding Series locations is missing the result of
filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed Multi-
Index level.

Returns

Series The result of the operation.

Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan, 1], index=['a', 'b', 'c', 'd', 'e'])
>>> a
a    1.0
b    1.0
c    1.0
d   NaN
e    1.0
dtype: float64
>>> b = pd.Series([0, 1, 2, np.nan, 1], index=['a', 'b', 'c', 'd', 'f'])
>>> b
a    0.0
b    1.0
c    2.0
d   NaN
f    1.0
dtype: float64
>>> a.gt(b, fill_value=0)
a   True
b  False
c  False
d  False
e   True
f  False
dtype: bool
```
pandas.Series.head

Series.head \((n=5)\)
Return the first \(n\) rows.

This function returns the first \(n\) rows for the object based on position. It is useful for quickly testing if your object has the right type of data in it.

For negative values of \(n\), this function returns all rows except the last \(n\) rows, equivalent to \(df[:-n]\).

**Parameters**

- \(n\) [int, default 5] Number of rows to select.

**Returns**

- **same type as caller** The first \(n\) rows of the caller object.

**See also:**

DataFrame.tail Returns the last \(n\) rows.

**Examples**

```python
>>> df = pd.DataFrame({'animal': ['alligator', 'bee', 'falcon', 'lion',
... 'monkey', 'parrot', 'shark', 'whale', 'zebra']})
>>> df
   animal
0  alligator
1       bee
2    falcon
3      lion
4     monkey
5    parrot
6      shark
7     whale
8     zebra

Viewing the first 5 lines

```python
>>> df.head()
   animal
0  alligator
1       bee
2    falcon
3      lion
4     monkey
```

Viewing the first \(n\) lines (three in this case)

```python
>>> df.head(3)
   animal
0  alligator
1       bee
2    falcon
```

For negative values of \(n\)
```python
>>> df.head(-3)
animal
0  alligator
1    bee
2   falcon
3    lion
4   monkey
5  parrot
```

**pandas.Series.hist**

Series.hist(by=None, ax=None, grid=True, xlabelsize=None, xrot=None, ylabelsize=None, yrot=None, figsize=None, bins=10, backend=None, legend=False, **kwargs)

Draw histogram of the input series using matplotlib.

**Parameters**

- **by** [object, optional] If passed, then used to form histograms for separate groups.
- **ax** [matplotlib axis object] If not passed, uses gca().
- **grid** [bool, default True] Whether to show axis grid lines.
- **xlabelsize** [int, default None] If specified changes the x-axis label size.
- **xrot** [float, default None] Rotation of x axis labels.
- **ylabelsize** [int, default None] If specified changes the y-axis label size.
- **yrot** [float, default None] Rotation of y axis labels.
- **figsize** [tuple, default None] Figure size in inches by default.
- **bins** [int or sequence, default 10] Number of histogram bins to be used. If an integer is given, bins + 1 bin edges are calculated and returned. If bins is a sequence, gives bin edges, including left edge of first bin and right edge of last bin. In this case, bins is returned unmodified.
- **backend** [str, default None] Backend to use instead of the backend specified in the option plotting.backend. For instance, `matplotlib`. Alternatively, to specify the plotting.backend for the whole session, set `pd.options.plotting.backend`.

New in version 1.0.0.

- **legend** [bool, default False] Whether to show the legend.

New in version 1.1.0.

**kwargs** To be passed to the actual plotting function.

**Returns**

matplotlib.AxesSubplot A histogram plot.

**See also:**

pandas.Series.idxmax

Series.idxmax (axis=0, skipna=True, *args, **kwargs)
Return the row label of the maximum value.
If multiple values equal the maximum, the first row label with that value is returned.

Parameters
axis [int, default 0] For compatibility with DataFrame.idxmax. Redundant for application on Series.
skipna [bool, default True] Exclude NA/null values. If the entire Series is NA, the result will be NA.
*args, **kwargs Additional arguments and keywords have no effect but might be accepted for compatibility with NumPy.

Returns
Index Label of the maximum value.

Raises
ValueError If the Series is empty.

See also:
numpy.argmax Return indices of the maximum values along the given axis.
DataFrame.idxmax Return index of first occurrence of maximum over requested axis.
Series.idxmin Return index label of the first occurrence of minimum of values.

Notes
This method is the Series version of ndarray.argmax. This method returns the label of the maximum, while ndarray.argmax returns the position. To get the position, use series.values.argmax().

Examples

```python
>>> s = pd.Series(data=[1, None, 4, 3, 4],
                index=['A', 'B', 'C', 'D', 'E'])
>>> s
A    1.0
B    NaN
C    4.0
D    3.0
E    4.0
dtype: float64
>>> s.idxmax()
'C'
```

If skipna is False and there is an NA value in the data, the function returns nan.

```python
>>> s.idxmax(skipna=False)
nan
```
pandas.Series.idxmin

Series.idxmin (axis=0, skipna=True, *args, **kwargs)
Return the row label of the minimum value.
If multiple values equal the minimum, the first row label with that value is returned.

Parameters
axis [int, default 0] For compatibility with DataFrame.idxmin. Redundant for application on Series.
skipna [bool, default True] Exclude NA/null values. If the entire Series is NA, the result will be NA.
*args, **kwargs Additional arguments and keywords have no effect but might be accepted for compatibility with NumPy.

Returns
Index Label of the minimum value.

Raises
ValueError If the Series is empty.

See also:
numpy.argmin Return indices of the minimum values along the given axis.
DataFrame.idxmin Return index of first occurrence of minimum over requested axis.
Series.idxmax Return index label of the first occurrence of maximum of values.

Notes
This method is the Series version of ndarray.argmin. This method returns the label of the minimum, while ndarray.argmin returns the position. To get the position, use series.values.argmin().

Examples

```python
>>> s = pd.Series(data=[1, None, 4, 1],
...                index=['A', 'B', 'C', 'D'])
>>> s
A    1.0
B    NaN
C    4.0
D    1.0
dtype: float64

>>> s.idxmin()
'A'
```
If skipna is False and there is an NA value in the data, the function returns nan.

```python
>>> s.idxmin(skipna=False)
nan
```
**pandas.Series.infer_objects**

Series.infer_objects()

Attempt to infer better dtypes for object columns.

Attempts soft conversion of object-dtyped columns, leaving non-object and unconvertible columns unchanged. The inference rules are the same as during normal Series/DataFrame construction.

**Returns**

converted [same type as input object]

**See also:**

to_datetime Convert argument to datetime.
to_timedelta Convert argument to timedelta.
to_numeric Convert argument to numeric type.
convert_dtypes Convert argument to best possible dtype.

**Examples**

```python
>>> df = pd.DataFrame({"A": ["a", 1, 2, 3]})
>>> df = df.iloc[:1]
>>> df
   A
0  1
1  2
2  3
```

```
>>> df.dtypes
A object
dtype: object
```

```
>>> df.infer_objects().dtypes
A int64
dtype: object
```

**pandas.Series.interpolate**

Series.interpolate(method='linear', axis=0, limit=None, inplace=False, limit_direction=None, limit_area=None, downcast=None, **kwargs)

Please note that only method='linear' is supported for DataFrame/Series with a MultiIndex.

**Parameters**

method [str, default ‘linear’] Interpolation technique to use. One of:

- ‘linear’: Ignore the index and treat the values as equally spaced. This is the only method supported on MultiIndexes.
- ‘time’: Works on daily and higher resolution data to interpolate given length of interval.
- ‘index’, ‘values’: use the actual numerical values of the index.
`pandas`: powerful Python data analysis toolkit, Release 1.1.1

- `pad`: Fill in NaNs using existing values.
- `nearest`, `zero`, `slinear`, `quadratic`, `cubic`, `spline`, `barycentric`, `polynomial`: Passed to `scipy.interpolate.interp1d`. These methods use the numerical values of the index. Both `polynomial` and `spline` require that you also specify an `order` (int), e.g. `df.interpolate(method='polynomial', order=5).
- `krogh`, `piecewise_polynomial`, `spline`, `pchip`, `akima`, `cubicspline`: Wrappers around the SciPy interpolation methods of similar names. See Notes.
- `from_derivatives`: Refers to `scipy.interpolate.BPoly.from_derivatives` which replaces `piecewise_polynomial` interpolation method in scipy 0.18.

**axis** [{0 or ‘index’, 1 or ‘columns’, None}, default None] Axis to interpolate along.

**limit** [int, optional] Maximum number of consecutive NaNs to fill. Must be greater than 0.

**inplace** [bool, default False] Update the data in place if possible.

**limit_direction** [{‘forward’, ‘backward’, ‘both’}, Optional] Consecutive NaNs will be filled in this direction.

If limit is specified:

- If `method` is `pad` or `ffill`, `limit_direction` must be `forward`.
- If `method` is `backfill` or `bfill`, `limit_direction` must be `backwards`.

If `limit` is not specified:

- If `method` is `backfill` or `bfill`, the default is `backward`
- else the default is `forward`

Changed in version 1.1.0: raises ValueError if `limit_direction` is `forward` or `both` and method is `backfill` or `bfill`. raises ValueError if `limit_direction` is `backward` or `both` and method is `pad` or `ffill`.

**limit_area** [{None, ‘inside’, ‘outside’}, default None] If limit is specified, consecutive NaNs will be filled with this restriction.

- None: No fill restriction.
- ‘inside’: Only fill NaNs surrounded by valid values (interpolate).
- ‘outside’: Only fill NaNs outside valid values (extrapolate).

New in version 0.23.0.

**downcast** [optional, ‘infer’ or None, defaults to None] Downcast dtypes if possible.

**kwargs** Keyword arguments to pass on to the interpolating function.

**Returns**

Series or DataFrame Returns the same object type as the caller, interpolated at some or all NaN values.

**See also:**

- `fillna` Fill missing values using different methods.
- `scipy.interpolate.Akima1DInterpolator` Piecewise cubic polynomials (Akima interpolator).
scipy.interpolate.BPoly.from_derivatives Piecewise polynomial in the Bernstein basis.

scipy.interpolate.interp1d Interpolate a 1-D function.

scipy.interpolate.KroghInterpolator Interpolate polynomial (Krogh interpolator).

scipy.interpolate.PchipInterpolator PCHIP 1-d monotonic cubic interpolation.

scipy.interpolate.CubicSpline Cubic spline data interpolator.

Notes

The `krogh`, `piecewise_polynomial`, `spline`, `pchip` and `akima` methods are wrappers around the respective SciPy implementations of similar names. These use the actual numerical values of the index. For more information on their behavior, see the SciPy documentation and SciPy tutorial.

Examples

Filling in NaN in a Series via linear interpolation.

```python
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s
0    0.0
1    1.0
2  NaN
3    3.0
dtype: float64

>>> s.interpolate()
0    0.0
1    1.0
2    2.0
3    3.0
dtype: float64
```

Filling in NaN in a Series by padding, but filling at most two consecutive NaN at a time.

```python
>>> s = pd.Series([np.nan, "single_one", np.nan,
... "fill_two_more", np.nan, np.nan, np.nan,
... 4.71, np.nan])
>>> s
0    NaN
1  single_one
2    NaN
3  fill_two_more
4    NaN
5    NaN
6    NaN
7    4.71
8    NaN
dtype: object

>>> s.interpolate(method='pad', limit=2)
0    NaN
1  single_one
2  single_one
3  fill_two_more
4  fill_two_more
```

(continues on next page)
Filling in NaN in a Series via polynomial interpolation or splines: Both ‘polynomial’ and ‘spline’ methods require that you also specify an order (int).

```python
>>> s = pd.Series([0, 2, np.nan, 8])
>>> s.interpolate(method='polynomial', order=2)
0    0.000000
1    2.000000
2    4.666667
3    8.000000
 dtype: float64
```

Fill the DataFrame forward (that is, going down) along each column using linear interpolation.

Note how the last entry in column ‘a’ is interpolated differently, because there is no entry after it to use for interpolation. Note how the first entry in column ‘b’ remains NaN, because there is no entry before it to use for interpolation.

```python
>>> df = pd.DataFrame([(0.0, np.nan, -1.0, 1.0),
...                     (np.nan, 2.0, np.nan, np.nan),
...                     (2.0, 3.0, np.nan, 9.0),
...                     (np.nan, 4.0, -4.0, 16.0)],
...                   columns=list('abcd'))
>>> df.interpolate(method='linear', limit_direction='forward', axis=0)
   a     b     c     d
0  0.0  NaN  -1.0   1.0
1  1.0  2.0  NaN  NaN
2  2.0  3.0  NaN   9.0
3  2.0  4.0  NaN  16.0
```

Using polynomial interpolation.

```python
>>> df['d'].interpolate(method='polynomial', order=2)
0     1.0
1     4.0
2     9.0
3    16.0
Name: d, dtype: float64
```
pandas.Series.isin

Series.isin(values)
Whether elements in Series are contained in values.

Return a boolean Series showing whether each element in the Series matches an element in the passed sequence of values exactly.

Parameters

values [set or list-like] The sequence of values to test. Passing in a single string will raise a TypeError. Instead, turn a single string into a list of one element.

Returns

Series Series of booleans indicating if each element is in values.

Raises

TypeError
• If values is a string

See also:

DataFrame.isin Equivalent method on DataFrame.

Examples

```python
>>> s = pd.Series(['lama', 'cow', 'lama', 'beetle', 'lama', 'hippo'], name='animal')
>>> s.isin(['cow', 'lama'])
0    True
1    True
2    True
3    False
4    True
5    False
Name: animal, dtype: bool
```

Passing a single string as s.isin('lama') will raise an error. Use a list of one element instead:

```python
>>> s.isin(['lama'])
0    True
1    False
2    True
3    False
4    True
5    False
Name: animal, dtype: bool
```
Series.isna()

Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as None or \texttt{numpy.NaN}, gets mapped to True values. Everything else gets mapped to False values. Characters such as empty strings ' ' or \texttt{numpy.inf} are not considered NA values (unless you set \texttt{pandas.options.mode.use_inf_as_na} = True).

Returns

Series Mask of bool values for each element in Series that indicates whether an element is not an NA value.

See also:

Series.isnull Alias of isna.

Series.notna Boolean inverse of isna.

Series.dropna Omit axes labels with missing values.

isna Top-level isna.

Examples

Show which entries in a DataFrame are NA.

```python
>>> df = pd.DataFrame({'age': [5, 6, np.NaN],
...                     'born': [pd.NaT, pd.Timestamp('1939-05-27'),
...                            pd.Timestamp('1940-04-25')],
...                     'name': ['Alfred', 'Batman', ''],
...                     'toy': [None, 'Batmobile', 'Joker']})
>>> df
   age    born      name    toy
0   5.0    NaT    Alfred   None
1  6.0 1939-05-27  Batman  Batmobile
2  NaN 1940-04-25    Joker
```

```python
>>> df.isna()
   age    born      name    toy
0  False   True    False   True
1  False  False  False    False
2   True  False  False  False
```

Show which entries in a Series are NA.

```python
>>> ser = pd.Series([5, 6, np.NaN])
>>> ser
0   5.0
1   6.0
2  NaN
   dtype: float64
```

```python
>>> ser.isna()
0   False
```

(continues on next page)
pandas.Series.isnull

Series.isnull()
Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as None or numpy.NaN, gets mapped to True values. Everything else gets mapped to False values. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.use_inf_as_na = True).

Returns

Series  Mask of bool values for each element in Series that indicates whether an element is not an NA value.

See also:

Series.isnull  Alias of isna.
Series.notna  Boolean inverse of isna.
Series.dropna  Omit axes labels with missing values.
isna  Top-level isna.

Examples

Show which entries in a DataFrame are NA.

```
>>> df = pd.DataFrame({'age': [5, 6, np.NaN],
...    'born': [pd.NaT, pd.Timestamp('1939-05-27'),
...             pd.Timestamp('1940-04-25')],
...    'name': ['Alfred', 'Batman', ''],
...    'toy': [None, 'Batmobile', 'Joker']})
>>> df
   age  born           name  toy
0  5.0   NaT  Alfred    None
1  6.0 1939-05-27  Batman  Batmobile
2 NaN 1940-04-25       Joker
```

```
>>> df.isna()
   age  born  name  toy
0  False  True  False  True
1  False  False  False  False
2   True  False  False  False
```

Show which entries in a Series are NA.

```
>>> ser = pd.Series([5, 6, np.NaN])
>>> ser
0  5.0
```

(continues on next page)
1  6.0
2  NaN
dtype: float64

>>> ser.isna()
0  False
1  False
2  True
dtype: bool

pandas.Series.item

Series.item()
Return the first element of the underlying data as a python scalar.

Returns
scalar  The first element of %(klass)s.

Raises
ValueError  If the data is not length-1.

pandas.Series.items

Series.items()
Lazily iterate over (index, value) tuples.

This method returns an iterable tuple (index, value). This is convenient if you want to create a lazy iterator.

Returns
iterable  Iterable of tuples containing the (index, value) pairs from a Series.

See also:

DataFrame.items  Iterate over (column name, Series) pairs.
DataFrame.iterrows  Iterate over DataFrame rows as (index, Series) pairs.

Examples

>>> s = pd.Series(['A', 'B', 'C'])
>>> for index, value in s.items():
...     print(f"Index : {index}, Value : {value}"")
Index : 0, Value : A
Index : 1, Value : B
Index : 2, Value : C
pandas.Series.iteritems

Series.iteritems()
  Lazily iterate over (index, value) tuples.
  
  This method returns an iterable tuple (index, value). This is convenient if you want to create a lazy iterator.

  Returns

  iterable  Iterable of tuples containing the (index, value) pairs from a Series.

See also:

  DataFrame.items  Iterate over (column name, Series) pairs.
  DataFrame.iterrows  Iterate over DataFrame rows as (index, Series) pairs.

Examples

```python
>>> s = pd.Series(['A', 'B', 'C'])
>>> for index, value in s.items():
...    print(f"Index : {index}, Value : {value}")
Index : 0, Value : A
Index : 1, Value : B
Index : 2, Value : C
```

pandas.Series.keys

Series.keys()
  Return alias for index.

  Returns

  Index  Index of the Series.

pandas.Series.kurt

Series.kurt(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)
  Return unbiased kurtosis over requested axis.

  Kurtosis obtained using Fisher’s definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1.

Parameters

  axis  [{index (0)}] Axis for the function to be applied on.
  skipna  [bool, default True] Exclude NA/null values when computing the result.
  level  [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.
  numeric_only  [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

  **kwargs  Additional keyword arguments to be passed to the function.

Returns
scalar or Series (if level specified)

**pandas.Series.kurtosis**

```
pandas.Series.kurtosis(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)
```

Return unbiased kurtosis over requested axis. Kurtosis obtained using Fisher's definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1.

**Parameters**

- `axis` ([index (0)]) Axis for the function to be applied on.
- `skipna` [bool, default True] Exclude NA/null values when computing the result.
- `level` [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.
- `numeric_only` [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.
- `**kwargs` Additional keyword arguments to be passed to the function.

**Returns**

scalar or Series (if level specified)

**pandas.Series.last**

```
pandas.Series.last(offset)
```

Select final periods of time series data based on a date offset.

When having a DataFrame with dates as index, this function can select the last few rows based on a date offset.

**Parameters**

- `offset` [str, DateOffset, dateutil.relativedelta] The offset length of the data that will be selected. For instance, ‘3D’ will display all the rows having their index within the last 3 days.

**Returns**

Series or DataFrame A subset of the caller.

**Raises**

- `TypeError` If the index is not a `DatetimeIndex`.

See also:

- `first` Select initial periods of time series based on a date offset.
- `at_time` Select values at a particular time of the day.
- `between_time` Select values between particular times of the day.
Examples

```python
>>> i = pd.date_range('2018-04-09', periods=4, freq='2D')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
   A
2018-04-09  1
2018-04-11  2
2018-04-13  3
2018-04-15  4

Get the rows for the last 3 days:

```python
>>> ts.last('3D')
   A
2018-04-13  3
2018-04-15  4
```

Notice the data for 3 last calendar days were returned, not the last 3 observed days in the dataset, and therefore data for 2018-04-11 was not returned.

**pandas.Series.last_valid_index**

Series.*last_valid_index*()

Return index for last non-NA/null value.

Returns

scalar [type of index]

Notes

If all elements are non-NA/null, returns None. Also returns None for empty Series/DataFrame.

**pandas.Series.le**

Series.*le*(other, level=None, fill_value=None, axis=0)

Return Less than or equal to of series and other, element-wise (binary operator *le*).

Equivalent to `series <= other`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

- other [Series or scalar value]
- fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.
- level [int or name] Broadcast across a level, matching Index values on the passed Multi-Index level.

Returns

Series The result of the operation.
Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan, 1], index=['a', 'b', 'c', 'd', 'e'])
>>> a
a    1.0
b    1.0
c    1.0
d     NaN
e    1.0
dtype: float64
>>> b = pd.Series([0, 1, 2, np.nan, 1], index=['a', 'b', 'c', 'd', 'f'])
>>> b
a    0.0
b    1.0
c    2.0
d     NaN
f    1.0
dtype: float64
>>> a.le(b, fill_value=0)
a    False
b     True
c     True
d    False
e    False
f     True
dtype: bool
```

**pandas.Series.lt**

Series.lt(other, level=None, fill_value=None, axis=0)

Return Less than of series and other, element-wise (binary operator lt).

Equivalent to series < other, but with support to substitute a fill_value for missing data in either one of the inputs.

**Parameters**

- **other** [Series or scalar value]
- **fill_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.
- **level** [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

**Returns**

Series The result of the operation.
Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan, 1], index=['a', 'b', 'c', 'd', 'e'])
>>> a
a 1.0
b 1.0
c 1.0
d NaN
e 1.0
dtype: float64
>>> b = pd.Series([0, 1, 2, np.nan, 1], index=['a', 'b', 'c', 'd', 'f'])
>>> b
a 0.0
b 1.0
c 2.0
d NaN
f 1.0
dtype: float64
>>> a.lt(b, fill_value=0)
a False
b False
c True
d False
e False
f True
dtype: bool
```

**pandas.Series.mad**

`Series.mad(axis=None, skipna=None, level=None)`

Return the mean absolute deviation of the values for the requested axis.

**Parameters**

- `axis` [[index (0)]] Axis for the function to be applied on.
- `skipna` [bool, default None] Exclude NA/null values when computing the result.
- `level` [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

**Returns**

scalar or Series (if level specified)

**pandas.Series.map**

`Series.map(arg, na_action=None)`

Map values of Series according to input correspondence.

Used for substituting each value in a Series with another value, that may be derived from a function, a dict or a Series.

**Parameters**

**na_action**  

{{None, ‘ignore’}, default None} If ‘ignore’, propagate NaN values, without passing them to the mapping correspondence.

**Returns**

Series  
Same index as caller.

**See also:**

*Series.apply*  
For applying more complex functions on a Series.

*DataFrame.apply*  
Apply a function row-/column-wise.

*DataFrame.applymap*  
Apply a function elementwise on a whole DataFrame.

**Notes**

When *arg* is a dictionary, values in Series that are not in the dictionary (as keys) are converted to NaN. However, if the dictionary is a dict subclass that defines `__missing__` (i.e. provides a method for default values), then this default is used rather than NaN.

**Examples**

```python
>>> s = pd.Series(['cat', 'dog', np.nan, 'rabbit'])
```

```python
0       cat
1      dog
2    NaN
3     rabbit
dtype: object
```

map accepts a dict or a Series. Values that are not found in the dict are converted to NaN, unless the dict has a default value (e.g. defaultdict):

```python
>>> s.map({‘cat’: ‘kitten’, ‘dog’: ‘puppy’})
```

```python
0     kitten
1     puppy
2    NaN
3    NaN
dtype: object
```

It also accepts a function:

```python
>>> s.map(‘I am a {}’.format)
```

```python
0     I am a cat
1     I am a dog
2     I am a nan
3     I am a rabbit
dtype: object
```

To avoid applying the function to missing values (and keep them as NaN) `na_action='ignore'` can be used:

```python
>>> s.map(‘I am a {}’.format, na_action='ignore')
```

```python
0     I am a cat
1     I am a dog
```

(continues on next page)
pandas.Series.mask

```python
pandas.Series.mask
```

Parameters

- `cond` [bool Series/DataFrame, array-like, or callable] Where `cond` is False, keep the original value. Where True, replace with corresponding value from `other`. If `cond` is callable, it is computed on the Series/DataFrame and should return boolean Series/DataFrame or array. The callable must not change input Series/DataFrame (though pandas doesn’t check it).

- `other` [scalar, Series/DataFrame, or callable] Entries where `cond` is True are replaced with corresponding value from `other`. If other is callable, it is computed on the Series/DataFrame and should return scalar or Series/DataFrame. The callable must not change input Series/DataFrame (though pandas doesn’t check it).

- `inplace` [bool, default False] Whether to perform the operation in place on the data.

- `axis` [int, default None] Alignment axis if needed.

- `level` [int, default None] Alignment level if needed.

- `errors` [str, {‘raise’, ‘ignore’}, default ‘raise’] Note that currently this parameter won’t affect the results and will always coerce to a suitable dtype.
  - ‘raise’ : allow exceptions to be raised.
  - ‘ignore’ : suppress exceptions. On error return original object.

- `try_cast` [bool, default False] Try to cast the result back to the input type (if possible).

Returns

Same type as caller

See also:

- `DataFrame.where()` Return an object of same shape as self.

Notes

The mask method is an application of the if-then idiom. For each element in the calling DataFrame, if `cond` is `False` the element is used; otherwise the corresponding element from the DataFrame `other` is used.

The signature for `DataFrame.where()` differs from `numpy.where()`. Roughly `df1.where(m, df2)` is equivalent to `np.where(m, df1, df2)`.

For further details and examples see the `mask` documentation in `indexing`. 

| 2 NaN |
| 3 I am a rabbit |
| dtype: object |
Examples

```python
>>> s = pd.Series(range(5))
>>> s.where(s > 0)
0    NaN
1     1.0
2     2.0
3     3.0
4     4.0
dtype: float64

>>> s.mask(s > 0)
0    0.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64

>>> s.where(s > 1, 10)
0    10
1    10
2     2
3     3
4     4
dtype: int64

>>> df = pd.DataFrame(np.arange(10).reshape(-1, 2), columns=['A', 'B'])

>>> df
   A  B
0  0  1
1  2  3
2  4  5
3  6  7
4  8  9

>>> m = df % 3 == 0

>>> df.where(m, -df)
   A   B
0   0  -1
1 -2   3
2 -4  -5
3  6 -7
4 -8   9

>>> df.where(m, -df) == np.where(m, df, -df)
   A   B
0  True  True
1  True  True
2  True  True
3  True  True
4  True  True

>>> df.where(m, -df) == df.mask(~m, -df)
   A   B
0  True  True
1  True  True
2  True  True
3  True  True
4  True  True
```
pandas.Series.max

Series.max(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

Return the maximum of the values for the requested axis.

If you want the index of the maximum, use idxmax. This is the equivalent of the numpy.ndarray method argmax.

Parameters

- **axis** ([index (0)]) Axis for the function to be applied on.
- **skipna** [bool, default True] Exclude NA/null values when computing the result.
- **level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.
- **numeric_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.
- **kwargs** Additional keyword arguments to be passed to the function.

Returns

- scalar or Series (if level specified)

See also:

- Series.sum Return the sum.
- Series.min Return the minimum.
- Series.max Return the maximum.
- Series.idxmin Return the index of the minimum.
- Series.idxmax Return the index of the maximum.
- DataFrame.sum Return the sum over the requested axis.
- DataFrame.min Return the minimum over the requested axis.
- DataFrame.max Return the maximum over the requested axis.
- DataFrame.idxmin Return the index of the minimum over the requested axis.
- DataFrame.idxmax Return the index of the maximum over the requested axis.

Examples

```python
>>> idx = pd.MultiIndex.from_arrays([
...     ['warm', 'warm', 'cold', 'cold'],
...     ['dog', 'falcon', 'fish', 'spider'],
...     names=['blooded', 'animal'])
>>> s = pd.Series([4, 2, 0, 8], name='legs', index=idx)
```

```
blooded  animal
warm    dog  4
talcon  2
cold    fish  0
spider  8
Name: legs, dtype: int64
```
Max using level names, as well as indices.

```python
>>> s.max()
8
```

```python
>>> s.max(level='blooded')
blooded
  warm  4
  cold  8
Name: legs, dtype: int64
```

```python
>>> s.max(level=0)
blooded
  warm  4
  cold  8
Name: legs, dtype: int64
```

### pandas.Series.mean

**Series.mean** *(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)*

Return the mean of the values for the requested axis.

**Parameters**

- **axis** [{index (0)] Axis for the function to be applied on.
- **skipna** [bool, default True] Exclude NA/null values when computing the result.
- **level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.
- **numeric_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.
- ****kwargs Additional keyword arguments to be passed to the function.

**Returns**

- scalar or Series (if level specified)

### pandas.Series.median

**Series.median** *(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)*

Return the median of the values for the requested axis.

**Parameters**

- **axis** [{index (0)] Axis for the function to be applied on.
- **skipna** [bool, default True] Exclude NA/null values when computing the result.
- **level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.
- **numeric_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.
**kwargs Additional keyword arguments to be passed to the function.

**Returns**

scalar or Series (if level specified)

***

**pandas.Series.memory_usage**

Series.memory_usage (index=True, deep=False)

Return the memory usage of the Series.

The memory usage can optionally include the contribution of the index and of elements of object dtype.

**Parameters**

- **index** [bool, default True] Specifies whether to include the memory usage of the Series index.
- **deep** [bool, default False] If True, introspect the data deeply by interrogating object dtypes for system-level memory consumption, and include it in the returned value.

**Returns**

- **int** Bytes of memory consumed.

**See also:**

- `numpy.ndarray.nbytes` Total bytes consumed by the elements of the array.
- `DataFrame.memory_usage` Bytes consumed by a DataFrame.

**Examples**

```python
>>> s = pd.Series(range(3))
>>> s.memory_usage()
152
```

Not including the index gives the size of the rest of the data, which is necessarily smaller:

```python
>>> s.memory_usage(index=False)
24
```

The memory footprint of object values is ignored by default:

```python
>>> s = pd.Series(['a', 'b'])
>>> s.values
array(['a', 'b'], dtype=object)
>>> s.memory_usage()
144
>>> s.memory_usage(deep=True)
260
```
pandas.Series.min

Series.min(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)
Return the minimum of the values for the requested axis.

If you want the index of the minimum, use idxmin. This is the equivalent of the numpy.ndarray method argmin.

Parameters
axis [(index (0))] Axis for the function to be applied on.
skipna [bool, default True] Exclude NA/null values when computing the result.
level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.
numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.
**kwargs Additional keyword arguments to be passed to the function.

Returns
scalar or Series (if level specified)

See also:
Series.sum Return the sum.
Series.min Return the minimum.
Series.max Return the maximum.
Series.idxmin Return the index of the minimum.
Series.idxmax Return the index of the maximum.
DataFrame.sum Return the sum over the requested axis.
DataFrame.min Return the minimum over the requested axis.
DataFrame.max Return the maximum over the requested axis.
DataFrame.idxmin Return the index of the minimum over the requested axis.
DataFrame.idxmax Return the index of the maximum over the requested axis.

Examples

```python
>>> idx = pd.MultiIndex.from_arrays([...
... ['warm', 'warm', 'cold', 'cold'],
... ['dog', 'falcon', 'fish', 'spider'],
... names=['blooded', 'animal'])
>>> s = pd.Series([4, 2, 0, 8], name='legs', index=idx)
>>> s
blooded animal
warm dog 4
  falcon 2
cold fish 0
  spider 8
Name: legs, dtype: int64
```
Min using level names, as well as indices.

```
>>> s.min()
0
```

```python
>>> s.min(level='blooded')
blooded
    warm  2
    cold  0
Name: legs, dtype: int64
```

```python
>>> s.min(level=0)
blooded
    warm  2
    cold  0
Name: legs, dtype: int64
```

**pandas.Series.mod**

`Series.mod(other, level=None, fill_value=None, axis=0)`

Return Modulo of series and other, element-wise (binary operator mod).

Equivalent to `series % other`, but with support to substitute a fill_value for missing data in either one of the inputs.

**Parameters**

- `other` [Series or scalar value]
- `fill_value` [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.
- `level` [int or name] Broadcast across a level, matching Index values on the passed Multi-Index level.

**Returns**

`Series` The result of the operation.

**See also:**

`Series.rmod` Reverse of the Modulo operator, see Python documentation for more details.

**Examples**

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
```

(continues on next page)
pandas.Series.mode

Series.mode \( (\text{dropna}=\text{True}) \)

Return the mode(s) of the dataset.

Always returns Series even if only one value is returned.

Parameters

- \text{dropna} \ [\text{bool, default True}] \ Don’t consider counts of NaN/NaT.

Returns

- Series Modes of the Series in sorted order.

pandas.Series.mul

Series.mul \( (\text{other}, \text{level}=\text{None}, \text{fill_value}=\text{None}, \text{axis}=0) \)

Return Multiplication of series and other, element-wise (binary operator mul).

Equivalent to series \* other, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

- \text{other} \ [\text{Series or scalar value}]
- \text{fill_value} \ [\text{None or float value, default None (NaN)}] \ Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.
- \text{level} \ [\text{int or name}] \ Broadcast across a level, matching Index values on the passed Multi-Index level.

Returns

- Series The result of the operation.

See also:

- \text{Series.rmul} \ Reverse of the Multiplication operator, see Python documentation for more details.
Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a 1.0
b 1.0
c 1.0
d NaN
dtype: float64
```

```python
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
```

```python
>>> b
a 1.0
b NaN
d 1.0
e NaN
dtype: float64
```

```python
>>> a.multiply(b, fill_value=0)
a 1.0
b 0.0
c 0.0
d 0.0
e NaN
dtype: float64
```

**pandas.Series.multiply**

`Series.multiply(other, level=None, fill_value=None, axis=0)`

Return Multiplication of series and other, element-wise (binary operator `mul`). Equivalent to `series * other`, but with support to substitute a `fill_value` for missing data in either one of the inputs.

**Parameters**

- `other` [Series or scalar value]
- `fill_value` [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.
- `level` [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

**Returns**

- `Series` The result of the operation.

**See also:**

- `Series.rmul` Reverse of the Multiplication operator, see [Python documentation](https://docs.python.org/3/library/stdtypes.html#type-operations) for more details.
Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.multiply(b, fill_value=0)
a    1.0
b    0.0
c    0.0
d    0.0
e    NaN
dtype: float64
```

**pandas.Series.ne**

Series.ne(other, level=None, fill_value=None, axis=0)

Return Not equal to of series and other, element-wise (binary operator ne).

Equivalent to `series != other`, but with support to substitute a fill_value for missing data in either one of the inputs.

**Parameters**

- **other** [Series or scalar value]
- **fill_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.
- **level** [int or name] Broadcast across a level, matching Index values on the passed Multi-Index level.

**Returns**

- **Series** The result of the operation.
Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d   NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b   NaN
d    1.0
e   NaN
dtype: float64
>>> a.ne(b, fill_value=0)
a    False
b     True
c     True
d     True
e     True
dtype: bool
```

**pandas.Series.nlargest**

Series.nlargest(n=5, keep='first')

Return the largest n elements.

**Parameters**

- **n** [int, default 5] Return this many descending sorted values.
- **keep** [‘first’, ‘last’, ‘all’], default ‘first’ When there are duplicate values that cannot all fit in a Series of n elements:
  - **first** [return the first n occurrences in order] of appearance.
  - **last** [return the last n occurrences in reverse] order of appearance.
  - **all** [keep all occurrences. This can result in a Series of] size larger than n.

**Returns**

- **Series** The n largest values in the Series, sorted in decreasing order.

**See also:**

- **Series.nsmallest** Get the n smallest elements.
- **Series.sort_values** Sort Series by values.
- **Series.head** Return the first n rows.
Notes

Faster than `.sort_values(ascending=False).head(n)` for small \( n \) relative to the size of the Series object.

Examples

```python
>>> countries_population = {
    "Italy": 59000000,  "France": 65000000,
    ...  "Malta": 434000,   "Maldives": 434000,
    ...  "Brunei": 434000,  "Iceland": 337000,
    ...  "Nauru": 11300,    "Tuvalu": 11300,
    ...  "Anguilla": 11300, "Montserrat": 5200
}

>>> s = pd.Series(countries_population)

>>> s
Italy     59000000
France   65000000
Malta     434000
Maldives  434000
Brunei    434000
Iceland   337000
Nauru     11300
Tuvalu    11300
Anguilla  11300
Montserrat 5200
dtype: int64

The \( n \) largest elements where \( n=5 \) by default.

```python
>>> s.nlargest()
France   65000000
Italy     59000000
Malta     434000
Maldives  434000
Brunei    434000
dtype: int64
```

The \( n \) largest elements where \( n=3 \). Default \textit{keep} value is ‘first’ so Malta will be kept.

```python
>>> s.nlargest(3)
France   65000000
Italy     59000000
Malta     434000
dtype: int64
```

The \( n \) largest elements where \( n=3 \) and keeping the last duplicates. Brunei will be kept since it is the last with value 434000 based on the index order.

```python
>>> s.nlargest(3, keep='last')
France   65000000
Italy     59000000
Brunei    434000
dtype: int64
```

The \( n \) largest elements where \( n=3 \) with all duplicates kept. Note that the returned Series has five elements due to the three duplicates.
>>> s.nlargest(3, keep='all')
France 65000000
Italy 59000000
Malta 434000
Maldives 434000
Brunei 434000
dtype: int64

**pandas.Series.notna**

`Series.notna()`

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to True. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.use_inf_as_na = True). NA values, such as None or numpy.NaN, get mapped to False values.

**Returns**

- **Series** Mask of bool values for each element in Series that indicates whether an element is not an NA value.

**See also:**

- **Series.notnull** Alias of notna.
- **Series.isna** Boolean inverse of notna.
- **Series.dropna** Omit axes labels with missing values.
- **notna** Top-level notna.

**Examples**

Show which entries in a DataFrame are not NA.

```python
>>> df = pd.DataFrame({'age': [5, 6, np.NaN],
                               pd.Timestamp('1940-04-25')],
                      'name': ['Alfred', 'Batman', ''],
                      'toy': [None, 'Batmobile', 'Joker']})

>>> df
          age  born    name  toy
0      5.0  NaT  Alfred  None
1      6.0 1939-05-27  Batman  Batmobile
2    NaN  1940-04-25       Joker

>>> df.notna()
          age  born    name  toy
0      True  False  True  False
1      True   True  True   True
2     False  True  True   True
```

Show which entries in a Series are not NA.
pandas: powerful Python data analysis toolkit, Release 1.1.1

```python
>>> ser = pd.Series([5, 6, np.NaN])
>>> ser
0   5.0
1   6.0
2   NaN
dtype: float64

>>> ser.notna()
0   True
1   True
2   False
dtype: bool
```

**pandas.Series.notnull**

Series.notnull()  

Detect existing (non-missing) values.  

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to True. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.use_inf_as_na = True). NA values, such as None or numpy.NaN, get mapped to False values.

**Returns**

Series Mask of bool values for each element in Series that indicates whether an element is not an NA value.

**See also:**

Series.notnull Alias of notna.

Series.isna Boolean inverse of notna.

Series.dropna Omit axes labels with missing values.

notna Top-level notna.

**Examples**

Show which entries in a DataFrame are not NA.

```python
>>> df = pd.DataFrame({'age': [5, 6, np.NaN],
... 'born': [pd.NaT, pd.Timestamp('1939-05-27'),
... pd.Timestamp('1940-04-25')],
... 'name': ['Alfred', 'Batman', ''],
... 'toy': [None, 'Batmobile', 'Joker']})

>>> df
   age  born   name    toy
0   5.0  NaT  Alfred  None
1   6.0 1939-05-27  Batman  Batmobile
2   NaN 1940-04-25  Joker

>>> df.notna()
   age   born   name    toy
0   True   True  True  True
1   True  True  True  True
2   False  True  False  True
```

(continues on next page)
Show which entries in a Series are not NA.

```python
>>> ser = pd.Series([5, 6, np.NaN])
>>> ser
0   5.0
1   6.0
2   NaN
dtype: float64

>>> ser.notna()
0   True
1   True
2  False
dtype: bool
```

**pandas.Series.nsmallest**

Series.nsmallest (n=5, keep='first')

Return the smallest n elements.

Parameters

- **n** [int, default 5] Return this many ascending sorted values.
- **keep** [{‘first’, ‘last’, ‘all’}, default ‘first’] When there are duplicate values that cannot all fit in a Series of n elements:
  - **first** [return the first n occurrences in order] of appearance.
  - **last** [return the last n occurrences in reverse] order of appearance.
  - **all** [keep all occurrences. This can result in a Series of] size larger than n.

Returns

- **Series** The n smallest values in the Series, sorted in increasing order.

See also:

- **Series.nlargest** Get the n largest elements.
- **Series.sort_values** Sort Series by values.
- **Series.head** Return the first n rows.
Notes

Faster than `.sort_values().head(n)` for small `n` relative to the size of the `Series` object.

Examples

```python
>>> countries_population = {"Italy": 59000000, "France": 65000000,
... "Brunei": 434000, "Malta": 434000,
... "Maldives": 434000, "Iceland": 337000,
... "Nauru": 11300, "Tuvalu": 11300,
... "Anguilla": 11300, "Montserrat": 5200}
>>> s = pd.Series(countries_population)
>>> s
Italy    59000000
France   65000000
Brunei   434000
Malta    434000
Maldives 434000
Iceland  337000
Nauru    11300
Tuvalu   11300
Anguilla 11300
Montserrat 5200
dtype: int64
The `n` smallest elements where `n=5` by default.

```python
>>> s.nsmallest()
Montserrat    5200
Nauru         11300
Tuvalu        11300
Anguilla      11300
Iceland       337000
dtype: int64
```

The `n` smallest elements where `n=3`. Default `keep` value is `first` so Nauru and Tuvalu will be kept.

```python
>>> s.nsmallest(3)
Montserrat    5200
Nauru         11300
Tuvalu        11300
Anguilla      11300
Iceland       337000
dtype: int64
```

The `n` smallest elements where `n=3` and keeping the last duplicates. Anguilla and Tuvalu will be kept since they are the last with value 11300 based on the index order.

```python
>>> s.nsmallest(3, keep='last')
Montserrat    5200
Anguilla      11300
Tuvalu        11300
```

The `n` smallest elements where `n=3` with all duplicates kept. Note that the returned Series has four elements due to the three duplicates.
```python
>>> s.nsmallest(3, keep='all')
Montserrat  5200
Nauru       11300
Tuvalu      11300
Anguilla    11300
dtype: int64
```

### pandas.Series.nunique

Series.nunique(dropna=True)
Return number of unique elements in the object.
Excludes NA values by default.

**Parameters**

- **dropna** [bool, default True] Don’t include NaN in the count.

**Returns**

- **int**

**See also:**

DataFrame.nunique Method nunique for DataFrame.
Series.count Count non-NA/null observations in the Series.

**Examples**

```python
>>> s = pd.Series([1, 3, 5, 7, 7])
>>> s
0  1
1  3
2  5
3  7
4  7
dtype: int64

>>> s.nunique()
4
```

### pandas.Series.pad

Series.pad(axis=None, inplace=False, limit=None, downcast=None)
Synonym for DataFrame.fillna() with method='ffill'.

**Returns**

- **{klass} or None** Object with missing values filled or None if inplace=True.
pandas.Series.pct_change

Series.pct_change(periods=1, fill_method='pad', limit=None, freq=None, **kwargs)
Percentage change between the current and a prior element.

Computes the percentage change from the immediately previous row by default. This is useful in comparing the percentage of change in a time series of elements.

Parameters

- **periods** [int, default 1] Periods to shift for forming percent change.
- **fill_method** [str, default ‘pad’] How to handle NAs before computing percent changes.
- **limit** [int, default None] The number of consecutive NAs to fill before stopping.
- **freq** [DateOffset, timedelta, or str, optional] Increment to use from time series API (e.g. ‘M’ or BDay()).
- ****kwargs Additional keyword arguments are passed into DataFrame.shift or Series.shift.

Returns

- **chg** [Series or DataFrame] The same type as the calling object.

See also:

- Series.diff Compute the difference of two elements in a Series.
- DataFrame.diff Compute the difference of two elements in a DataFrame.
- Series.shift Shift the index by some number of periods.
- DataFrame.shift Shift the index by some number of periods.

Examples

Series

```python
>>> s = pd.Series([90, 91, 85])
>>> s
0   90
1   91
2   85
dtype: int64

>>> s.pct_change()
0   NaN
1  0.011111
2 -0.065934
dtype: float64

>>> s.pct_change(periods=2)
0   NaN
1   NaN
2 -0.055556
dtype: float64
```

See the percentage change in a Series where filling NAs with last valid observation forward to next valid.
>>> s = pd.Series([90, 91, None, 85])
>>> s
0    90.0
1    91.0
2     NaN
3    85.0
dtype: float64

>>> s.pct_change(fill_method='ffill')
0    NaN
dtype: float64

Dataframe

Percentage change in French franc, Deutsche Mark, and Italian lira from 1980-01-01 to 1980-03-01.

>>> df = pd.DataFrame(
... 'FR': [4.0405, 4.0963, 4.3149],
... 'GR': [1.7246, 1.7482, 1.8519],
... 'IT': [804.74, 810.01, 860.13]),
... index=['1980-01-01', '1980-02-01', '1980-03-01'])

>>> df
   FR     GR    IT
1980-01-01  4.0405  1.7246  804.74
1980-02-01  4.0963  1.7482  810.01
1980-03-01  4.3149  1.8519  860.13

>>> df.pct_change()
   FR      GR      IT
1980-01-01 NaN    NaN    NaN
1980-02-01 0.0138 0.0137 0.0065
1980-03-01 0.0534 0.0593 0.0619

Percentage of change in GOOG and APPL stock volume. Shows computing the percentage change between columns.

>>> df = pd.DataFrame(
... '2016': [1769950, 30586265],
... '2015': [1500923, 40912316],
... '2014': [1371819, 41403351]),
... index=['GOOG', 'APPL'])

>>> df
   2016   2015   2014
GOOG    1769950  1500923  1371819
APPL    30586265  40912316  41403351

>>> df.pct_change(axis='columns')
   2016   2015   2014
GOOG  NaN -0.151997 -0.086016
APPL  NaN  0.337604  0.012002
pandas.Series.pipe

Series.pipe(func, *args, **kwargs)
Apply func(self, *args, **kwargs).

Parameters

- **func** [function] Function to apply to the Series/DataFrame. args, and kwargs are passed into func. Alternatively a (callable, data_keyword) tuple where data_keyword is a string indicating the keyword of callable that expects the Series/DataFrame.
- **args** [iterable, optional] Positional arguments passed into func.
- **kwargs** [mapping, optional] A dictionary of keyword arguments passed into func.

Returns

- **object** [the return type of func.]

See also:

- **DataFrame.apply** Apply a function along input axis of DataFrame.
- **DataFrame.applymap** Apply a function elementwise on a whole DataFrame.
- **Series.map** Apply a mapping correspondence on a Series.

Notes

Use .pipe when chaining together functions that expect Series, DataFrames or GroupBy objects. Instead of writing

```python
>>> func(g(h(df), arg1=a), arg2=b, arg3=c)
```

You can write

```python
>>> (df.pipe(h)
...   .pipe(g, arg1=a)
...   .pipe(func, arg2=b, arg3=c)
... )
```

If you have a function that takes the data as (say) the second argument, pass a tuple indicating which keyword expects the data. For example, suppose f takes its data as arg2:

```python
>>> (df.pipe(h)
...   .pipe(g, arg1=a)
...   .pipe((func, 'arg2'), arg1=a, arg3=c)
... )
```
pandas.Series.plot

Series.plot(*args, **kwargs)
Make plots of Series or DataFrame.

Uses the backend specified by the option `plotting.backend`. By default, matplotlib is used.

Parameters

data [Series or DataFrame] The object for which the method is called.
x [label or position, default None] Only used if data is a DataFrame.
y [label, position or list of label, positions, default None] Allows plotting of one column versus another. Only used if data is a DataFrame.

kind [str] The kind of plot to produce:
• ‘line’ : line plot (default)
• ‘bar’ : vertical bar plot
• ‘barh’ : horizontal bar plot
• ‘hist’ : histogram
• ‘box’ : boxplot
• ‘kde’ : Kernel Density Estimation plot
• ‘density’ : same as ‘kde’
• ‘area’ : area plot
• ‘pie’ : pie plot
• ‘scatter’ : scatter plot
• ‘hexbin’ : hexbin plot.

ax [matplotlib axes object, default None] An axes of the current figure.
subplots [bool, default False] Make separate subplots for each column.
sharex [bool, default True if ax is None else False] In case subplots=True, share x axis and set some x axis labels to invisible; defaults to True if ax is None otherwise False if an ax is passed in; Be aware, that passing in both an ax and sharex=True will alter all x axis labels for all axis in a figure.
sharey [bool, default False] In case subplots=True, share y axis and set some y axis labels to invisible.

layout [tuple, optional] (rows, columns) for the layout of subplots.

figsize [a tuple (width, height) in inches] Size of a figure object.
use_index [bool, default True] Use index as ticks for x axis.

title [str or list] Title to use for the plot. If a string is passed, print the string at the top of the figure. If a list is passed and subplots is True, print each item in the list above the corresponding subplot.
grid [bool, default None (matlab style default)] Axis grid lines.
legend [bool or {‘reverse’}] Place legend on axis subplots.

style [list or dict] The matplotlib line style per column.
logx [bool or ‘sym’, default False] Use log scaling or symlog scaling on x axis. .. versionchanged:: 0.25.0

logy [bool or ‘sym’ default False] Use log scaling or symlog scaling on y axis. .. versionchanged:: 0.25.0

loglog [bool or ‘sym’, default False] Use log scaling or symlog scaling on both x and y axes. .. versionchanged:: 0.25.0

xticks [sequence] Values to use for the xticks.

yticks [sequence] Values to use for the yticks.

xlim [2-tuple/list] Set the x limits of the current axes.

ylim [2-tuple/list] Set the y limits of the current axes.

xlabel [label, optional] Name to use for the xlabel on x-axis. Default uses index name as xlabel.

New in version 1.1.0.

ylabel [label, optional] Name to use for the ylabel on y-axis. Default will show no ylabel.

New in version 1.1.0.

rot [int, default None] Rotation for ticks (xticks for vertical, yticks for horizontal plots).

fontsize [int, default None] Font size for xticks and yticks.

colormap [str or matplotlib colormap object, default None] Colormap to select colors from. If string, load colormap with that name from matplotlib.

colorbar [bool, optional] If True, plot colorbar (only relevant for ‘scatter’ and ‘hexbin’ plots).

position [float] Specify relative alignments for bar plot layout. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center).

table [bool, Series or DataFrame, default False] If True, draw a table using the data in the DataFrame and the data will be transposed to meet matplotlib’s default layout. If a Series or DataFrame is passed, use passed data to draw a table.

yerr [DataFrame, Series, array-like, dict and str] See Plotting with Error Bars for detail.

xerr [DataFrame, Series, array-like, dict and str] Equivalent to yerr.

stacked [bool, default False in line and bar plots, and True in area plot] If True, create stacked plot.

sort_columns [bool, default False] Sort column names to determine plot ordering.

secondary_y [bool or sequence, default False] Whether to plot on the secondary y-axis if a list/tuple, which columns to plot on secondary y-axis.

mark_right [bool, default True] When using a secondary_y axis, automatically mark the column labels with “(right)” in the legend.

include_bool [bool, default is False] If True, boolean values can be plotted.

backend [str, default None] Backend to use instead of the backend specified in the option plotting.backend. For instance, ‘matplotlib’. Alternatively, to specify the plotting.backend for the whole session, set pd.options.plotting.backend.

New in version 1.0.0.
**kwargs Options to pass to matplotlib plotting method.

**Returns**

`matplotlib.axes.Axes` or `numpy.ndarray` of them If the backend is not the default matplotlib one, the return value will be the object returned by the backend.

**Notes**

- See matplotlib documentation online for more on this subject
- If kind = ‘bar’ or ‘barh’, you can specify relative alignments for bar plot layout by position keyword. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)

### pandas.Series.pop

**Series**.pop(item)

Return item and drops from series. Raise KeyError if not found.

**Parameters**

- **item** [label] Index of the element that needs to be removed.

**Returns**

Value that is popped from series.

**Examples**

```python
>>> ser = pd.Series([1, 2, 3])
>>> ser.pop(0)
1
```

```python
>>> ser
1  2
2  3
dtype: int64
```

### pandas.Series.pow

**Series**.pow(other, level=None, fill_value=None, axis=0)

Return Exponential power of series and other, element-wise (binary operator `pow`). Equivalent to `series ** other`, but with support to substitute a fill_value for missing data in either one of the inputs.

**Parameters**

- **other** [Series or scalar value]
- **fill_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.
**level** [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

**Returns**

Series The result of the operation.

**See also:**

*Series.rpow* Reverse of the Exponential power operator, see Python documentation for more details.

**Examples**

```python
gf = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
gf
a 1.0
b 1.0
c 1.0
d NaN
dtype: float64
gf = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
gf
a 1.0
b NaN
d 1.0
e NaN
dtype: float64
gf.pow(f, fill_value=0)
a 1.0
b 1.0
c 1.0
d 0.0
e NaN
dtype: float64
```

**pandas.Series.prod**

Series.prod(axis=None, skipna=None, level=None, numeric_only=None, min_count=0, **kwargs)

Return the product of the values for the requested axis.

**Parameters**

axis [[index (0)]] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

min_count [int, default 0] The required number of valid values to perform the operation. If fewer than min_count non-NA values are present the result will be NA.
New in version 0.22.0: Added with the default being 0. This means the sum of an all-NA or empty Series is 0, and the product of an all-NA or empty Series is 1.

**kwargs Additional keyword arguments to be passed to the function.

Returns
scalar or Series (if level specified)

Examples
By default, the product of an empty or all-NA Series is 1

```python
>>> pd.Series([]).prod()
1.0
```

This can be controlled with the min_count parameter

```python
>>> pd.Series([]).prod(min_count=1)
nan
```

Thanks to the skipna parameter, min_count handles all-NA and empty series identically.

```python
>>> pd.Series([np.nan]).prod()
1.0
```

```python
>>> pd.Series([np.nan]).prod(min_count=1)
nan
```

`pandas.Series.product`

Series.product(\texttt{axis=\textit{None}}, \texttt{skipna=\textit{None}}, \texttt{level=\textit{None}}, \texttt{numeric\_only=\textit{None}}, \texttt{min\_count=0}, **\texttt{kwargs})

Return the product of the values for the requested axis.

Parameters

\begin{description}
\item[\texttt{axis}] [[index (0))] Axis for the function to be applied on.
\item[\texttt{skipna}] [bool, default True] Exclude NA/null values when computing the result.
\item[\texttt{level}] [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.
\item[\texttt{numeric\_only}] [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.
\item[\texttt{min\_count}] [int, default 0] The required number of valid values to perform the operation. If fewer than \texttt{min\_count} non-NA values are present the result will be NA.
\end{description}

New in version 0.22.0: Added with the default being 0. This means the sum of an all-NA or empty Series is 0, and the product of an all-NA or empty Series is 1.

**kwargs Additional keyword arguments to be passed to the function.

Returns
scalar or Series (if level specified)
Examples

By default, the product of an empty or all-NA Series is 1

```python
>>> pd.Series([]).prod()
1.0
```

This can be controlled with the `min_count` parameter

```python
>>> pd.Series([]).prod(min_count=1)
nan
```

Thanks to the `skipna` parameter, `min_count` handles all-NA and empty series identically.

```python
>>> pd.Series([np.nan]).prod()
1.0

>>> pd.Series([np.nan]).prod(min_count=1)
nan
```

`pandas.Series.quantile`

`Series.quantile(q=0.5, interpolation='linear')`  
Return value at the given quantile.

**Parameters**

- `q` [float or array-like, default 0.5 (50% quantile)] The quantile(s) to compute, which can lie in range: 0 <= q <= 1.
- `interpolation` [{'linear', 'lower', 'higher', 'midpoint', 'nearest'}] This optional parameter specifies the interpolation method to use, when the desired quantile lies between two data points i and j:
  - linear: \( i + (j - i) \times \text{fraction} \), where \( \text{fraction} \) is the fractional part of the index surrounded by \( i \) and \( j \).
  - lower: \( i \).
  - higher: \( j \).
  - nearest: \( i \) or \( j \) whichever is nearest.
  - midpoint: \( (i + j) / 2 \).

**Returns**

- float or Series If `q` is an array, a Series will be returned where the index is `q` and the values are the quantiles, otherwise a float will be returned.

See also:

- `core.window.Rolling.quantile` Calculate the rolling quantile.
- `numpy.percentile` Returns the q-th percentile(s) of the array elements.
Examples

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s.quantile(.5)
2.5
>>> s.quantile([.25, .5, .75])
0.25  1.75
0.50  2.50
0.75  3.25
dtype: float64
```

**pandas.Series.radd**

**Series.radd**(other, level=None, fill_value=None, axis=0)

Return Addition of series and other, element-wise (binary operator radd).

Equivalent to other + series, but with support to substitute a fill_value for missing data in either one of the inputs.

**Parameters**

- **other** [Series or scalar value]
- **fill_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.
- **level** [int or name] Broadcast across a level, matching Index values on the passed Multi-Index level.

**Returns**

**Series** The result of the operation.

**See also:**

**Series.add** Element-wise Addition, see Python documentation for more details.

**Examples**

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a  1.0
b  1.0
c  1.0
d  NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a  1.0
b  NaN
c  1.0
d  1.0
e  NaN
dtype: float64
>>> a.add(b, fill_value=0)
```

(continues on next page)
pandas.Series.rank

`Series.rank` *(axis=0, method='average', numeric_only=None, na_option='keep', ascending=True, pct=False)*

Compute numerical data ranks (1 through n) along axis.

By default, equal values are assigned a rank that is the average of the ranks of those values.

**Parameters**

- `axis` 
  - `{0 or 'index', 1 or 'columns'}, default 0
    - Index to direct ranking.

- `method` 
  - `{'average', 'min', 'max', 'first', 'dense'}, default 'average'
    - How to rank the group of records that have the same value (i.e. ties):
      - `average`: average rank of the group
      - `min`: lowest rank in the group
      - `max`: highest rank in the group
      - `first`: ranks assigned in order they appear in the array
      - `dense`: like `min`, but rank always increases by 1 between groups.

- `numeric_only` 
  - `[bool, optional]` For DataFrame objects, rank only numeric columns if set to True.

- `na_option` 
  - `{'keep', 'top', 'bottom'}, default 'keep'
    - How to rank NaN values:
      - `keep`: assign NaN rank to NaN values
      - `top`: assign smallest rank to NaN values if ascending
      - `bottom`: assign highest rank to NaN values if ascending.

- `ascending` 
  - `[bool, default True]` Whether or not the elements should be ranked in ascending order.

- `pct` 
  - `[bool, default False]` Whether or not to display the returned rankings in percentile form.

**Returns**

- `same type as caller` 
  - Return a Series or DataFrame with data ranks as values.

**See also:**

- `core.groupby.GroupBy.rank` 
  - Rank of values within each group.
Examples

```python
>>> df = pd.DataFrame(data={'Animal': ['cat', 'penguin', 'dog', 'spider', 'snake'],
                          'Number_legs': [4, 2, 4, 8, np.nan]})
>>> df
    Animal  Number_legs
0     cat          4.0
1  penguin         2.0
2      dog          4.0
3    spider          8.0
4    snake         NaN
```

The following example shows how the method behaves with the above parameters:

- default_rank: this is the default behaviour obtained without using any parameter.
- max_rank: setting `method = 'max'` the records that have the same values are ranked using the highest rank (e.g.: since ‘cat’ and ‘dog’ are both in the 2nd and 3rd position, rank 3 is assigned.)
- NA_bottom: choosing `na_option = 'bottom'`, if there are records with NaN values they are placed at the bottom of the ranking.
- pct_rank: when setting `pct = True`, the ranking is expressed as percentile rank.

```python
>>> df['default_rank'] = df['Number_legs'].rank()
>>> df['max_rank'] = df['Number_legs'].rank(method='max')
>>> df['NA_bottom'] = df['Number_legs'].rank(na_option='bottom')
>>> df['pct_rank'] = df['Number_legs'].rank(pct=True)
>>> df
```

```
    Animal  Number_legs  default_rank  max_rank  NA_bottom  pct_rank
0     cat          4.0          2.5        3.0       2.5      0.625
1  penguin         2.0          1.0        1.0       1.0      0.250
2      dog          4.0          2.5        3.0       2.5      0.625
3    spider          8.0          4.0        4.0       4.0      1.000
4    snake         NaN          NaN        NaN       NaN     NaN
```

### pandas.Series.ravel

**Series.ravel** *(order='C')*

Return the flattened underlying data as an ndarray.

**Returns**

- `numpy.ndarray or ndarray-like` Flattened data of the Series.

**See also:**

- `numpy.ndarray.ravel` Return a flattened array.
**pandas.Series.rdiv**

Series.rdiv(other, level=None, fill_value=None, axis=0)

Return Floating division of series and other, element-wise (binary operator rtruediv).

Equivalent to other / series, but with support to substitute a fill_value for missing data in either one of the inputs.

**Parameters**

- **other** [Series or scalar value]
- **fill_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.
- **level** [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

**Returns**

Series The result of the operation.

**See also:**

**Series.truediv** Element-wise Floating division, see Python documentation for more details.

**Examples**

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a 1.0
b 1.0
c 1.0
d NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a 1.0
b NaN
d 1.0
e NaN
dtype: float64
>>> a.divide(b, fill_value=0)
astype: float64
a 1.0
b inf
c inf
d 0.0
e NaN
dtype: float64
```
pandas.Series.rdivmod

Series.rdivmod(other, level=None, fill_value=None, axis=0)

Return Integer division and modulo of series and other, element-wise (binary operator rdivmod).

Equivalent to other divmod series, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

2-Tuple of Series The result of the operation.

See also:

Series.divmod Element-wise Integer division and modulo, see Python documentation for more details.

pandas.Series.reindex

Series.reindex(index=None, **kwargs)

Conform Series to new index with optional filling logic.

Places NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and copy=False.

Parameters

index [array-like, optional] New labels / index to conform to, should be specified using keywords. Preferably an Index object to avoid duplicating data.

method [{None, ‘backfill’/’bfill’, ‘pad’/’ffill’, ‘nearest’}] Method to use for filling holes in reindexed DataFrame. Please note: this is only applicable to DataFrames/Series with a monotonically increasing/decreasing index.

• None (default): don’t fill gaps
• pad / ffill: Propagate last valid observation forward to next valid.
• backfill / bfill: Use next valid observation to fill gap.
• nearest: Use nearest valid observations to fill gap.

copy [bool, default True] Return a new object, even if the passed indexes are the same.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

copy [scalar, default np.NaN] Value to use for missing values. Defaults to NaN, but can be any “compatible” value.
limit [int, default None] Maximum number of consecutive elements to forward or back-
ward fill.

tolerance [optional] Maximum distance between original and new labels for inexact 
matches. The values of the index at the matching locations most satisfy the equa-
tion $\text{abs}(\text{index[indexer]} - \text{target}) \leq \text{tolerance}$.

Tolerance may be a scalar value, which applies the same tolerance to all values, or 
list-like, which applies variable tolerance per element. List-like includes list, tuple, 
array, Series, and must be the same size as the index and its dtype must exactly match 
the index’s type.

Returns

Series with changed index.

See also:

Dataframe.set_index Set row labels.
Dataframe.reset_index Remove row labels or move them to new columns.
Dataframe.reindex_like Change to same indices as other Dataframe.

Examples

Dataframe.reindex supports two calling conventions

- (index=index_labels, columns=column_labels, ...)
- (labels, axis={'index', 'columns'}, ...)

We highly recommend using keyword arguments to clarify your intent.

Create a dataframe with some fictional data.

```python
>>> index = ['Firefox', 'Chrome', 'Safari', 'IE10', 'Konqueror']
>>> df = pd.DataFrame({'http_status': [200, 200, 404, 404, 301],
...                    'response_time': [0.04, 0.02, 0.07, 0.08, 1.0]},
...                   index=index)
>>> df
                        http_status  response_time
Firefox             200            0.04
Chrome              200            0.02
Safari              404            0.07
IE10                404            0.08
Konqueror           301            1.00
```

Create a new index and reindex the dataframe. By default values in the new index that do not have 
corresponding records in the dataframe are assigned NaN.

```python
>>> new_index = ['Safari', 'Iceweasel', 'Comodo Dragon', 'IE10',
...               'Chrome']
>>> df.reindex(new_index)
                         http_status  response_time
Safari             404.0            0.07
Iceweasel          NaN             NaN
Comodo Dragon       NaN             NaN
IE10               404.0            0.08
Chrome             200.0            0.02
```
We can fill in the missing values by passing a value to the keyword `fill_value`. Because the index is not monotonically increasing or decreasing, we cannot use arguments to the keyword `method` to fill the NaN values.

```python
>>> df.reindex(new_index, fill_value=0)
```

<table>
<thead>
<tr>
<th>http_status</th>
<th>response_time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Safari</td>
<td>404 0.07</td>
</tr>
<tr>
<td>Iceweasel</td>
<td>0 0.00</td>
</tr>
<tr>
<td>Comodo Dragon</td>
<td>0 0.00</td>
</tr>
<tr>
<td>IE10</td>
<td>404 0.08</td>
</tr>
<tr>
<td>Chrome</td>
<td>200 0.02</td>
</tr>
</tbody>
</table>

```python
>>> df.reindex(new_index, fill_value='missing')
```

<table>
<thead>
<tr>
<th>http_status</th>
<th>response_time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Safari</td>
<td>404 0.07</td>
</tr>
<tr>
<td>Iceweasel</td>
<td>missing missing</td>
</tr>
<tr>
<td>Comodo Dragon</td>
<td>missing missing</td>
</tr>
<tr>
<td>IE10</td>
<td>404 0.08</td>
</tr>
<tr>
<td>Chrome</td>
<td>200 0.02</td>
</tr>
</tbody>
</table>

We can also reindex the columns.

```python
>>> df.reindex(columns=['http_status', 'user_agent'])
```

<table>
<thead>
<tr>
<th>http_status</th>
<th>200</th>
<th>NaN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firefox</td>
<td>200</td>
<td>NaN</td>
</tr>
<tr>
<td>Chrome</td>
<td>200</td>
<td>NaN</td>
</tr>
<tr>
<td>Safari</td>
<td>404</td>
<td>NaN</td>
</tr>
<tr>
<td>IE10</td>
<td>404</td>
<td>NaN</td>
</tr>
<tr>
<td>Konqueror</td>
<td>301</td>
<td>NaN</td>
</tr>
</tbody>
</table>

Or we can use “axis-style” keyword arguments

```python
>>> df.reindex(['http_status', 'user_agent'], axis="columns")
```

<table>
<thead>
<tr>
<th>http_status</th>
<th>200</th>
<th>NaN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firefox</td>
<td>200</td>
<td>NaN</td>
</tr>
<tr>
<td>Chrome</td>
<td>200</td>
<td>NaN</td>
</tr>
<tr>
<td>Safari</td>
<td>404</td>
<td>NaN</td>
</tr>
<tr>
<td>IE10</td>
<td>404</td>
<td>NaN</td>
</tr>
<tr>
<td>Konqueror</td>
<td>301</td>
<td>NaN</td>
</tr>
</tbody>
</table>

To further illustrate the filling functionality in `reindex`, we will create a dataframe with a monotonically increasing index (for example, a sequence of dates).

```python
>>> date_index = pd.date_range('1/1/2010', periods=6, freq='D')
>>> df2 = pd.DataFrame({"prices": [100, 101, np.nan, 100, 89, 88]},
                     index=date_index)
>>> df2
```

<table>
<thead>
<tr>
<th>prices</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010-01-01</td>
</tr>
<tr>
<td>2010-01-02</td>
</tr>
<tr>
<td>2010-01-03</td>
</tr>
<tr>
<td>2010-01-04</td>
</tr>
<tr>
<td>2010-01-05</td>
</tr>
<tr>
<td>2010-01-06</td>
</tr>
</tbody>
</table>

Suppose we decide to expand the dataframe to cover a wider date range.
The index entries that did not have a value in the original data frame (for example, ‘2009-12-29’) are by default filled with NaN. If desired, we can fill in the missing values using one of several options.

For example, to back-propagate the last valid value to fill the NaN values, pass bfill as an argument to the method keyword.

Please note that the NaN value present in the original dataframe (at index value 2010-01-03) will not be filled by any of the value propagation schemes. This is because filling while reindexing does not look at dataframe values, but only compares the original and desired indexes. If you do want to fill in the NaN values present in the original dataframe, use thefillna() method.

See the user guide for more.

pandas.Series.reindex_like

Series.reindex_like(other, method=None, copy=True, limit=None, tolerance=None)  
Return an object with matching indices as other object.

Conform the object to the same index on all axes. Optional filling logic, placing NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and copy=False.

Parameters

other [Object of the same data type] Its row and column indices are used to define the new indices of this object.

method [None, ‘backfill’/’bfill’, ‘pad’/’ffill’, ‘nearest’] Method to use for filling holes in reindexed DataFrame. Please note: this is only applicable to DataFrames/Series with a monotonically increasing/decreasing index.
• None (default): don’t fill gaps
• pad / ffill: propagate last valid observation forward to next valid
• backfill / bfill: use next valid observation to fill gap
• nearest: use nearest valid observations to fill gap.

copy [bool, default True] Return a new object, even if the passed indexes are the same.

limit [int, default None] Maximum number of consecutive labels to fill for inexact matches.

tolerance [optional] Maximum distance between original and new labels for inexact matches. The values of the index at the matching locations most satisfy the equation \( \text{abs(index[indexer] - target)} \leq \text{tolerance} \).

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index’s type.

Returns

Series or DataFrame  Same type as caller, but with changed indices on each axis.

See also:

DataFrame.set_index  Set row labels.

DataFrame.reset_index  Remove row labels or move them to new columns.

DataFrame.reindex  Change to new indices or expand indices.

Notes

Same as calling .reindex(index=other.index, columns=other.columns,...).

Examples

```python
>>> df1 = pd.DataFrame([[24.3, 75.7, 'high'],
...                     [31, 87.8, 'high'],
...                     [22, 71.6, 'medium'],
...                     [35, 95, 'medium']],
...                     columns=['temp_celsius', 'temp_fahrenheit',
...                              'windspeed'],
...                     index=pd.date_range(start='2014-02-12',
...                                         end='2014-02-15', freq='D'))
```

```plaintext
>>> df1
          temp_celsius  temp_fahrenheit windspeed
2014-02-12      24.3            75.7    high
2014-02-13      31.0            87.8    high
2014-02-14      22.0            71.6    medium
2014-02-15      35.0            95.0    medium
```
```python
>>> df2 = pd.DataFrame([[28, 'low'],
...                     [30, 'low'],
...                     [35.1, 'medium']],
...                    columns=['temp_celsius','windspeed'],
...                    index=pd.DatetimeIndex(['2014-02-12', '2014-02-13',
...                                             '2014-02-15']))
```

```
>>> df2
  temp_celsius windspeed
2014-02-12   28.0      low
2014-02-13   30.0      low
2014-02-15  35.1    medium
```

```python
>>> df2.reindex_like(df1)
  temp_celsius  temp_fahrenheit windspeed
2014-02-12     28.0         NaN          low
2014-02-13     30.0         NaN          low
2014-02-14     NaN         NaN           NaN
2014-02-15  35.1    medium
```

**pandas.Series.rename**

Series.rename(index=None, *, axis=None, copy=True, inplace=False, level=None, errors='ignore')  
Alter Series index labels or name.

Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is. Extra labels listed don’t throw an error.

Alternatively, change Series.name with a scalar value.

See the user guide for more.

**Parameters**

- **axis** [{0 or “index”}] Unused. Accepted for compatibility with DataFrame method only.

- **index** [scalar, hashable sequence, dict-like or function, optional] Functions or dict-like are transformations to apply to the index. Scalar or hashable sequence-like will alter the Series.name attribute.

****kwargs Additional keyword arguments passed to the function. Only the “inplace” keyword is used.

**Returns**

Series Series with index labels or name altered.

See also:

- **Dataframe.rename** Corresponding DataFrame method.

- **Series.rename_axis** Set the name of the axis.
Examples

```python
>>> s = pd.Series([1, 2, 3])
>>> s
0 1
1 2
2 3
dtype: int64
>>> s.rename("my_name")  # scalar, changes Series.name
0 1
1 2
2 3
Name: my_name, dtype: int64
>>> s.rename(lambda x: x ** 2)  # function, changes labels
0 1
1 2
4 3
dtype: int64
>>> s.rename({1: 3, 2: 5})  # mapping, changes labels
0 1
3 2
5 3
dtype: int64
```

pandas.Series.rename_axis

Series.rename_axis(**kwargs)
Set the name of the axis for the index or columns.

Parameters

mapper [scalar, list-like, optional] Value to set the axis name attribute.

index, columns [scalar, list-like, dict-like or function, optional] A scalar, list-like, dict-like or functions transformations to apply to that axis’ values. Note that the columns parameter is not allowed if the object is a Series. This parameter only apply for DataFrame type objects.

Use either mapper and axis to specify the axis to target with mapper, or index and/or columns.

Changed in version 0.24.0.

axis [{0 or 'index', 1 or 'columns'}, default 0] The axis to rename.

copy [bool, default True] Also copy underlying data.

inplace [bool, default False] Modifies the object directly, instead of creating a new Series or DataFrame.

Returns

Series, DataFrame, or None The same type as the caller or None if inplace is True.

See also:

Series.rename Alter Series index labels or name.

DataFrame.rename Alter DataFrame index labels or name.
**Index.rename** Set new names on index.

**Notes**

Dataframe.rename_axis supports two calling conventions

- (index=index_mapper, columns=columns_mapper, ...)
- (mapper, axis={"index", 'columns'}, ...)

The first calling convention will only modify the names of the index and/or the names of the Index object that is the columns. In this case, the parameter copy is ignored.

The second calling convention will modify the names of the the corresponding index if mapper is a list or a scalar. However, if mapper is dict-like or a function, it will use the deprecated behavior of modifying the axis labels.

We highly recommend using keyword arguments to clarify your intent.

**Examples**

**Series**

```python
>>> s = pd.Series(['dog', 'cat', 'monkey'])
>>> s
0   dog
1   cat
2  monkey
dtype: object
>>> s.rename_axis("animal")
animal
0   dog
1   cat
2  monkey
dtype: object
```

**DataFrame**

```python
>>> df = pd.DataFrame({"num_legs": [4, 4, 2],
...                     "num_arms": [0, 0, 2],
...                     ["dog", "cat", "monkey"]})
>>> df
num_legs  num_arms
dog       4      0
cat       4      0
monkey    2      2
>>> df.rename_axis("animal")
>>> df
num_legs  num_arms
animal    
0   dog
1   cat
2  monkey
>>> df.rename_axis("limbs", axis="columns")
>>> df
limbs   num_legs  num_arms
animal  
```

(continues on next page)
MultiIndex

```
>>> df.index = pd.MultiIndex.from_product([["mammal"],
...                                       ["dog", "cat", "monkey"],
...                                       names=['type', 'name'])
>>> df
limbs     num_legs   num_arms
type  name
mammal  dog       4       0
         cat       4       0
         monkey   2       2
```

```
>>> df.rename_axis(index={'type': 'class})
limbs     num_legs   num_arms
class  name
mammal  dog       4       0
         cat       4       0
         monkey   2       2
```

```
>>> df.rename_axis(columns=str.upper)
LIMBS     num_legs   num_arms
type  name
mammal  dog       4       0
         cat       4       0
         monkey   2       2
```

**pandas.Series.reorder_levels**

Series.**reorder_levels**(order)
Rearrange index levels using input order.

May not drop or duplicate levels.

**Parameters**

- **order** [list of int representing new level order] Reference level by number or key.

**Returns**

type of caller (new object)
pandas.Series.repeat

Series.repeat(repeats, axis=None)
Repeat elements of a Series.

Returns a new Series where each element of the current Series is repeated consecutively a given number of times.

Parameters

- **repeats** [int or array of ints] The number of repetitions for each element. This should be a non-negative integer. Repeating 0 times will return an empty Series.
- **axis** [None] Must be None. Has no effect but is accepted for compatibility with numpy.

Returns

Series Newly created Series with repeated elements.

See also:

- Index.repeat Equivalent function for Index.
- numpy.repeat Similar method for numpy.ndarray.

Examples

```python
g = pd.Series(['a', 'b', 'c'])
g
0   a
1   b
2   c
dtype: object
g.repeat(2)
0   a
0   a
1   b
1   b
2   c
2   c
dtype: object
g.repeat([1, 2, 3])
0   a
1   b
1   b
2   c
2   c
2   c
dtype: object
```
Series.replace(to_replace=None, value=None, inplace=False, limit=None, regex=False, method='pad')

Replace values given in to_replace with value.

Values of the Series are replaced with other values dynamically. This differs from updating with .loc or .iloc, which require you to specify a location to update with some value.

**Parameters**

**to_replace** [str, regex, list, dict, Series, int, float, or None] How to find the values that will be replaced.

- numeric, str or regex:
  - numeric: numeric values equal to to_replace will be replaced with value
  - str: string exactly matching to_replace will be replaced with value
  - regex: regexs matching to_replace will be replaced with value
- list of str, regex, or numeric:
  - First, if to_replace and value are both lists, they **must** be the same length.
  - Second, if regex=True then all of the strings in both lists will be interpreted as regexs otherwise they will match directly. This doesn’t matter much for value since there are only a few possible substitution regexes you can use.
  - str, regex and numeric rules apply as above.
- dict:
  - Dicts can be used to specify different replacement values for different existing values. For example, {'a': 'b', 'y': 'z'} replaces the value ‘a’ with ‘b’ and ‘y’ with ‘z’. To use a dict in this way the value parameter should be None.
  - For a DataFrame a dict can specify that different values should be replaced in different columns. For example, {'a': 1, 'b': 'z'} looks for the value 1 in column ‘a’ and the value ‘z’ in column ‘b’ and replaces these values with whatever is specified in value. The value parameter should not be None in this case. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
  - For a DataFrame nested dictionaries, e.g., {'a': {'b': np.nan}}, are read as follows: look in column ‘a’ for the value ‘b’ and replace it with NaN. The value parameter should be None to use a nested dict in this way. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) **cannot** be regular expressions.
- None:
  - This means that the regex argument must be a string, compiled regular expression, or list, dict, ndarray or Series of such elements. If value is also None then this must be a nested dictionary or Series.

See the examples section for examples of each of these.

**value** [scalar, dict, list, str, regex, default None] Value to replace any values matching to_replace with. For a DataFrame a dict of values can be used to specify which
value to use for each column (columns not in the dict will not be filled). Regular
eexpressions, strings and lists or dicts of such objects are also allowed.

inplace [bool, default False] If True, in place. Note: this will modify any other views on
this object (e.g. a column from a DataFrame). Returns the caller if this is True.

limit [int, default None] Maximum size gap to forward or backward fill.

regex [bool or same types as to_replace, default False] Whether to interpret to_replace
and/or value as regular expressions. If this is True then to_replace must be a string.
Alternatively, this could be a regular expression or a list, dict, or array of regular
expressions in which case to_replace must be None.

method {{'pad', 'ffill', 'bfill', None}} The method to use when for replacement, when
to_replace is a scalar, list or tuple and value is None.

Changed in version 0.23.0: Added to DataFrame.

Returns

Series Object after replacement.

Raises

AssertionError

• If regex is not a bool and to_replace is not None.

TypeError

• If to_replace is not a scalar, array-like, dict, or None
• If to_replace is a dict and value is not a list, dict, ndarray, or Series
• If to_replace is None and regex is not compilable into a regular expression or is a
list, dict, ndarray, or Series.
• When replacing multiple bool or datetime64 objects and the arguments to
to_replace does not match the type of the value being replaced

ValueError

• If a list or an ndarray is passed to to_replace and value but they are not the
same length.

See also:

Series.fillna Fill NA values.

Series.where Replace values based on boolean condition.

Series.str.replace Simple string replacement.

Notes

• Regex substitution is performed under the hood with re.sub. The rules for substitution for re.
sub are the same.

• Regular expressions will only substitute on strings, meaning you cannot provide, for example, a
regular expression matching floating point numbers and expect the columns in your frame that have
a numeric dtype to be matched. However, if those floating point numbers are strings, then you can
do this.
• This method has a lot of options. You are encouraged to experiment and play with this method to gain intuition about how it works.

• When dict is used as the to_replace value, it is like key(s) in the dict are the to_replace part and value(s) in the dict are the value parameter.

Examples

Scalar `to_replace` and `value`

```python
>>> s = pd.Series([0, 1, 2, 3, 4])
>>> s.replace(0, 5)
0   5
1   1
2   2
3   3
4   4
dtype: int64
```

```python
>>> df = pd.DataFrame({'A': [0, 1, 2, 3, 4],
                     'B': [5, 6, 7, 8, 9],
                     'C': ['a', 'b', 'c', 'd', 'e']})
>>> df.replace(0, 5)
   A  B  C
0  5  5  a
1  1  6  b
2  2  7  c
3  3  8  d
4  4  9  e
```

List-like `to_replace`

```python
>>> df.replace([0, 1, 2, 3], 4)
   A  B  C
0  4  5  a
1  4  6  b
2  4  7  c
3  4  8  d
4  4  9  e
```

```python
>>> df.replace([0, 1, 2, 3], [4, 3, 2, 1])
   A  B  C
0  4  5  a
1  3  6  b
2  2  7  c
3  1  8  d
4  4  9  e
```

```python
>>> s.replace([1, 2], method='bfill')
0  0
1  3
2  3
3  3
4  4
dtype: int64
```

dict-like `to_replace`
pandas: powerful Python data analysis toolkit, Release 1.1.1

```python
>>> df.replace({0: 10, 1: 100})
  A  B  C
0  10  5  a
1  100 6  b
2  2  7  c
3  3  8  d
4  4  9  e
```

```python
>>> df.replace({'A': 0, 'B': 5}, 100)
  A  B  C
0  100 100  a
1   1   6  b
2  2  7  c
3  3  8  d
4  4  9  e
```

```python
>>> df.replace({'A': {0: 100, 4: 400}})
  A  B  C
0  100  5  a
1   1   6  b
2  2  7  c
3  3  8  d
4  400  9  e
```

### Regular expression `to_replace`

```python
>>> df = pd.DataFrame({'A': ['bat', 'foo', 'bait'],
                    'B': ['abc', 'bar', 'xyz']})
```

```python
>>> df.replace(to_replace=r'^ba.$', value='new', regex=True)
  A  B
0 new  abc
1 foo  new
2 bait xyz
```

```python
>>> df.replace({'A': r'^ba.$'}, {'A': 'new'}, regex=True)
  A  B
0 new  abc
1 foo  bar
2 bait xyz
```

```python
>>> df.replace(regex=r'^ba.$', value='new')
  A  B
0 new  abc
1 foo  new
2 bait xyz
```

```python
>>> df.replace(regex=[r'^ba.$', 'foo'], value='new')
  A  B
0 new  abc
```

(continues on next page)
Note that when replacing multiple bool or datetime64 objects, the data types in the `to_replace` parameter must match the data type of the value being replaced:

```python
>>> df = pd.DataFrame({'A': [True, False, True],
                    'B': [False, True, False]})
>>> df.replace({'a string': 'new value', 'True': False})  # raises
Traceback (most recent call last):
...  TypeError: Cannot compare types 'ndarray(dtype=bool)' and 'str'
```

This raises a `TypeError` because one of the dict keys is not of the correct type for replacement.

Compare the behavior of `s.replace({'a': None})` and `s.replace('a', None)` to understand the peculiarities of the `to_replace` parameter:

```python
>>> s = pd.Series([10, 'a', 'a', 'b', 'a'])
>>> s.replace({'a': None})
0     10
1     10
2     10
3     b
4     b
dtype: object
```

When one uses a dict as the `to_replace` value, it is like the value(s) in the dict are equal to the `value` parameter. `s.replace({'a': None})` is equivalent to `s.replace(to_replace={'a': None}, value=None, method=None):

```python
>>> s.replace({'a': None})
0  10
1  None
2  None
3   b
4  None
dtype: object
```

When `value=None` and `to_replace` is a scalar, list or tuple, `replace` uses the method parameter (default ‘pad’) to do the replacement. So this is why the ‘a’ values are being replaced by 10 in rows 1 and 2 and ‘b’ in row 4 in this case. The command `s.replace('a', None)` is actually equivalent to `s.replace(to_replace='a', value=None, method='pad')`:

```python
>>> s.replace('a', None)
0   10
1  10
2  10
3   b
4   b
dtype: object
```

### pandas.Series.resample

`Series.resample` (rule, axis=0, closed=​None, label=​None, convention='​start', kind=​None, offset=​None, base=​None, on=​None, level=​None, origin='​start_day', offset=​None)

Resample time-series data.

Convenience method for frequency conversion and resampling of time series. Object must have a datetime-like index (`DateTimeIndex`, `PeriodIndex`, or `TimedeltaIndex`), or pass datetime-like values to the `on` or `level` keyword.

**Parameters**
rule [DateOffset, Timedelta or str] The offset string or object representing target conversion.

axis [{0 or ‘index’, 1 or ‘columns’}, default 0] Which axis to use for up- or down-sampling. For Series this will default to 0, i.e. along the rows. Must be DatetimeIndex, TimedeltaIndex or PeriodIndex.


label [{‘right’, ‘left’}, default None] Which bin edge label to label bucket with. The default is ‘left’ for all frequency offsets except for ‘M’, ‘A’, ‘Q’, ‘BM’, ‘BA’, ‘BQ’, and ‘W’ which all have a default of ‘right’.

convention [{‘start’, ‘end’, ‘s’, ‘e’}, default ‘start’] For PeriodIndex only, controls whether to use the start or end of rule.

kind [{‘timestamp’, ‘period’}, optional, default None] Pass ‘timestamp’ to convert the resulting index to a DateTimeIndex or ‘period’ to convert it to a PeriodIndex. By default the input representation is retained.

loffset [timedelta, default None] Adjust the resampled time labels.

Deprecated since version 1.1.0: You should add the loffset to the df.index after the resample. See below.

base [int, default 0] For frequencies that evenly subdivide 1 day, the “origin” of the aggregated intervals. For example, for ‘5min’ frequency, base could range from 0 through 4. Defaults to 0.

Deprecated since version 1.1.0: The new arguments that you should use are ‘offset’ or ‘origin’.

on [str, optional] For a DataFrame, column to use instead of index for resampling. Column must be datetime-like.

level [str or int, optional] For a MultiIndex, level (name or number) to use for resampling. level must be datetime-like.

origin [{‘epoch’, ‘start’, ‘start_day’}, Timestamp or str, default ‘start_day’] The timestamp on which to adjust the grouping. The timezone of origin must match the timezone of the index. If a timestamp is not used, these values are also supported:

• ‘epoch’: origin is 1970-01-01
• ‘start’: origin is the first value of the timeseries
• ‘start_day’: origin is the first day at midnight of the timeseries

New in version 1.1.0.

offset [Timedelta or str, default is None] An offset timedelta added to the origin.

New in version 1.1.0.

Returns

Resampler object

See also:

groupby Group by mapping, function, label, or list of labels.

Series.resample Resample a Series.
**DataFrame.resample**  Resample a DataFrame.

**Notes**

See the user guide for more.

To learn more about the offset strings, please see this link.

**Examples**

Start by creating a series with 9 one minute timestamps.

```python
>>> index = pd.date_range('1/1/2000', periods=9, freq='T')
>>> series = pd.Series(range(9), index=index)
>>> series
2000-01-01 00:00:00    0
2000-01-01 00:01:00    1
2000-01-01 00:02:00    2
2000-01-01 00:03:00    3
2000-01-01 00:04:00    4
2000-01-01 00:05:00    5
2000-01-01 00:06:00    6
2000-01-01 00:07:00    7
2000-01-01 00:08:00    8
Freq: T, dtype: int64
```

Downsample the series into 3 minute bins and sum the values of the timestamps falling into a bin.

```python
>>> series.resample('3T').sum()
2000-01-01 00:00:00  3
2000-01-01 00:03:00 12
2000-01-01 00:06:00 21
Freq: 3T, dtype: int64
```

Downsample the series into 3 minute bins as above, but label each bin using the right edge instead of the left. Please note that the value in the bucket used as the label is not included in the bucket, which it labels. For example, in the original series the bucket `2000-01-01 00:03:00` contains the value 3, but the summed value in the resampled bucket with the label `2000-01-01 00:03:00` does not include 3 (if it did, the summed value would be 6, not 3). To include this value close the right side of the bin interval as illustrated in the example below this one.

```python
>>> series.resample('3T', label='right').sum()
2000-01-01 00:03:00  3
2000-01-01 00:06:00 12
2000-01-01 00:09:00 21
Freq: 3T, dtype: int64
```

Downsample the series into 3 minute bins as above, but close the right side of the bin interval.

```python
>>> series.resample('3T', label='right', closed='right').sum()
2000-01-01 00:00:00  0
2000-01-01 00:03:00  6
2000-01-01 00:06:00 15
2000-01-01 00:09:00 15
Freq: 3T, dtype: int64
```
Upsample the series into 30 second bins.

```python
>>> series.resample('30S').asfreq()[0:5]  # Select first 5 rows
2000-01-01 00:00:00 0.0
2000-01-01 00:00:30 NaN
2000-01-01 00:01:00 1.0
2000-01-01 00:01:30 NaN
2000-01-01 00:02:00 2.0
Freq: 30S, dtype: float64
```

Upsample the series into 30 second bins and fill the NaN values using the `pad` method.

```python
>>> series.resample('30S').pad()[0:5]
2000-01-01 00:00:00 0
2000-01-01 00:00:30 0
2000-01-01 00:01:00 1
2000-01-01 00:01:30 1
2000-01-01 00:02:00 2
Freq: 30S, dtype: int64
```

Upsample the series into 30 second bins and fill the NaN values using the `bfill` method.

```python
>>> series.resample('30S').bfill()[0:5]
2000-01-01 00:00:00 0
2000-01-01 00:00:30 1
2000-01-01 00:01:00 1
2000-01-01 00:01:30 2
2000-01-01 00:02:00 2
Freq: 30S, dtype: int64
```

Pass a custom function via `apply`

```python
>>> def custom_resampler(array_like):
...     return np.sum(array_like) + 5
...
>>> series.resample('3T').apply(custom_resampler)
2000-01-01 00:00:00 8
2000-01-01 00:03:00 17
2000-01-01 00:06:00 26
Freq: 3T, dtype: int64
```

For a Series with a PeriodIndex, the keyword `convention` can be used to control whether to use the start or end of `rule`.

Resample a year by quarter using ‘start’ `convention`. Values are assigned to the first quarter of the period.

```python
>>> s = pd.Series([1, 2], index=pd.period_range('2012-01-01',
...                freq='A',
...                periods=2))
...>>> s
2012  1
2013  2
Freq: A-DEC, dtype: int64
>>> s.resample('Q', convention='start').asfreq()
2012Q1  1.0
2012Q2  NaN
2012Q3  NaN
2012Q4  NaN
```

(continues on next page)
Resample quarters by month using ‘end’ convention. Values are assigned to the last month of the period.

```python
>>> q = pd.Series([1, 2, 3, 4], index=pd.period_range('2018-01-01',...                        freq='Q',...                        periods=4))
>>> q
2018Q1 1
2018Q2 2
2018Q3 3
2018Q4 4
Freq: Q-DEC, dtype: int64
>>> q.resample('M', convention='end').asfreq()
2018-03 1.0
2018-04 NaN
2018-05 NaN
2018-06 2.0
2018-07 NaN
2018-08 NaN
2018-09 3.0
2018-10 NaN
2018-11 NaN
2018-12 4.0
Freq: M, dtype: float64
```

For DataFrame objects, the keyword `on` can be used to specify the column instead of the index for resampling.

```python
>>> d = dict({'price': [10, 11, 9, 13, 14, 18, 17, 19],...                        'volume': [50, 60, 40, 100, 50, 100, 40, 50]})
>>> df = pd.DataFrame(d)
>>> df['week_starting'] = pd.date_range('01/01/2018',...                        periods=8,...                        freq='W')
>>> df
   price  volume  week_starting
0    10      50  2018-01-07
1    11      60  2018-01-14
2     2      40  2018-01-21
3    13     100  2018-01-28
4    14      50  2018-02-04
5    18     100  2018-02-11
6    17      40  2018-02-18
7    19      50  2018-02-25
>>> df.resample('M', on='week_starting').mean()
   price  volume
week_starting
2018-01-31  10.75  62.5
2018-02-28  17.00  60.0
```

For a DataFrame with MultiIndex, the keyword `level` can be used to specify on which level the resampling needs to take place.
```python
>>> days = pd.date_range('1/1/2000', periods=4, freq='D')
>>> d2 = dict({'price': [10, 11, 9, 13, 14, 18, 17, 19], ...
...     'volume': [50, 60, 40, 100, 50, 100, 40, 50]})
>>> df2 = pd.DataFrame(d2,
...     index=pd.MultiIndex.from_product([days,
...         ['morning', ...
...         'afternoon']])
... )
>>> df2
   price  volume
2000-01-01 morning   10    50
      afternoon   11    60
2000-01-02 morning    9    40
      afternoon   13   100
2000-01-03 morning   14    50
      afternoon   18   100
2000-01-04 morning   17    40
      afternoon   19    50
>>> df2.resample('D', level=0).sum()
   price  volume
2000-01-01      21   110
2000-01-02      22   140
2000-01-03      32   150
2000-01-04      36    90
If you want to adjust the start of the bins based on a fixed timestamp:
```
>>> ts.resample('17min', origin='2000-01-01').sum()
2000-10-01 23:24:00    3
2000-10-01 23:41:00   15
2000-10-01 23:58:00   45
2000-10-02 00:15:00   45
Freq: 17T, dtype: int64

If you want to adjust the start of the bins with an offset Timedelta, the two following lines are equivalent:

>>> ts.resample('17min', origin='start').sum()
2000-10-01 23:30:00    9
2000-10-01 23:47:00   21
2000-10-02 00:04:00   54
2000-10-02 00:21:00   24
Freq: 17T, dtype: int64

>>> ts.resample('17min', offset='23h30min').sum()
2000-10-01 23:30:00    9
2000-10-01 23:47:00   21
2000-10-02 00:04:00   54
2000-10-02 00:21:00   24
Freq: 17T, dtype: int64

To replace the use of the deprecated base argument, you can now use offset, in this example it is equivalent to have base=2:

>>> ts.resample('17min', offset='2min').sum()
2000-10-01 23:16:00    0
2000-10-01 23:33:00    9
2000-10-01 23:50:00   36
2000-10-02 00:07:00   39
2000-10-02 00:24:00   24
Freq: 17T, dtype: int64

To replace the use of the deprecated loffset argument:

>>> from pandas.tseries.frequencies import to_offset
>>> loffset = '19min'
>>> ts_out = ts.resample('17min').sum()
>>> ts_out.index = ts_out.index + to_offset(loffset)

>>> ts_out
2000-10-01 23:33:00    0
2000-10-01 23:50:00    9
2000-10-02 00:07:00   21
2000-10-02 00:24:00   54
2000-10-02 00:41:00   24
Freq: 17T, dtype: int64
pandas.Series.reset_index

Series.reset_index(level=None, drop=False, name=None, inplace=False)
Generate a new DataFrame or Series with the index reset.

This is useful when the index needs to be treated as a column, or when the index is meaningless and needs to be reset to the default before another operation.

Parameters

- **level** [int, str, tuple, or list, default optional] For a Series with a MultiIndex, only remove the specified levels from the index. Removes all levels by default.

- **drop** [bool, default False] Just reset the index, without inserting it as a column in the new DataFrame.

- **name** [object, optional] The name to use for the column containing the original Series values. Uses self.name by default. This argument is ignored when drop is True.

- **inplace** [bool, default False] Modify the Series in place (do not create a new object).

Returns

Series or DataFrame When drop is False (the default), a DataFrame is returned. The newly created columns will come first in the DataFrame, followed by the original Series values. When drop is True, a Series is returned. In either case, if inplace=True, no value is returned.

See also:

- **DataFrame.reset_index** Analogous function for DataFrame.

Examples

```python
>>> s = pd.Series([1, 2, 3, 4], name='foo',
                 index=pd.Index(['a', 'b', 'c', 'd'], name='idx'))
Generate a DataFrame with default index.
```

```python
>>> s.reset_index()
idx  foo
0   a   1
1   b   2
2   c   3
3   d   4
```

To specify the name of the new column use *name*.

```python
>>> s.reset_index(name='values')
idx   values
0   a     1
1   b     2
2   c     3
3   d     4
```

To generate a new Series with the default set *drop* to True.
To update the Series in place, without generating a new one set `inplace` to True. Note that it also requires `drop=True`.

```python
>>> s.reset_index(inplace=True, drop=True)
>>> s
0 1
1 2
2 3
3 4
Name: foo, dtype: int64
```

The `level` parameter is interesting for Series with a multi-level index.

```python
>>> arrays = [np.array(['bar', 'bar', 'baz', 'baz']),
            np.array(['one', 'two', 'one', 'two'])]
>>> s2 = pd.Series(...
                 range(4), name='foo',
                 index=pd.MultiIndex.from_arrays(arrays,
                                                  names=['a', 'b']))
```

To remove a specific level from the Index, use `level`.

```python
>>> s2.reset_index(level='a')
   a  foo
   b
one  bar  0
two  bar  1
one  baz  2
two  baz  3
```

If `level` is not set, all levels are removed from the Index.

```python
>>> s2.reset_index()
   a  b  foo
   0  bar one  0
   1  bar two  1
   2  baz one  2
   3  baz two  3
```

**pandas.Series.rfloordiv**

Series `rfloordiv`(other, level=None, fill_value=None, axis=0)

Return integer division of series and other, element-wise (binary operator `rfloordiv`).

Equivalent to `other // series`, but with support to substitute a fill_value for missing data in either one of the inputs.

**Parameters**

- `other` [Series or scalar value]
fill_value  [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level  [int or name] Broadcast across a level, matching Index values on the passed Multi-Index level.

Returns

Series  The result of the operation.

See also:

Series.floordiv  Element-wise Integer division, see Python documentation for more details.

Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a 1.0
b 1.0
c 1.0
d NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a 1.0
b NaN
d 1.0
e NaN
dtype: float64
>>> a.floordiv(b, fill_value=0)
a 1.0
b NaN
c NaN
d 0.0
e NaN
dtype: float64
```

pandas.Series.rmod

Series.rmod (other, level=None, fill_value=None, axis=0)

Return Modulo of series and other, element-wise (binary operator rmod).

Equivalent to other % series, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other  [Series or scalar value]

fill_value  [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.
level [int or name] Broadcast across a level, matching Index values on the passed Multi-
Index level.

Returns
Series The result of the operation.

See also:

Series.mod Element-wise Modulo, see Python documentation for more details.

Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a 1.0
b 1.0
c 1.0
d NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a 1.0
b NaN
d 1.0
e NaN
dtype: float64
>>> a.mod(b, fill_value=0)
a 0.0
b NaN
c NaN
d 0.0
e NaN
dtype: float64
```

pandas.Series.rmul

Series.rmul(other, level=None, fill_value=None, axis=0)
Return Multiplication of series and other, element-wise (binary operator rmul).

Equivalent to other * series, but with support to substitute a fill_value for missing data in either
one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values,
and any new element needed for successful Series alignment, with this value before
computation. If data in both corresponding Series locations is missing the result of
filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed Multi-
Index level.

Returns
Series The result of the operation.
See also:

*Series.mul* Element-wise Multiplication, see Python documentation for more details.

**Examples**

```python
gg
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a 1.0
b 1.0
c 1.0
d NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a 1.0
b NaN
d 1.0
e NaN
dtype: float64
>>> a.multiply(b, fill_value=0)
a 1.0
b 0.0
c 0.0
d 0.0
e NaN
dtype: float64
```

**pandas.Series.rolling**

Series.rolling(*window*, *min_periods=None*, *center=False*, *win_type=None*, *on=None*, *axis=0*, *closed=None*)

Provide rolling window calculations.

**Parameters**

*window* [int, offset, or BaseIndexer subclass] Size of the moving window. This is the number of observations used for calculating the statistic. Each window will be a fixed size.

If its an offset then this will be the time period of each window. Each window will be a variable sized based on the observations included in the time-period. This is only valid for datetimelike indexes.

If a BaseIndexer subclass is passed, calculates the window boundaries based on the defined get_window_bounds method. Additional rolling keyword arguments, namely *min_periods*, *center*, and *closed* will be passed to get_window_bounds.

*min_periods* [int, default None] Minimum number of observations in window required to have a value (otherwise result is NA). For a window that is specified by an offset, *min_periods* will default to 1. Otherwise, *min_periods* will default to the size of the window.

*center* [bool, default False] Set the labels at the center of the window.

*win_type* [str, default None] Provide a window type. If *None*, all points are evenly weighted. See the notes below for further information.
**DataFrame**

- **on** [str, optional] For a DataFrame, a datetime-like column or MultiIndex level on which to calculate the rolling window, rather than the DataFrame’s index. Provided integer column is ignored and excluded from result since an integer index is not used to calculate the rolling window.

- **axis** [int or str, default 0]

- **closed** [str, default None] Make the interval closed on the ‘right’, ‘left’, ‘both’ or ‘neither’ endpoints. For offset-based windows, it defaults to ‘right’. For fixed windows, defaults to ‘both’. Remaining cases not implemented for fixed windows.

**Returns**

- a Window or Rolling sub-classed for the particular operation

**See also:**

- `expanding` Provides expanding transformations.
- `ewm` Provides exponential weighted functions.

**Notes**

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

To learn more about the offsets & frequency strings, please see this link.

The recognized win_types are:

- `boxcar`
- `triang`
- `blackman`
- `hamming`
- `bartlett`
- `parzen`
- `bohman`
- `blackmanharris`
- `nuttall`
- `barthann`
- `kaiser` (needs parameter: beta)
- `gaussian` (needs parameter: std)
- `general_gaussian` (needs parameters: power, width)
- `slepian` (needs parameter: width)
- `exponential` (needs parameter: tau), center is set to None.

If `win_type=None` all points are evenly weighted. To learn more about different window types see `scipy.signal window functions`.

Certain window types require additional parameters to be passed. Please see the third example below on how to add the additional parameters.
Examples

```python
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]})
>>> df
     B
0  0.0
1  1.0
2  2.0
3  NaN
4  4.0

Rolling sum with a window length of 2, using the ‘triang’ window type.

```python
>>> df.rolling(2, win_type='triang').sum()
     B
0   NaN
1  0.5
2  1.5
3   NaN
4   NaN
``` 

Rolling sum with a window length of 2, using the ‘gaussian’ window type (note how we need to specify std).

```python
>>> df.rolling(2, win_type='gaussian').sum(std=3)
     B
0   NaN
1  0.986207
2  2.958621
3   NaN
4   NaN
``` 

Rolling sum with a window length of 2, min_periods defaults to the window length.

```python
>>> df.rolling(2).sum()
     B
0   NaN
1   1.0
2   3.0
3   NaN
4   NaN
``` 

Same as above, but explicitly set the min_periods

```python
>>> df.rolling(2, min_periods=1).sum()
     B
0  0.0
1  1.0
2  3.0
3  2.0
4  4.0
``` 

Same as above, but with forward-looking windows

```python
>>> indexer = pd.api.indexers.FixedForwardWindowIndexer(window_size=2)
>>> df.rolling(window=indexer, min_periods=1).sum()
``` 

(continues on next page)
A ragged (meaning not-a-regular frequency), time-indexed DataFrame

```python
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]},
                   index = [pd.Timestamp('20130101 09:00:00'),
                             pd.Timestamp('20130101 09:00:02'),
                             pd.Timestamp('20130101 09:00:03'),
                             pd.Timestamp('20130101 09:00:05'),
                             pd.Timestamp('20130101 09:00:06')])
>>> df
B
2013-01-01 09:00:00 0.0
2013-01-01 09:00:02 1.0
2013-01-01 09:00:03 2.0
2013-01-01 09:00:05 NaN
2013-01-01 09:00:06 4.0
```

Contrasting to an integer rolling window, this will roll a variable length window corresponding to the time period. The default for min_periods is 1.

```python
>>> df.rolling('2s').sum()
B
2013-01-01 09:00:00 0.0
2013-01-01 09:00:02 1.0
2013-01-01 09:00:03 3.0
2013-01-01 09:00:05 NaN
2013-01-01 09:00:06 4.0
```

**pandas.Series.round**

Series.round(decimals=0, *args, **kwargs)

Round each value in a Series to the given number of decimals.

**Parameters**

- `decimals` [int, default 0] Number of decimal places to round to. If decimals is negative, it specifies the number of positions to the left of the decimal point.

- `*args`, `**kwargs` Additional arguments and keywords have no effect but might be accepted for compatibility with NumPy.

**Returns**

Series Rounded values of the Series.

**See also:**

- `numpy.around` Round values of an np.array.
- `DataFrame.round` Round values of a DataFrame.
Examples

```python
>>> s = pd.Series([0.1, 1.3, 2.7])
>>> s.round()
0   0.0
1   1.0
2   3.0
dtype: float64
```

pandas.Series.rpow

`Series.rpow(other, level=None, fill_value=None, axis=0)`

Return Exponential power of series and other, element-wise (binary operator `rpow`).
Equivalent to `other ** series`, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

- `other` [Series or scalar value]
- `fill_value` [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.
- `level` [int or name] Broadcast across a level, matching Index values on the passed Multi-Index level.

Returns

Series The result of the operation.

See also:

`Series.pow` Element-wise Exponential power, see Python documentation for more details.

Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a  1.0
b  1.0
c  1.0
d  NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a  1.0
b  NaN
d  1.0
e  NaN
dtype: float64
>>> a.pow(b, fill_value=0)
a  1.0
b  1.0
(continues on next page)
```
Series.rsub

Series.rsub (other, level=None, fill_value=None, axis=0)
Return Subtraction of series and other, element-wise (binary operator rsub).

Equivalent to other - series, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

Series.sub Element-wise Subtraction, see Python documentation for more details.

Examples

```python
c 1.0
d 0.0
e NaN
dtype: float64
```

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a 1.0
b 1.0
c 1.0
d NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a 1.0
b NaN
d 1.0
e NaN
dtype: float64
>>> a.subtract(b, fill_value=0)
a 0.0
b 1.0
c 1.0
d -1.0
e NaN
dtype: float64
```
pandas.Series.rtruediv

Series.rtruediv(other, level=None, fill_value=None, axis=0)
Return Floating division of series and other, element-wise (binary operator rtruediv).
Equivalent to other / series, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters
other [Series or scalar value]
fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.
level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns
Series The result of the operation.

See also:
Series.truediv Element-wise Floating division, see Python documentation for more details.

Examples

```python
c>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
c>>> a
a 1.0
c 1.0
d NaN
dtype: float64
c>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
c>>> b
a 1.0
c NaN
d 1.0
e NaN
dtype: float64
c>>> a.divide(b, fill_value=0)
c a
b inf
c inf
d 0.0
e NaN
dtype: float64
```
pandas.Series.sample

Series.sample(n=None, frac=None, replace=False, weights=None, random_state=None, axis=None)

Return a random sample of items from an axis of object.

You can use random_state for reproducibility.

Parameters

n [int, optional] Number of items from axis to return. Cannot be used with frac. Default = 1 if frac = None.

frac [float, optional] Fraction of axis items to return. Cannot be used with n.

replace [bool, default False] Allow or disallow sampling of the same row more than once.

weights [str or ndarray-like, optional] Default ‘None’ results in equal probability weighting. If passed a Series, will align with target object on index. Index values in weights not found in sampled object will be ignored and index values in sampled object not in weights will be assigned weights of zero. If called on a DataFrame, will accept the name of a column when axis = 0. Unless weights are a Series, weights must be same length as axis being sampled. If weights do not sum to 1, they will be normalized to sum to 1. Missing values in the weights column will be treated as zero. Infinite values not allowed.

random_state [int, array-like, BitGenerator, np.random.RandomState, optional] If int, array-like, or BitGenerator (NumPy>=1.17), seed for random number generator If np.random.RandomState, use as numpy RandomState object.

Changed in version 1.1.0: array-like and BitGenerator (for NumPy>=1.17) object now passed to np.random.RandomState() as seed

axis [[0 or ‘index’, 1 or ‘columns’, None], default None] Axis to sample. Accepts axis number or name. Default is stat axis for given data type (0 for Series and DataFrames).

Returns

Series or DataFrame A new object of same type as caller containing n items randomly sampled from the caller object.

See also:

DataFrameGroupBy.sample Generates random samples from each group of a DataFrame object.

SeriesGroupBy.sample Generates random samples from each group of a Series object.

numpy.random.choice Generates a random sample from a given 1-D numpy array.

Notes

If frac > 1, replacement should be set to True.
Examples

```python
>>> df = pd.DataFrame({'num_legs': [2, 4, 8, 0],
...                    'num_wings': [2, 0, 0, 0],
...                    'num_specimen_seen': [10, 2, 1, 8]},
...                   index=['falcon', 'dog', 'spider', 'fish'])

>>> df

<table>
<thead>
<tr>
<th>num_legs</th>
<th>num_wings</th>
<th>num_specimen_seen</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>2</td>
<td>10</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>8</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>8</td>
</tr>
</tbody>
</table>

Extract 3 random elements from the Series df['num_legs']: Note that we use random_state to ensure the reproducibility of the examples.

```python
>>> df['num_legs'].sample(n=3, random_state=1)

fish 0
spider 8
falcon 2
Name: num_legs, dtype: int64
```

A random 50% sample of the DataFrame with replacement:

```python
>>> df.sample(frac=0.5, replace=True, random_state=1)

<table>
<thead>
<tr>
<th>num_legs</th>
<th>num_wings</th>
<th>num_specimen_seen</th>
</tr>
</thead>
<tbody>
<tr>
<td>dog 4</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>fish 0</td>
<td>0</td>
<td>8</td>
</tr>
</tbody>
</table>
```

An upsample sample of the DataFrame with replacement: Note that replace parameter has to be True for frac parameter > 1.

```python
>>> df.sample(frac=2, replace=True, random_state=1)

<table>
<thead>
<tr>
<th>num_legs</th>
<th>num_wings</th>
<th>num_specimen_seen</th>
</tr>
</thead>
<tbody>
<tr>
<td>dog 4</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>fish 0</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>falcon 2</td>
<td>2</td>
<td>10</td>
</tr>
<tr>
<td>falcon 2</td>
<td>2</td>
<td>10</td>
</tr>
<tr>
<td>fish 0</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>dog 4</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>fish 0</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>dog 4</td>
<td>0</td>
<td>2</td>
</tr>
</tbody>
</table>
```

Using a DataFrame column as weights. Rows with larger value in the num_specimen_seen column are more likely to be sampled.

```python
>>> df.sample(n=2, weights='num_specimen_seen', random_state=1)

<table>
<thead>
<tr>
<th>num_legs</th>
<th>num_wings</th>
<th>num_specimen_seen</th>
</tr>
</thead>
<tbody>
<tr>
<td>falcon 2</td>
<td>2</td>
<td>10</td>
</tr>
<tr>
<td>fish 0</td>
<td>0</td>
<td>8</td>
</tr>
</tbody>
</table>
```
**pandas.Series.searchsorted**

Series.searchsorted(value, side='left', sorter=None)

Find indices where elements should be inserted to maintain order.

Find the indices into a sorted Series `self` such that, if the corresponding elements in `value` were inserted before the indices, the order of `self` would be preserved.

**Note:** The Series must be monotonically sorted, otherwise wrong locations will likely be returned. Pandas does not check this for you.

**Parameters**

- **value** [array_like] Values to insert into `self`.
- **side** [{'left', 'right'}, optional] If ‘left’, the index of the first suitable location found is given. If ‘right’, return the last such index. If there is no suitable index, return either 0 or N (where N is the length of `self`).
- **sorter** [1-D array_like, optional] Optional array of integer indices that sort `self` into ascending order. They are typically the result of `np.argsort`.

**Returns**

- **int or array of int** A scalar or array of insertion points with the same shape as `value`.

Changed in version 0.24.0: If `value` is a scalar, an int is now always returned. Previously, scalar inputs returned an 1-item array for Series and Categorical.

**See also:**

- **sort_values** Sort by the values along either axis.
- **numpy.searchsorted** Similar method from NumPy.

**Notes**

Binary search is used to find the required insertion points.

**Examples**

```python
>>> ser = pd.Series([1, 2, 3])
>>> ser
0    1
1    2
2    3
dtype: int64

>>> ser.searchsorted(4)
3

>>> ser.searchsorted([0, 4])
array([0, 3])
```
>>> ser.searchsorted([1, 3], side='left')
array([0, 2])

>>> ser.searchsorted([1, 3], side='right')
array([1, 3])

>>> ser = pd.Categorical(...
...    ['apple', 'bread', 'bread', 'cheese', 'milk'], ordered=True ...
...)

>>> ser
Categories (4, object): ['apple' < 'bread' < 'cheese' < 'milk']

>>> ser.searchsorted('bread')
1

>>> ser.searchsorted(['bread'], side='right')
array([3])

If the values are not monotonically sorted, wrong locations may be returned:

>>> ser = pd.Series([2, 1, 3])

>>> ser
0 2
1 1
2 3
dtype: int64

>>> ser.searchsorted(1)
0  # wrong result, correct would be 1

pandas.Series.sem

Series.sem(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)  
Return unbiased standard error of the mean over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters

axis  [{index (0)}]  
skipna  [bool, default True]  Exclude NA/null values. If an entire row/column is NA, the result will be NA.
level  [int or level name, default None]  If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

ddof  [int, default 1]  Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.
numeric_only  [bool, default None]  Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

Returns

3.3. Series
scalar or Series (if level specified)

**pandas.Series.set_axis**

*pandas.Series.set_axis*(labels, axis=0, inplace=False)
Assign desired index to given axis.

Indexes for row labels can be changed by assigning a list-like or Index.

**Parameters**

- **labels** [list-like, Index] The values for the new index.
- **axis** [0 or ‘index’], default 0] The axis to update. The value 0 identifies the rows.
- **inplace** [bool, default False] Whether to return a new Series instance.

**Returns**

- **renamed** [Series or None] An object of type Series if inplace=False, None otherwise.

**See also:**

*Series.rename_axis* Alter the name of the index.

**Examples**

```python
>>> s = pd.Series([1, 2, 3])
>>> s
0    1
1    2
2    3
dtype: int64
```

```python
>>> s.set_axis(['a', 'b', 'c'], axis=0)
a    1
b    2
c    3
dtype: int64
```

**pandas.Series.shift**

*pandas.Series.shift*(periods=1, freq=None, axis=0, fill_value=None)
Shift index by desired number of periods with an optional time freq.

When *freq* is not passed, shift the index without realigning the data. If *freq* is passed (in this case, the index must be date or datetime, or it will raise a *NotImplementedError*), the index will be increased using the periods and the *freq* *freq* can be inferred when specified as “infer” as long as either freq or inferred_freq attribute is set in the index.

**Parameters**

- **periods** [int] Number of periods to shift. Can be positive or negative.
- **freq** [DateOffset, tseries.offsets, timedelta, or str, optional] Offset to use from the tseries module or time rule (e.g. ‘EOM’). If *freq* is specified then the index values are shifted but the data is not realigned. That is, use *freq* if you would like to extend the index
when shifting and preserve the original data. If \texttt{freq} is specified as “infer” then it will be inferred from the \texttt{freq} or \texttt{inferred\_freq} attributes of the index. If neither of those attributes exist, a \texttt{ValueError} is thrown.

\textbf{axis} \hspace{1em} [0 or ‘index’, 1 or ‘columns’, None], default None \hspace{1em} Shift direction.

\textbf{fill\_value} \hspace{1em} [object, optional] The scalar value to use for newly introduced missing values. the default depends on the dtype of \texttt{self}. For numeric data, \texttt{np.nan} is used. For datetime, timedelta, or period data, etc. \texttt{NaT} is used. For extension dtypes, \texttt{self.\texttt{dtype}}.\texttt{na\_value} is used.

Changed in version 1.1.0.

**Returns**

- \textbf{Series} \hspace{1em} Copy of input object, shifted.

**See also:**

- \texttt{Index\_shift} \hspace{1em} Shift values of Index.
- \texttt{DatetimeIndex\_shift} \hspace{1em} Shift values of DatetimeIndex.
- \texttt{PeriodIndex\_shift} \hspace{1em} Shift values of PeriodIndex.
- \texttt{tshift} \hspace{1em} Shift the time index, using the index’s frequency if available.

**Examples**

```python
>>> df = pd.DataFrame({"Col1": [10, 20, 15, 30, 45],
... "Col2": [13, 23, 18, 33, 48],
... "Col3": [17, 27, 22, 37, 52]},
... index=pd.date_range("2020-01-01", "2020-01-05"))
>>> df
       Col1  Col2  Col3
2020-01-01   10    13    17
2020-01-02   20    23    27
2020-01-03   15    18    22
2020-01-04   30    33    37
2020-01-05   45    48    52

>>> df.shift(periods=3)
       Col1  Col2  Col3
2020-01-01    NaN    NaN    NaN
2020-01-02    NaN    NaN    NaN
2020-01-03    NaN    NaN    NaN
2020-01-04  10.0  13.0  17.0
2020-01-05  20.0  23.0  27.0

>>> df.shift(periods=1, axis="columns")
       Col1  Col2  Col3
2020-01-01    NaN  10.0  13.0
2020-01-02    NaN  20.0  23.0
2020-01-03    NaN  15.0  18.0
2020-01-04    NaN  30.0  33.0
2020-01-05    NaN  45.0  48.0
```
```
>>> df.shift(periods=3, fill_value=0)
          Col1  Col2  Col3
2020-01-01    0    0    0
2020-01-02    0    0    0
2020-01-03    0    0    0
2020-01-04   10   13   17
2020-01-05   20   23   27
```
```
>>> df.shift(periods=3, freq="D")
          Col1  Col2  Col3
2020-01-04   10   13   17
2020-01-05   20   23   27
2020-01-06   15   18   22
2020-01-07   30   33   37
2020-01-08   45   48   52
```
```
>>> df.shift(periods=3, freq="infer")
          Col1  Col2  Col3
2020-01-04   10   13   17
2020-01-05   20   23   27
2020-01-06   15   18   22
2020-01-07   30   33   37
2020-01-08   45   48   52
```

**pandas.Series.skew**

```
Series.skew(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)
```

Return unbiased skew over requested axis.

Normalized by N-1.

**Parameters**

- **axis** [{index (0)] Axis for the function to be applied on.
- **skipna** [bool, default True] Exclude NA/null values when computing the result.
- **level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.
- **numeric_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.
- **kwargs** Additional keyword arguments to be passed to the function.

**Returns**

- scalar or Series (if level specified)
pandas.Series.slice_shift

Series.slice_shift(periods=1, axis=0)
Equivalent to shift without copying data.
The shifted data will not include the dropped periods and the shifted axis will be smaller than the original.

Parameters

periods [int] Number of periods to move, can be positive or negative.

Returns

shifted [same type as caller]

Notes
While the slice_shift is faster than shift, you may pay for it later during alignment.

pandas.Series.sort_index

Series.sort_index(axis=0, level=None, ascending=True, inplace=False, kind='quicksort', na_position='last', sort_remaining=True, ignore_index=False, key=None)
Sort Series by index labels.
Returns a new Series sorted by label if inplace argument is False, otherwise updates the original series and returns None.

Parameters

axis [int, default 0] Axis to direct sorting. This can only be 0 for Series.
level [int, optional] If not None, sort on values in specified index level(s).
ascending [bool or list of bools, default True] Sort ascending vs. descending. When the index is a MultiIndex the sort direction can be controlled for each level individually.
inplace [bool, default False] If True, perform operation in-place.
kind [{‘quicksort’, ‘mergesort’, ‘heapsort’}, default ‘quicksort’] Choice of sorting algorithm. See also numpy.sort() for more information. ‘mergesort’ is the only stable algorithm. For DataFrames, this option is only applied when sorting on a single column or label.
na_position [{‘first’, ‘last’}, default ‘last’] If ‘first’ puts NaNs at the beginning, ‘last’ puts NaNs at the end. Not implemented for MultiIndex.
sort_remaining [bool, default True] If True and sorting by level and index is multilevel, sort by other levels too (in order) after sorting by specified level.
ignore_index [bool, default False] If True, the resulting axis will be labeled 0, 1, ..., n - 1.
New in version 1.0.0.
key [callable, optional] If not None, apply the key function to the index values before sorting. This is similar to the key argument in the builtin sorted() function, with the notable difference that this key function should be vectorized. It should expect an Index and return an Index of the same shape.
New in version 1.1.0.
Returns

Series The original Series sorted by the labels.

See also:

DataFrame.sort_index Sort DataFrame by the index.
DataFrame.sort_values Sort DataFrame by the value.
Series.sort_values Sort Series by the value.

Examples

```python
>>> s = pd.Series(['a', 'b', 'c', 'd'], index=[3, 2, 1, 4])
>>> s.sort_index()  
1   c
2   b
3   a
4   d
dtype: object

Sort Descending

>>> s.sort_index(ascending=False)  
4   d
3   a
2   b
1   c
dtype: object

Sort Inplace

>>> s.sort_index(inplace=True)

>>> s  
1   c
2   b
3   a
4   d
dtype: object

By default NaNs are put at the end, but use na_position to place them at the beginning

```python
>>> s = pd.Series(['a', 'b', 'c', 'd'], index=[3, 2, 1, np.nan])
>>> s.sort_index(na_position='first')  
NaN  d
1.0  c
2.0  b
3.0  a
dtype: object

Specify index level to sort

```python
>>> arrays = [np.array(['qux', 'qux', 'foo', 'foo',
... 'baz', 'baz', 'bar', 'bar']),
... np.array(['two', 'one', 'two', 'one',
... 'two', 'one', 'two', 'one'])]
>>> s = pd.Series([1, 2, 3, 4, 5, 6, 7, 8], index=arrays)
```

(continues on next page)
```python
>>> s.sort_index(level=1)
bar one 8
baz one 6
foo one 4
qux one 2
bar two 7
baz two 5
foo two 3
qux two 1
dtype: int64

Does not sort by remaining levels when sorting by levels

```python
>>> s.sort_index(level=1, sort_remaining=False)
qux one 2
foo one 4
baz one 6
bar one 8
qux two 1
foo two 3
baz two 5
bar two 7
dtype: int64

Apply a key function before sorting

```python
>>> s = pd.Series([1, 2, 3, 4], index=['A', 'b', 'C', 'd'])
>>> s.sort_index(key=lambda x : x.str.lower())
A 1
b 2
C 3
d 4
dtype: int64
```

**pandas.Series.sort_values**

Series.sort_values(axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last', ignore_index=False, key=None)

Sort by the values.

Sort a Series in ascending or descending order by some criterion.

**Parameters**

- **axis** ([0 or ‘index’], default 0) Axis to direct sorting. The value ‘index’ is accepted for compatibility with DataFrame.sort_values.
- **ascending** [bool, default True] If True, sort values in ascending order, otherwise descending.
- **inplace** [bool, default False] If True, perform operation in-place.
- **kind** ['quicksort', 'mergesort' or 'heapsort', default 'quicksort'] Choice of sorting algorithm. See also numpy.sort() for more information. ‘mergesort’ is the only stable algorithm.
- **na_position** ['first' or 'last', default ‘last’] Argument ‘first’ puts NaNs at the beginning, ‘last’ puts NaNs at the end.
ignore_index  [bool, default False] If True, the resulting axis will be labeled 0, 1, ..., n - 1.
        New in version 1.0.0.

key  [callable, optional] If not None, apply the key function to the series values before sorting. This is similar to the key argument in the builtin sorted() function, with the notable difference that this key function should be vectorized. It should expect a Series and return an array-like.
        New in version 1.1.0.

Returns

Series  Series ordered by values.

See also:

Series.sort_index  Sort by the Series indices.

DataFrame.sort_values  Sort DataFrame by the values along either axis.

DataFrame.sort_index  Sort DataFrame by indices.

Examples

```python
>>> s = pd.Series([np.nan, 1, 3, 10, 5])
>>> s
0    NaN
1    1.0
2    3.0
3   10.0
4    5.0
dtype: float64

Sort values ascending order (default behaviour)

```python
>>> s.sort_values(ascending=True)
1    1.0
2    3.0
4    5.0
3   10.0
0    NaN
dtype: float64
```

Sort values descending order

```python
>>> s.sort_values(ascending=False)
3   10.0
4    5.0
2    3.0
1    1.0
0    NaN
dtype: float64
```

Sort values inplace
Sorting values:

```python
>>> s.sort_values(ascending=False, inplace=True)
```
```
 0 NaN
 1 1.0
 2 3.0
 3 10.0
 4 5.0
```

```
dtype: float64
```

Sort values putting NAs first:

```python
>>> s.sort_values(na_position='first')
```
```
 0 NaN
 1 1.0
 2 3.0
 3 10.0
 4 5.0
```
```
dtype: float64
```

Sorting a series of strings:

```python
>>> s = pd.Series(['z', 'b', 'd', 'a', 'c'])
```
```
```
>>> s.sort_values()
```
```
 0 z
 1 b
 2 d
 3 a
 4 c
```
```
dtype: object
```

Sort using a key function. Your `key` function will be given the `Series` of values and should return an array-like:

```python
>>> s.sort_values(key=lambda x: x.str.lower())
```
```
 0 a
 1 B
 2 c
 3 D
 4 e
```
```
dtype: object
```

NumPy ufuncs work well here. For example, we can sort by the `sin` of the value.
More complicated user-defined functions can be used, as long as they expect a Series and return an array-like

```python
>>> s.sort_values(key=lambda x: (np.tan(x.cumsum())))
0  -4
3   2
4   4
1  -2
2   0
dtype: int64
```

```
pandas.Series.sparse
Series.sparse()
Accessor for SparseSparse from other sparse matrix data types.
```

```
pandas.Series.squeeze
Series.squeeze(axis=None)
Squeeze 1 dimensional axis objects into scalars.
Series or DataFrames with a single element are squeezed to a scalar. DataFrames with a single column or a single row are squeezed to a Series. Otherwise the object is unchanged.
This method is most useful when you don’t know if your object is a Series or DataFrame, but you do know it has just a single column. In that case you can safely call squeeze to ensure you have a Series.

Parameters
axis [{0 or ‘index’, 1 or ‘columns’, None}, default None] A specific axis to squeeze. By default, all length-1 axes are squeezed.

Returns
DataFrame, Series, or scalar The projection after squeezing axis or all the axes.

See also:
Series.iloc Integer-location based indexing for selecting scalars.
DataFrame.iloc Integer-location based indexing for selecting Series.
Series.to_frame Inverse of DataFrame.squeeze for a single-column DataFrame.
Examples

```python
>>> primes = pd.Series([2, 3, 5, 7])
```

Slicing might produce a Series with a single value:

```python
>>> even_primes = primes[primes % 2 == 0]
>>> even_primes
0 2
dtype: int64
```

```python
>>> even_primes.squeeze()
2
```

Squeezing objects with more than one value in every axis does nothing:

```python
>>> odd_primes = primes[primes % 2 == 1]
>>> odd_primes
1 3
2 5
3 7
dtype: int64
```

```python
>>> odd_primes.squeeze()
1 3
2 5
3 7
dtype: int64
```

Squeezing is even more effective when used with DataFrames.

```python
>>> df = pd.DataFrame([[1, 2], [3, 4]], columns=['a', 'b'])
>>> df
   a  b
0 1  2
1 3  4
```

Slicing a single column will produce a DataFrame with the columns having only one value:

```python
>>> df_a = df[['a']]
>>> df_a
   a
0 1
1 3
```

So the columns can be squeezed down, resulting in a Series:

```python
>>> df_a.squeeze('columns')
0 1
1 3
Name: a, dtype: int64
```

Slicing a single row from a single column will produce a single scalar DataFrame:

```python
>>> df_0a = df.loc[df.index < 1, ['a']]
>>> df_0a
(continues on next page)
Squeezing the rows produces a single scalar Series:

```python
gf_0a.squeeze('rows')
a    1
Name: 0, dtype: int64
```

Squeezing all axes will project directly into a scalar:

```python
gf_0a.squeeze()
1
```

**pandas.Series.std**

Series.\texttt{std}(\texttt{axis=None, skipna=None, level=None, ddof=1, numeric_only=None, }\texttt{**kwargs})

Return sample standard deviation over requested axis.

Normalized by \(N-1\) by default. This can be changed using the \texttt{ddof} argument.

**Parameters**

- **axis** [(index (0))]  
  [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

- **skipna** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

- **ddof** [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is \(N - ddof\), where \(N\) represents the number of elements.

- **numeric_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**Returns**

- scalar or Series (if level specified)

**pandas.Series.str**

Series.\texttt{str}()

Vectorized string functions for Series and Index.

NAs stay NA unless handled otherwise by a particular method. Patterned after Python’s string methods, with some inspiration from R’s stringr package.
Examples

```python
>>> s = pd.Series(["A_Str_Series"])  
 0  A_Str_Series
  dtype: object

>>> s.str.split("_")  
 0  [A, Str, Series]
  dtype: object

>>> s.str.replace("_", "")  
 0  AStrSeries
  dtype: object
```

pandas.Series.sub

Series.sub(other, level=None, fill_value=None, axis=0)
Return Subtraction of series and other, element-wise (binary operator sub).

Equivalent to series - other, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]
fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.
level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

Series.rsub Reverse of the Subtraction operator, see Python documentation for more details.

Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=["a", "b", "c", "d"])  
   a  
  a  1.0  
  b  1.0  
  c  1.0  
  d  NaN  
  dtype: float64

>>> b = pd.Series([1, np.nan, 1, np.nan], index=["a", "b", "d", "e"])  
   a  
  a  1.0
```
b    NaN
d    1.0
e    NaN
dtype: float64

>>> a.subtract(b, fill_value=0)
a    0.0
b    1.0
c    1.0
d   -1.0
e    NaN
dtype: float64

pandas.Series.subtract

Series.subtract (other, level=None, fill_value=None, axis=0)
Return Subtraction of series and other, element-wise (binary operator sub).

Equivalent to series - other, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]
fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.
level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

Series The result of the operation.

See also:

Series.rsub Reverse of the Subtraction operator, see Python documentation for more details.

Examples

>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64

>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b  NaN
d    1.0
e    NaN

(continues on next page)
pandas.Series.sum

Series.sum(axis=None, skipna=None, level=None, numeric_only=None, min_count=0, **kwargs)

Return the sum of the values for the requested axis.

This is equivalent to the method numpy.sum.

Parameters

axis [[index (0)]] Axis for the function to be applied on.
skipna [bool, default True] Exclude NA/null values when computing the result.
level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.
numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.
min_count [int, default 0] The required number of valid values to perform the operation. If fewer than min_count non-NA values are present the result will be NA.

New in version 0.22.0: Added with the default being 0. This means the sum of an all-NA or empty Series is 0, and the product of an all-NA or empty Series is 1.

**kwargs Additional keyword arguments to be passed to the function.

Returns

scalar or Series (if level specified)

See also:

Series.sum Return the sum.
Series.min Return the minimum.
Series.max Return the maximum.
Series.idxmin Return the index of the minimum.
Series.idxmax Return the index of the maximum.
DataFrame.sum Return the sum over the requested axis.
DataFrame.min Return the minimum over the requested axis.
DataFrame.max Return the maximum over the requested axis.
DataFrame.idxmin Return the index of the minimum over the requested axis.
DataFrame.idxmax Return the index of the maximum over the requested axis.
Examples

```python
>>> idx = pd.MultiIndex.from_arrays([...
...     ['warm', 'warm', 'cold', 'cold'],
...     ['dog', 'falcon', 'fish', 'spider']],
...     names=['blooded', 'animal'])
>>> s = pd.Series([4, 2, 0, 8], name='legs', index=idx)
>>> s
blooded animal
  warm    dog    4
  falcon   2
  cold     fish   0
  spider  8
Name: legs, dtype: int64

>>> s.sum()
14

Sum using level names, as well as indices.

```python
>>> s.sum(level='blooded')
blooded
  warm    6
  cold    8
Name: legs, dtype: int64
```

```python
>>> s.sum(level=0)
blooded
  warm    6
  cold    8
Name: legs, dtype: int64
```

By default, the sum of an empty or all-NA Series is 0.

```python
>>> pd.Series([]).sum()  # min_count=0 is the default
0.0
```

This can be controlled with the `min_count` parameter. For example, if you’d like the sum of an empty series to be NaN, pass `min_count=1`.

```python
>>> pd.Series([]).sum(min_count=1)
nan
```

Thanks to the `skipna` parameter, `min_count` handles all-NA and empty series identically.

```python
>>> pd.Series([np.nan]).sum()
0.0

>>> pd.Series([np.nan]).sum(min_count=1)
nan
```
pandas.Series.swapaxes

Series.swapaxes(axis1, axis2, copy=True)
Interchange axes and swap values axes appropriately.

Returns
y [same as input]

pandas.Series.swaplevel

Series.swaplevel(i=-2, j=-1, copy=True)
Swap levels i and j in a MultiIndex.
Default is to swap the two innermost levels of the index.

Parameters
i, j [int, str] Level of the indices to be swapped. Can pass level name as string.

copy [bool, default True] Whether to copy underlying data.

Returns
Series Series with levels swapped in MultiIndex.

pandas.Series.tail

Series.tail(n=5)
Return the last n rows.
This function returns last n rows from the object based on position. It is useful for quickly verifying data, for example, after sorting or appending rows.

For negative values of n, this function returns all rows except the first n rows, equivalent to df[n:].

Parameters
n [int, default 5] Number of rows to select.

Returns
type of caller The last n rows of the caller object.

See also:

DataFrame.head The first n rows of the caller object.

Examples

```python
>>> df = pd.DataFrame({'animal': ['alligator', 'bee', 'falcon', 'lion',
...                           'monkey', 'parrot', 'shark', 'whale', 'zebra']})
>>> df
animal
0  alligator
1    bee
2  falcon
3   lion
```

(continues on next page)
Viewing the last 5 lines

```python
>>> df.tail()
animal
4  monkey
5  parrot
6  shark
7  whale
8  zebra
```

Viewing the last $n$ lines (three in this case)

```python
>>> df.tail(3)
animal
6  shark
7  whale
8  zebra
```

For negative values of $n$

```python
>>> df.tail(-3)
animal
3  lion
4  monkey
5  parrot
6  shark
7  whale
8  zebra
```

**pandas.Series.take**

Series.take (indices, axis=0, is_copy=None, **kwargs)

Return the elements in the given positional indices along an axis.

This means that we are not indexing according to actual values in the index attribute of the object. We are indexing according to the actual position of the element in the object.

**Parameters**

- **indices** [array-like] An array of ints indicating which positions to take.
- **axis** [(0 or ‘index’, 1 or ‘columns’, None), default 0] The axis on which to select elements. 0 means that we are selecting rows, 1 means that we are selecting columns.
- **is_copy** [bool] Before pandas 1.0, is_copy=False can be specified to ensure that the return value is an actual copy. Starting with pandas 1.0, take always returns a copy, and the keyword is therefore deprecated.
  
  Deprecated since version 1.0.0.

- **kwargs** For compatibility with numpy.take(). Has no effect on the output.
Returns

taken [same type as caller] An array-like containing the elements taken from the object.

See also:

DataFrame.loc Select a subset of a DataFrame by labels.

DataFrame.iloc Select a subset of a DataFrame by positions.

numpy.take Take elements from an array along an axis.

Examples

```python
>>> df = pd.DataFrame([('falcon', 'bird', 389.0),
                      ('parrot', 'bird', 24.0),
                      ('lion', 'mammal', 80.5),
                      ('monkey', 'mammal', np.nan)],
                      columns=['name', 'class', 'max_speed'],
                      index=[0, 2, 3, 1])
>>> df
   name  class  max_speed
0   falcon  bird      389.0
2    parrot  bird       24.0
3     lion  mammal     80.5
1   monkey  mammal       NaN

Take elements at positions 0 and 3 along the axis 0 (default).
Note how the actual indices selected (0 and 1) do not correspond to our selected indices 0 and 3. That's
because we are selecting the 0th and 3rd rows, not rows whose indices equal 0 and 3.

>>> df.take([0, 3])
   name  class  max_speed
0   falcon  bird      389.0
1   monkey  mammal       NaN

Take elements at indices 1 and 2 along the axis 1 (column selection).

>>> df.take([1, 2], axis=1)
   class  max_speed
0   bird      389.0
2   bird       24.0
3  mammal       80.5
1  mammal       NaN

We may take elements using negative integers for positive indices, starting from the end of the object, just
like with Python lists.

>>> df.take([-1, -2])
   name  class  max_speed
1   monkey  mammal       NaN
3     lion  mammal       80.5
```
**pandas.Series.to_clipboard**

```
Series.to_clipboard(excel=True, sep=None, **kwargs)
```

Copy object to the system clipboard.

Write a text representation of object to the system clipboard. This can be pasted into Excel, for example.

**Parameters**

- `excel` [bool, default True] Produce output in a csv format for easy pasting into excel.
  - True, use the provided separator for csv pasting.
  - False, write a string representation of the object to the clipboard.
- `sep` [str, default '\t'] Field delimiter.
- `**kwargs` These parameters will be passed to DataFrame.to_csv.

**See also:**

- `DataFrame.to_csv` Write a DataFrame to a comma-separated values (csv) file.
- `read_clipboard` Read text from clipboard and pass to read_table.

**Notes**

Requirements for your platform.

- Linux: `xclip`, or `xsel` (with PyQt4 modules)
- Windows: none
- OS X: none

**Examples**

Copy the contents of a DataFrame to the clipboard.

```python
>>> df = pd.DataFrame([[1, 2, 3], [4, 5, 6]], columns=['A', 'B', 'C'])
```

```python
>>> df.to_clipboard(sep=','
... # Wrote the following to the system clipboard:
... # ,A,B,C
... # 0,1,2,3
... # 1,4,5,6
```

We can omit the index by passing the keyword `index` and setting it to false.

```python
>>> df.to_clipboard(sep=','
... index=False)
... # Wrote the following to the system clipboard:
... # A,B,C
... # 1,2,3
... # 4,5,6
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.Series.to_csv
Series.to_csv(path_or_buf=None, sep=',', na_rep='', float_format=None, columns=None,
header=True, index=True, index_label=None, mode='w', encoding=None, compression='infer', quoting=None, quotechar='"', line_terminator=None, chunksize=None, date_format=None, doublequote=True, escapechar=None, decimal='.',
errors='strict')
Write object to a comma-separated values (csv) file.
Changed in version 0.24.0: The order of arguments for Series was changed.
Parameters
path_or_buf [str or file handle, default None] File path or object, if None is provided
the result is returned as a string. If a file object is passed it should be opened with
newline=”, disabling universal newlines.
Changed in version 0.24.0: Was previously named “path” for Series.
sep [str, default ‘,’] String of length 1. Field delimiter for the output file.
na_rep [str, default ‘’] Missing data representation.
float_format [str, default None] Format string for floating point numbers.
columns [sequence, optional] Columns to write.
header [bool or list of str, default True] Write out the column names. If a list of strings
is given it is assumed to be aliases for the column names.
Changed in version 0.24.0: Previously defaulted to False for Series.
index [bool, default True] Write row names (index).
index_label [str or sequence, or False, default None] Column label for index column(s)
if desired. If None is given, and header and index are True, then the index names are
used. A sequence should be given if the object uses MultiIndex. If False do not print
fields for index names. Use index_label=False for easier importing in R.
mode [str] Python write mode, default ‘w’.
encoding [str, optional] A string representing the encoding to use in the output file, defaults to ‘utf-8’.
compression [str or dict, default ‘infer’] If str, represents compression mode. If dict,
value at ‘method’ is the compression mode. Compression mode may be any of the
mode is ‘infer’ and path_or_buf is path-like, then detect compression mode from the
following extensions: ‘.gz’, ‘.bz2’, ‘.zip’ or ‘.xz’. (otherwise no compression). If dict
given and mode is one of {‘zip’, ‘gzip’, ‘bz2’}, or inferred as one of the above, other
entries passed as additional compression options.
Changed in version 1.0.0: May now be a dict with key ‘method’ as compression mode
and other entries as additional compression options if compression mode is ‘zip’.
Changed in version 1.1.0: Passing compression options as keys in dict is supported
for compression modes ‘gzip’ and ‘bz2’ as well as ‘zip’.
quoting [optional constant from csv module] Defaults to csv.QUOTE_MINIMAL.
If you have set a float_format then floats are converted to strings and thus
csv.QUOTE_NONNUMERIC will treat them as non-numeric.
quotechar [str, default ‘”’] String of length 1. Character used to quote fields.

3.3. Series

1217


line_ terminator [str, optional] The newline character or character sequence to use in the output file. Defaults to os.linesep, which depends on the OS in which this method is called (‘n’ for linux, ‘m’ for Windows, i.e.).

Changed in version 0.24.0.

chunksize [int or None] Rows to write at a time.

date_format [str, default None] Format string for datetime objects.

doublequote [bool, default True] Control quoting of quotechar inside a field.

escapechar [str, default None] String of length 1. Character used to escape sep and quotechar when appropriate.

decimal [str, default ‘.’] Character recognized as decimal separator. E.g. use ‘,’ for European data.

errors [str, default ‘strict’] Specifies how encoding and decoding errors are to be handled. See the errors argument for open() for a full list of options.

New in version 1.1.0.

Returns

None or str If path_or_buf is None, returns the resulting csv format as a string. Otherwise returns None.

See also:

read_csv Load a CSV file into a DataFrame.

to_excel Write DataFrame to an Excel file.

Examples

```python
>>> df = pd.DataFrame({'name': ['Raphael', 'Donatello'],
... 'mask': ['red', 'purple'],
... 'weapon': ['sai', 'bo staff']})

>>> df.to_csv(index=False)
'name,mask,weapon
Raphael,red,sai
Donatello,purple,bo staff'

Create ‘out.zip’ containing ‘out.csv’

```python
>>> compression_opts = dict(method='zip',
...                       archive_name='out.csv')
>>> df.to_csv('out.zip', index=False,
...            compression=compression_opts)
```

pandas.Series.to_dict

Series.to_dict(into=<class 'dict'>)
Convert Series to {label -> value} dict or dict-like object.

Parameters

into [class, default dict] The collections.abc.Mapping subclass to use as the return object. Can be the actual class or an empty instance of the mapping type you want. If you want a collections.defaultdict, you must pass it initialized.
Returns

collections.abc.Mapping  Key-value representation of Series.

Examples

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s.to_dict()
{0: 1, 1: 2, 2: 3, 3: 4}
>>> from collections import OrderedDict, defaultdict
>>> s.to_dict(OrderedDict)
OrderedDict([(0, 1), (1, 2), (2, 3), (3, 4)])
>>> dd = defaultdict(list)
>>> s.to_dict(dd)
defaultdict(<class 'list'>, {0: 1, 1: 2, 2: 3, 3: 4})
```

Series.to_excel

Series.to_excel(excel_writer,  sheet_name='Sheet1',  na_rep='',  float_format=None,  columns=None,  header=True,  index=True,  index_label=None,  startrow=0,  startcol=0,  engine=None,  merge_cells=True,  encoding=None,  inf_rep='inf',  verbose=True,  freeze_panes=None)

Write object to an Excel sheet.

To write a single object to an Excel .xlsx file it is only necessary to specify a target file name. To write to multiple sheets it is necessary to create an ExcelWriter object with a target file name, and specify a sheet in the file to write to.

Multiple sheets may be written to by specifying unique sheet_name. With all data written to the file it is necessary to save the changes. Note that creating an ExcelWriter object with a file name that already exists will result in the contents of the existing file being erased.

Parameters

excel_writer [str or ExcelWriter object] File path or existing ExcelWriter.

sheet_name [str, default ‘Sheet1’] Name of sheet which will contain DataFrame.

na_rep [str, default ‘’] Missing data representation.

float_format [str, optional] Format string for floating point numbers. For example float_format="%.2f" will format 0.1234 to 0.12.

columns [sequence or list of str, optional] Columns to write.

header [bool or list of str, default True] Write out the column names. If a list of string is given it is assumed to be aliases for the column names.

index [bool, default True] Write row names (index).

index_label [str or sequence, optional] Column label for index column(s) if desired. If not specified, and header and index are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

startrow [int, default 0] Upper left cell row to dump data frame.

startcol [int, default 0] Upper left cell column to dump data frame.
**pandas:** powerful Python data analysis toolkit, Release 1.1.1

**engine** [str, optional] Write engine to use, ‘openpyxl’ or ‘xlsxwriter’. You can also set this via the options `io.excel.xlsx.writer`, `io.excel.xlsx.writer`, and `io.excel.xlsm.writer`.

**merge_cells** [bool, default True] Write MultiIndex and Hierarchical Rows as merged cells.

**encoding** [str, optional] Encoding of the resulting excel file. Only necessary for xlwt, other writers support unicode natively.

**inf_rep** [str, default ‘inf’] Representation for infinity (there is no native representation for infinity in Excel).

**verbose** [bool, default True] Display more information in the error logs.

**freeze_panes** [tuple of int (length 2), optional] Specifies the one-based bottommost row and rightmost column that is to be frozen.

See also:

- `to_csv` Write DataFrame to a comma-separated values (csv) file.
- `ExcelWriter` Class for writing DataFrame objects into excel sheets.
- `read_excel` Read an Excel file into a pandas DataFrame.
- `read_csv` Read a comma-separated values (csv) file into DataFrame.

**Notes**

For compatibility with `to_csv()`, `to_excel` serializes lists and dicts to strings before writing. Once a workbook has been saved it is not possible write further data without rewriting the whole workbook.

**Examples**

Create, write to and save a workbook:

```python
>>> df1 = pd.DataFrame([['a', 'b'], ['c', 'd']],
                      index=['row 1', 'row 2'],
                      columns=['col 1', 'col 2'])
>>> df1.to_excel("output.xlsx")
```

To specify the sheet name:

```python
>>> df1.to_excel("output.xlsx",
               sheet_name='Sheet_name_1')
```

If you wish to write to more than one sheet in the workbook, it is necessary to specify an ExcelWriter object:

```python
>>> df2 = df1.copy()
>>> with pd.ExcelWriter('output.xlsx') as writer:
...     df1.to_excel(writer, sheet_name='Sheet_name_1')
...     df2.to_excel(writer, sheet_name='Sheet_name_2')
```

ExcelWriter can also be used to append to an existing Excel file:
```python
>>> with pd.ExcelWriter('output.xlsx', mode='a') as writer:
...     df.to_excel(writer, sheet_name='Sheet_name_3')
```

To set the library that is used to write the Excel file, you can pass the `engine` keyword (the default engine is automatically chosen depending on the file extension):

```python
>>> df1.to_excel('output1.xlsx', engine='xlsxwriter')
```

### pandas.Series.to_frame

**Series.to_frame** *(name=None)*

Convert Series to DataFrame.

**Parameters**

- **name** [object, default None] The passed name should substitute for the series name (if it has one).

**Returns**

- **DataFrame**  DataFrame representation of Series.

**Examples**

```python
>>> s = pd.Series(['a', 'b', 'c'], name='vals')

>>> s.to_frame()
   vals
0   a
1   b
2   c
```

### pandas.Series.to_hdf

**Series.to_hdf** *(path_or_buf, key, mode='a', complevel=None, complib=None, append=False, format=None, index=True, min_itemsize=None, nan_rep=None, dropna=None, data_columns=None, errors='strict', encoding='UTF-8')*

Write the contained data to an HDF5 file using HDFStore.

Hierarchical Data Format (HDF) is self-describing, allowing an application to interpret the structure and contents of a file with no outside information. One HDF file can hold a mix of related objects which can be accessed as a group or as individual objects.

In order to add another DataFrame or Series to an existing HDF file please use append mode and a different key.

For more information see the [user guide](#).

**Parameters**

- **path_or_buf** [str or pandas.HDFStore] File path or HDFStore object.
- **key** [str] Identifier for the group in the store.
- **mode** [[‘a’, ‘w’, ‘r+’], default ‘a’] Mode to open file:
• ‘w’: write, a new file is created (an existing file with the same name would be deleted).
• ‘a’: append, an existing file is opened for reading and writing, and if the file does not exist it is created.
• ‘r+’: similar to ‘a’, but the file must already exist.

**complevel** [{0-9}, optional] Specifies a compression level for data. A value of 0 disables compression.

**complib** [{'zlib', 'lz4', 'bzip2', 'blosc'}, default ‘zlib’] Specifies the compression library to be used. As of v0.20.2 these additional compressors for Blosc are supported (default if no compressor specified: ‘blosc:blosclz’): {'blosc:blosclz', 'blosc:lz4', 'blosc:lz4hc', 'blosc:snappy', 'blosc:zlib', 'blosc:zstd’}. Specifying a compression library which is not available issues a ValueError.

**append** [bool, default False] For Table formats, append the input data to the existing.

**format** [{‘fixed’, ‘table’, None}, default ‘fixed’] Possible values:
- ‘table’: Table format. Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data.
- If None, pd.get_option(‘io.hdf.default_format’) is checked, followed by fallback to “fixed”

**errors** [str, default ‘strict’] Specifies how encoding and decoding errors are to be handled. See the errors argument for open() for a full list of options.

**encoding** [str, default “UTF-8”]

**min_itemsize** [dict or int, optional] Map column names to minimum string sizes for columns.

**nan_rep** [Any, optional] How to represent null values as str. Not allowed with append=True.

**data_columns** [list of columns or True, optional] List of columns to create as indexed data columns for on-disk queries, or True to use all columns. By default only the axes of the object are indexed. See Query via data columns. Applicable only to format=’table’.

See also:

- **DataFrame.read_hdf** Read from HDF file.
- **DataFrame.to_parquet** Write a DataFrame to the binary parquet format.
- **DataFrame.to_sql** Write to a sql table.
- **DataFrame.to_feather** Write out feather-format for DataFrames.
- **DataFrame.to_csv** Write out to a csv file.
Examples

```python
>>> df = pd.DataFrame({'A': [1, 2, 3], 'B': [4, 5, 6]},
                   index=['a', 'b', 'c'])
>>> df.to_hdf('data.h5', key='df', mode='w')

We can add another object to the same file:

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s.to_hdf('data.h5', key='s')
```

Reading from HDF file:

```python
>>> pd.read_hdf('data.h5', 'df')
A  B
a 1 4
b 2 5
C 3 6

>>> pd.read_hdf('data.h5', 's')
0 1
1 2
2 3
3 4
dtype: int64
```

Deleting file with data:

```python
>>> import os
>>> os.remove('data.h5')
```

**pandas.Series.to_json**

Series.to_json(path_or_buf=None, orient=None, date_format=None, double_precision=10,
                force_ascii=True, date_unit='ms', default_handler=None, lines=False,
                compression='infer', index=True, indent=None)

Convert the object to a JSON string.

Note NaN's and None will be converted to null and datetime objects will be converted to UNIX timestamps.

**Parameters**

- **path_or_buf** [str or file handle, optional] File path or object. If not specified, the result is returned as a string.
- **orient** [str] Indication of expected JSON string format.
  - Series:
    - default is ‘index’
    - allowed values are: {‘split’,‘records’,‘index’,‘table’}.
  - DataFrame:
    - default is ‘columns’
    - allowed values are: {‘split’, ‘records’, ‘index’, ‘columns’, ‘values’, ‘table’}.
  - The format of the JSON string:
pandas: powerful Python data analysis toolkit, Release 1.1.1

- ‘split’ : dict like `{index -> [index], ‘columns’ -> [columns], ‘data’ -> [values]}
- ‘records’ : list like `[{column -> value}, . . . , {column -> value}]`
- ‘index’ : dict like `{index -> {column -> value}}`
- ‘columns’ : dict like `{column -> {index -> value}}`
- ‘values’ : just the values array
- ‘table’ : dict like `{‘schema’: {schema}, ‘data’: {data}}

Describing the data, where data component is like orient='records'.

Changed in version 0.20.0.

date_format [{None, ‘epoch’, ‘iso’}] Type of date conversion. ‘epoch’ = epoch milliseconds, ‘iso’ = ISO8601. The default depends on the orient. For orient='table', the default is ‘iso’. For all other orients, the default is ‘epoch’.

double_precision [int, default 10] The number of decimal places to use when encoding floating point values.

force_ascii [bool, default True] Force encoded string to be ASCII.

date_unit [str, default ‘ms’ (milliseconds)] The time unit to encode to, governs timestamp and ISO8601 precision. One of ‘s’, ‘ms’, ‘us’, ‘ns’ for second, millisecond, microsecond, and nanosecond respectively.

default_handler [callable, default None] Handler to call if object cannot otherwise be converted to a suitable format for JSON. Should receive a single argument which is the object to convert and return a serialisable object.

lines [bool, default False] If ‘orient’ is ‘records’ write out line delimited json format. Will throw ValueError if incorrect ‘orient’ since others are not list like.

compression [{‘infer’, ‘gzip’, ‘bz2’, ‘zip’, ‘xz’, None}] A string representing the compression to use in the output file, only used when the first argument is a filename. By default, the compression is inferred from the filename.

Changed in version 0.24.0: ‘infer’ option added and set to default

index [bool, default True] Whether to include the index values in the JSON string. Not including the index (index=False) is only supported when orient is ‘split’ or ‘table’.

New in version 0.23.0.

indent [int, optional] Length of whitespace used to indent each record.

New in version 1.0.0.

Returns

None or str If path_or_buf is None, returns the resulting json format as a string. Otherwise returns None.

See also:

read_json Convert a JSON string to pandas object.
Notes

The behavior of `indent=0` varies from the stdlib, which does not indent the output but does insert newlines. Currently, `indent=0` and the default `indent=None` are equivalent in pandas, though this may change in a future release.

Examples

```python
>>> import json
... df = pd.DataFrame(
...     [["a", "b"], ["c", "d"],
...     index=["row 1", "row 2"],
...     columns=["col 1", "col 2"],
...     )

>>> result = df.to_json(orient="split")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
{
    "columns": [
        "col 1",
        "col 2"
    ],
    "index": [
        "row 1",
        "row 2"
    ],
    "data": [
        ["a",
         "b"],
        ["c",
         "d"
        ]
    ]
}
```

Encoding/decoding a Dataframe using 'records' formatted JSON. Note that index labels are not preserved with this encoding.

```python
>>> result = df.to_json(orient="records")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
[
    {
        "col 1": "a",
        "col 2": "b"
    },
    {
        "col 1": "c",
        "col 2": "d"
    }
]```
Encoding/decoding a Dataframe using 'index' formatted JSON:

```python
>>> result = df.to_json(orient="index")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
{
  "row 1": {
    "col 1": "a",
    "col 2": "b"
  },
  "row 2": {
    "col 1": "c",
    "col 2": "d"
  }
}
```

Encoding/decoding a Dataframe using 'columns' formatted JSON:

```python
>>> result = df.to_json(orient="columns")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
{
  "col 1": {
    "row 1": "a",
    "row 2": "c"
  },
  "col 2": {
    "row 1": "b",
    "row 2": "d"
  }
}
```

Encoding/decoding a Dataframe using 'values' formatted JSON:

```python
>>> result = df.to_json(orient="values")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
[
  ["a", "b"],
  ["c", "d"]
]
```

Encoding with Table Schema:

```python
>>> result = df.to_json(orient="table")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
{
  "schema": {
    "fields": [
      {
        "name": "index",
        (continues on next page)
```
pandas.Series.to_latex

Series.to_latex(buf=None, columns=None, col_space=None, header=True, index=True, na_rep='NaN', formatters=None, float_format=None, sparsify=None, index_names=True, bold_rows=False, column_format=None, longtable=None, escape=None, encoding=None, decimal='.', multicolumn=None, multicolumn_format=None, multirow=None, caption=None, label=None)

Render object to a LaTeX tabular, longtable, or nested table/tabular.

Requires \usepackage{booktabs}. The output can be copy/pasted into a main LaTeX document or read from an external file with \input{table.tex}.

Changed in version 0.20.2: Added to Series.

Changed in version 1.0.0: Added caption and label arguments.

Parameters

- **buf** [str, Path or StringIO-like, optional, default None] Buffer to write to. If None, the output is returned as a string.
- **columns** [list of label, optional] The subset of columns to write. Writes all columns by default.
- **col_space** [int, optional] The minimum width of each column.
- **header** [bool or list of str, default True] Write out the column names. If a list of strings is given, it is assumed to be aliases for the column names.
index  [bool, default True] Write row names (index).

na_rep  [str, default ‘NaN’] Missing data representation.

formatters  [list of functions or dict of {str: function}, optional] Formatter functions to apply to columns’ elements by position or name. The result of each function must be a unicode string. List must be of length equal to the number of columns.

float_format  [one-parameter function or str, optional, default None] Formatter for floating point numbers. For example float_format="%.2f" and float_format="{:0.2f}".format will both result in 0.1234 being formatted as 0.12.

sparsify  [bool, optional] Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row. By default, the value will be read from the config module.

index_names  [bool, default True] Prints the names of the indexes.

bold_rows  [bool, default False] Make the row labels bold in the output.

column_format  [str, optional] The columns format as specified in \LaTeX{} table format e.g. ‘rcr’ for 3 columns. By default, ‘l’ will be used for all columns except columns of numbers, which default to ‘r’.

longtable  [bool, optional] By default, the value will be read from the pandas config module. Use a longtable environment instead of tabular. Requires adding a usepackage{longtable} to your \LaTeX{} preamble.

escape  [bool, optional] By default, the value will be read from the pandas config module. When set to False prevents from escaping latex special characters in column names.

encoding  [str, optional] A string representing the encoding to use in the output file, defaults to ‘utf-8’.

decimal  [str, default ‘.’] Character recognized as decimal separator, e.g. ‘,’ in Europe.

multicolumn  [bool, default True] Use multicolumn to enhance MultiIndex columns. The default will be read from the config module.

multicolumn_format  [str, default ‘l’] The alignment for multicolumns, similar to column_format The default will be read from the config module.

multirow  [bool, default False] Use multirow to enhance MultiIndex rows. Requires adding a usepackage{multirow} to your \LaTeX{} preamble. Will print centered labels (instead of top-aligned) across the contained rows, separating groups via clines. The default will be read from the pandas config module.

caption  [str, optional] The \LaTeX{} caption to be placed inside \caption{} in the output.

New in version 1.0.0.

label  [str, optional] The \LaTeX{} label to be placed inside \label{} in the output. This is used with \ref{} in the main .tex file.

New in version 1.0.0.

Returns

str or None  If buf is None, returns the result as a string. Otherwise returns None.

See also:
**Dataframe.to_string**  Render a DataFrame to a console-friendly tabular output.

**Dataframe.to_html**  Render a DataFrame as an HTML table.

**Examples**

```python
df = pd.DataFrame({'name': ['Raphael', 'Donatello'],
                   'mask': ['red', 'purple'],
                   'weapon': ['sai', 'bo staff']})

print(df.to_latex(index=False))
```

\begin{tabular}{lll}
\hline
name & mask & weapon \\
\hline
Raphael & red & sai \\
Donatello & purple & bo staff \\
\hline
\end{tabular}

**pandas.Series.to_list**

Series.to_list()

Return a list of the values.

These are each a scalar type, which is a Python scalar (for str, int, float) or a pandas scalar (for Timestamp/Timedelta/Interval/Period)

Returns

list

See also:

- numpy.ndarray.tolist Return the array as an a.ndim-levels deep nested list of Python scalars.

**pandas.Series.to_markdown**

Series.to_markdown(buf=None, mode=None, index=True, **kwargs)

Print Series in Markdown-friendly format.

New in version 1.0.0.

Parameters

- buf [str, Path or StringIO-like, optional, default None] Buffer to write to. If None, the output is returned as a string.
- mode [str, optional] Mode in which file is opened.
- index [bool, optional, default True] Add index (row) labels.

New in version 1.1.0.

**kwargs These parameters will be passed to tabulate.

Returns

str Series in Markdown-friendly format.
Examples

```python
>>> s = pd.Series(['elk', 'pig', 'dog', 'quetzal'], name='animal')
>>> print(s.to_markdown())
<table>
<thead>
<tr>
<th></th>
<th>animal</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>elk</td>
</tr>
<tr>
<td>1</td>
<td>pig</td>
</tr>
<tr>
<td>2</td>
<td>dog</td>
</tr>
<tr>
<td>3</td>
<td>quetzal</td>
</tr>
</tbody>
</table>
```

Output markdown with a tabulate option.

```python
>>> print(s.to_markdown(tablefmt='grid'))
+----+----------+
|    | animal   |
+====+==========+
| 0  | elk      |
| 1  | pig      |
| 2  | dog      |
| 3  | quetzal  |
+----+----------+
```

**pandas.Series.to_numpy**

`Series.to_numpy` *(dtype=None, copy=False, na_value=<object object>, **kwargs)*

A NumPy ndarray representing the values in this Series or Index.

New in version 0.24.0.

**Parameters**

- **dtype** [str or numpy.dtype, optional] The dtype to pass to `numpy.asarray()`.
- **copy** [bool, default False] Whether to ensure that the returned value is not a view on another array. Note that `copy=False` does not ensure that `to_numpy()` is no-copy. Rather, `copy=True` ensure that a copy is made, even if not strictly necessary.
- **na_value** [Any, optional] The value to use for missing values. The default value depends on `dtype` and the type of the array.

New in version 1.0.0.

- **kwargs** Additional keywords passed through to the `to_numpy` method of the underlying array (for extension arrays).

New in version 1.0.0.

**Returns**

- `numpy.ndarray`

**See also:**

- `Series.array` Get the actual data stored within.
**Index.array** Get the actual data stored within.

**DataFrame.to_numpy** Similar method for DataFrame.

**Notes**

The returned array will be the same up to equality (values equal in `self` will be equal in the returned array; likewise for values that are not equal). When `self` contains an ExtensionArray, the dtype may be different. For example, for a category-dtype Series, `to_numpy()` will return a NumPy array and the categorical dtype will be lost.

For NumPy dtypes, this will be a reference to the actual data stored in this Series or Index (assuming `copy=False`). Modifying the result in place will modify the data stored in the Series or Index (not that we recommend doing that).

For extension types, `to_numpy()` may require copying data and coercing the result to a NumPy type (possibly object), which may be expensive. When you need a no-copy reference to the underlying data, `Series.array` should be used instead.

This table lays out the different dtypes and default return types of `to_numpy()` for various dtypes within pandas.

<table>
<thead>
<tr>
<th>dtype</th>
<th>array type</th>
</tr>
</thead>
<tbody>
<tr>
<td>category[T]</td>
<td>ndarray[T] (same dtype as input)</td>
</tr>
<tr>
<td>period</td>
<td>ndarray[object] (Periods)</td>
</tr>
<tr>
<td>interval</td>
<td>ndarray[object] (Intervals)</td>
</tr>
<tr>
<td>IntegerNA</td>
<td>ndarray[object]</td>
</tr>
<tr>
<td>datetime64[ns]</td>
<td>datetime64[ns]</td>
</tr>
<tr>
<td>datetime64[ns, tz]</td>
<td>ndarray[object] (Timestamps)</td>
</tr>
</tbody>
</table>

**Examples**

```python
>>> ser = pd.Series(pd.Categorical(['a', 'b', 'a']))
>>> ser.to_numpy()
array(['a', 'b', 'a'], dtype=object)
```

Specify the `dtype` to control how datetime-aware data is represented. Use `dtype=object` to return an ndarray of pandas `Timestamp` objects, each with the correct `tz`.

```python
>>> ser = pd.Series(pd.date_range('2000', periods=2, tz='CET'))
>>> ser.to_numpy(dtype=object)
array([Timestamp('2000-01-01 00:00:00+0100', tz='CET', freq='D'),
      Timestamp('2000-01-02 00:00:00+0100', tz='CET', freq='D')],
      dtype=object)
```

Or `dtype='datetime64[ns]'` to return an ndarray of native datetime64 values. The values are converted to UTC and the timezone info is dropped.

```python
>>> ser.to_numpy(dtype="datetime64[ns]"
...array(['1999-12-31T23:00:00.000000000', '2000-01-01T23:00:00...'],
      dtype='datetime64[ns]')
```
pandas.Series.to_period

Series.to_period(freq=None, copy=True)
Convert Series from DatetimeIndex to PeriodIndex.

Parameters

freq [str, default None] Frequency associated with the PeriodIndex.
copy [bool, default True] Whether or not to return a copy.

Returns
Series Series with index converted to PeriodIndex.

pandas.Series.to_pickle

Series.to_pickle(path, compression='infer', protocol=5)
Pickle (serialize) object to file.

Parameters

path [str] File path where the pickled object will be stored.
protocol [int] Int which indicates which protocol should be used by the pickler, default HIGHEST_PROTOCOL (see [1] paragraph 12.1.2). The possible values are 0, 1, 2, 3, 4. A negative value for the protocol parameter is equivalent to setting its value to HIGHEST_PROTOCOL.

See also:

read_pickle Load pickled pandas object (or any object) from file.
DataFrame.to_hdf Write DataFrame to an HDF5 file.
DataFrame.to_sql Write DataFrame to a SQL database.
DataFrame.to_parquet Write a DataFrame to the binary parquet format.

Examples

```python
>>> original_df = pd.DataFrame({"foo": range(5), "bar": range(5, 10)})
>>> original_df
   foo  bar
0   0   5
1   1   6
2   2   7
3   3   8
4   4   9
>>> original_df.to_pickle("./dummy.pkl")

>>> unpickled_df = pd.read_pickle("./dummy.pkl")
```

(continues on next page)
pandas.Series.to_sql

pandas.Series.to_sql (name, con, schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None, method=None)

Write records stored in a DataFrame to a SQL database.

Databases supported by SQLAlchemy [1] are supported. Tables can be newly created, appended to, or overwritten.

Parameters

- **name** [str] Name of SQL table.
- **con** [sqlalchemy.engine.(Engine or Connection) or sqlite3.Connection] Using SQLAlchemy makes it possible to use any DB supported by that library. Legacy support is provided for sqlite3.Connection objects. The user is responsible for engine disposal and connection closure for the SQLAlchemy connectable See here.
- **schema** [str, optional] Specify the schema (if database flavor supports this). If None, use default schema.
- **if_exists** [{‘fail’, ‘replace’, ‘append’}, default ‘fail’] How to behave if the table already exists.
  - fail: Raise a ValueError.
  - replace: Drop the table before inserting new values.
  - append: Insert new values to the existing table.
- **index** [bool, default True] Write DataFrame index as a column. Uses index_label as the column name in the table.
- **index_label** [str or sequence, default None] Column label for index column(s). If None is given (default) and index is True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.
- **chunksize** [int, optional] Specify the number of rows in each batch to be written at a time. By default, all rows will be written at once.
- **dtype** [dict or scalar, optional] Specifying the datatype for columns. If a dictionary is used, the keys should be the column names and the values should be the SQLAlchemy types or strings for the sqlite3 legacy mode. If a scalar is provided, it will be applied to all columns.
- **method** [{None, ‘multi’, callable}, optional] Controls the SQL insertion clause used:
  - None: Uses standard SQL INSERT clause (one per row).
  - ‘multi’: Pass multiple values in a single INSERT clause.
 callable with signature (pd_table, conn, keys, data_iter).

Details and a sample callable implementation can be found in the section insert method.

New in version 0.24.0.

Raises

ValueError When the table already exists and if_exists is ‘fail’ (the default).

See also:

read_sql Read a DataFrame from a table.

Notes

Timezone aware datetime columns will be written as Timestamp with timezone type with SQLAlchemy if supported by the database. Otherwise, the datetimes will be stored as timezone unaware timestamps local to the original timezone.

New in version 0.24.0.

References

[1], [2]

Examples

Create an in-memory SQLite database.

```
>>> from sqlalchemy import create_engine
>>> engine = create_engine('sqlite://', echo=False)
```

Create a table from scratch with 3 rows.

```
>>> df = pd.DataFrame({'name' : ['User 1', 'User 2', 'User 3']})
>>> df
    name
0  User 1
1  User 2
2  User 3

>>> df.to_sql('users', con=engine)
```

```
>>> engine.execute("SELECT * FROM users").fetchall()
[(0, 'User 1'), (1, 'User 2'), (2, 'User 3')]
```

An sqlalchemy.engine.Connection can also be passed to con: >>> with engine.begin() as connection: ... df1 = pd.DataFrame(‘name’ : [‘User 4’, ‘User 5’]) ... df1.to_sql(‘users’, con=connection, if_exists=’append’)

This is allowed to support operations that require that the same DBAPI connection is used for the entire operation.
"pandas: powerful Python data analysis toolkit, Release 1.1.1"

```python
>>> df2 = pd.DataFrame({'name': ['User 6', 'User 7']})
>>> df2.to_sql('users', con=engine, if_exists='append')
>>> engine.execute("SELECT * FROM users").fetchall()
[(0, 'User 1'), (1, 'User 2'), (2, 'User 3'),
 (0, 'User 4'), (1, 'User 5'), (0, 'User 6'),
 (1, 'User 7')]

Overwrite the table with just df2.

```python
>>> df2.to_sql('users', con=engine, if_exists='replace',
... index_label='id')
>>> engine.execute("SELECT * FROM users").fetchall()
[(0, 'User 6'), (1, 'User 7')]

Specify the dtype (especially useful for integers with missing values). Notice that while pandas is forced to store the data as floating point, the database supports nullable integers. When fetching the data with Python, we get back integer scalars.

```python
>>> df = pd.DataFrame({'A': [1, None, 2]})
>>> df
A
0 1.0
1 NaN
2 2.0

```python
from sqlalchemy.types import Integer
>>> df.to_sql('integers', con=engine, index=False,
... dtype={'A': Integer()})
>>> engine.execute('SELECT * FROM integers').fetchall()
[(1, ), (None, ), (2, )]

```

**pandas.Series.to_string**

`Series.to_string(buf=None, na_rep='NaN', float_format=None, header=True, index=True, length=False, dtype=False, name=False, max_rows=None, min_rows=None)`

Render a string representation of the Series.

**Parameters**

- `buf` [StringIO-like, optional] Buffer to write to.
- `float_format` [one-parameter function, optional] Formatter function to apply to columns’ elements if they are floats, default None.
- `header` [bool, default True] Add the Series header (index name).
- `index` [bool, optional] Add index (row) labels, default True.
- `length` [bool, default False] Add the Series length.
- `dtype` [bool, default False] Add the Series dtype.
- `name` [bool, default False] Add the Series name if not None.
- `max_rows` [int, optional] Maximum number of rows to show before truncating. If None, show all.

3.3. Series

1235
min_rows [int, optional] The number of rows to display in a truncated repr (when number of rows is above max_rows).

Returns

str or None String representation of Series if buf=None, otherwise None.

pandas.Series.to_timestamp

Series.to_timestamp (freq=None, how='start', copy=True)
Cast to DatetimeIndex of Timestamps, at beginning of period.

Parameters

freq [str, default frequency of PeriodIndex] Desired frequency.
how [{‘s’, ‘e’, ‘start’, ‘end’}] Convention for converting period to timestamp; start of period vs. end.
copy [bool, default True] Whether or not to return a copy.

Returns

Series with DatetimeIndex

pandas.Series.to_xarray

Series.to_xarray ()
Return an xarray object from the pandas object.

Returns

xarray.DataArray or xarray.Dataset Data in the pandas structure converted to Dataset if the object is a DataFrame, or a DataArray if the object is a Series.

See also:

DataFrame.to_hdf Write DataFrame to an HDF5 file.
DataFrame.to_parquet Write a DataFrame to the binary parquet format.

Notes

See the xarray docs

Examples

```python
>>> df = pd.DataFrame({
    'falcon': ('bird', 389.0, 2),
    'parrot': ('bird', 24.0, 2),
    'lion': ('mammal', 80.5, 4),
    'monkey': ('mammal', np.nan, 4),
},
    columns=['name', 'class', 'max_speed',
             'num_legs'])
>>> df
   name  class  max_speed  num_legs
0  falcon   bird      389.0       2
```
1 parrot bird 24.0 2
2 lion mammal 80.5 4
3 monkey mammal NaN 4

```python
def.to_xarray()
def[['max_speed']].to_xarray()
dates = pd.to_datetime(['2018-01-01', '2018-01-01',
'2018-01-02', '2018-01-02'])
df_multiindex = pd.DataFrame({'date': dates,
'animal': ['falcon', 'parrot',
'falcon', 'parrot'],
'speed': [350, 18, 361, 15]})
df_multiindex = df_multiindex.set_index(['date', 'animal'])

def_multiindex
ds = df_multiindex.set_index(['date', 'animal'])
>>> df_multiindex.to_xarray()
<xarray.Dataset>
Dimensions: (animal: 2, date: 2)
Coordinates:
  * date (date) datetime64[ns] 2018-01-01 2018-01-02
  * animal (animal) object 'falcon' 'parrot'
Data variables:
  speed (date, animal) int64 350 18 361 15
```
pandas.Series.tolist

Series.tolist()
Return a list of the values.
These are each a scalar type, which is a Python scalar (for str, int, float) or a pandas scalar (for Timestamp/Timedelta/Interval/Period)

Returns
list

See also:

numpy.ndarray.tolist Return the array as an a.ndim-levels deep nested list of Python scalars.

pandas.Series.transform

Series.transform(func, axis=0, *args, **kwargs)
Call func on self producing a Series with transformed values.
Produced Series will have the same axis length as self.

Parameters

func [function, str, list or dict] Function to use for transforming the data. If a function, must either work when passed a Series or when passed to Series.apply.

Accepted combinations are:
• function
• string function name
• list of functions and/or function names, e.g. [np.exp, 'sqrt']
• dict of axis labels -> functions, function names or list of such.

axis [[0 or 'index']] Parameter needed for compatibility with DataFrame.

*args Positional arguments to pass to func.

**kwargs Keyword arguments to pass to func.

Returns

Series A Series that must have the same length as self.

Raises

ValueError [If the returned Series has a different length than self.]

See also:

Series.agg Only perform aggregating type operations.
Series.apply Invoke function on a Series.
Examples

```python
>>> df = pd.DataFrame({'A': range(3), 'B': range(1, 4)})
>>> df
   A  B
0  0  1
1  1  2
2  2  3
>>> df.transform(lambda x: x + 1)
   A  B
0  1  2
1  2  3
2  3  4
```

Even though the resulting Series must have the same length as the input Series, it is possible to provide several input functions:

```python
>>> s = pd.Series(range(3))
>>> s
0  0
1  1
2  2
dtype: int64
>>> s.transform([np.sqrt, np.exp])
    sqrt     exp
0  0.000000  1.000000
1  1.000000  2.718282
2  1.414214  7.389056
```

**pandas.Series.transpose**

Series.transpose(*args, **kwargs)

Return the transpose, which is by definition self.

Returns

%(klass)s

**pandas.Series.truediv**

Series.truediv(other, level=None, fill_value=None, axis=0)

Return Floating division of series and other, element-wise (binary operator truediv).

Equivalent to series / other, but with support to substitute a fill_value for missing data in either one of the inputs.

Parameters

other [Series or scalar value]

fill_value [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result of filling (at that location) will be missing.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

3.3. Series 1239
Returns

Series The result of the operation.

See also:

Series.rtruediv Reverse of the Floating division operator, see Python documentation for more details.

Examples

```python
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
 a  1.0
 b  1.0
 c  1.0
 d NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
 a  1.0
 b NaN
 d  1.0
 e NaN
dtype: float64
>>> a.divide(b, fill_value=0)
 a  1.0
 b inf
 c inf
 d  0.0
 e NaN
dtype: float64
```

pandas.Series.truncate

Series.truncate(before=None, after=None, axis=None, copy=True) Truncate a Series or DataFrame before and after some index value.

This is a useful shorthand for boolean indexing based on index values above or below certain thresholds.

Parameters

- **before** [date, str, int] Truncate all rows before this index value.
- **after** [date, str, int] Truncate all rows after this index value.
- **axis** [{0 or ‘index’, 1 or ‘columns’}, optional] Axis to truncate. Truncates the index (rows) by default.
- **copy** [bool, default is True] Return a copy of the truncated section.

Returns
type of caller The truncated Series or DataFrame.

See also:

DataFrame.loc Select a subset of a DataFrame by label.
**DataFrame.iloc** Select a subset of a DataFrame by position.

**Notes**

If the index being truncated contains only datetime values, *before* and *after* may be specified as strings instead of Timestamps.

**Examples**

```python
df = pd.DataFrame({'A': ['a', 'b', 'c', 'd', 'e'],
                  'B': ['f', 'g', 'h', 'i', 'j'],
                  'C': ['k', 'l', 'm', 'n', 'o']},
                  index=[1, 2, 3, 4, 5])

>>> df
   A  B  C
0  a  f  k
1  b  g  l
2  c  h  m
3  d  i  n
4  e  j  o

>>> df.truncate(before=2, after=4)
   A  B  C
0  b  g  l
1  c  h  m
2  d  i  n

The columns of a DataFrame can be truncated.

```python
df.truncate(before="A", after="B", axis="columns")
```

```plaintext
   A  B
0  a  f
1  b  g
2  c  h
3  d  i
4  e  j
```

For Series, only rows can be truncated.

```python
df['A'].truncate(before=2, after=4)
```

```plaintext
2  b
3  c
4  d
Name: A, dtype: object
```

The index values in truncate can be datetimes or string dates.

```python
dates = pd.date_range('2016-01-01', '2016-02-01', freq='s')
df = pd.DataFrame(index=dates, data={'A': 1})
df.tail()
```

```plaintext
2016-01-31 23:59:56 1
2016-01-31 23:59:57 1
2016-01-31 23:59:58 1
```

(continues on next page)
Because the index is a DatetimeIndex containing only dates, we can specify `before` and `after` as strings. They will be coerced to Timestamps before truncation.

```python
>>> df.truncate('2016-01-05', '2016-01-10').tail()
A
2016-01-09 23:59:56 1
2016-01-09 23:59:57 1
2016-01-09 23:59:58 1
2016-01-09 23:59:59 1
2016-01-10 00:00:00 1
```

Note that `truncate` assumes a 0 value for any unspecified time component (midnight). This differs from partial string slicing, which returns any partially matching dates.

```python
>>> df.loc['2016-01-05':'2016-01-10', :].tail()
A
2016-01-10 23:59:55 1
2016-01-10 23:59:56 1
2016-01-10 23:59:57 1
2016-01-10 23:59:58 1
2016-01-10 23:59:59 1
```

### pandas.Series.tshift

**Series.tshift** *(periods=1, freq=None, axis=0)*

Shift the time index, using the index’s frequency if available.

Deprecated since version 1.1.0: Use `shift` instead.

**Parameters**

- **periods** [int] Number of periods to move, can be positive or negative.
- **freq** [DateOffset, timedelta, or str, default None] Increment to use from the tseries module or time rule expressed as a string (e.g. ‘EOM’).
- **axis** *[0 or ‘index’, 1 or ‘columns’, None], default 0]* Corresponds to the axis that contains the Index.

**Returns**

- **shifted** [Series/DataFrame]
Notes

If freq is not specified then tries to use the freq or inferred_freq attributes of the index. If neither of those attributes exist, a ValueError is thrown.

pandas.Series.tz_convert

Series.tz_convert (tz, axis=0, level=None, copy=True)
Convert tz-aware axis to target time zone.

Parameters
- tz [str or tzinfo object]
- axis [the axis to convert]
- level [int, str, default None] If axis is a MultiIndex, convert a specific level. Otherwise must be None.
- copy [bool, default True] Also make a copy of the underlying data.

Returns
- {klass} Object with time zone converted axis.

Raises
- TypeError If the axis is tz-naive.

pandas.Series.tz_localize

Series.tz_localize (tz, axis=0, level=None, copy=True, ambiguous='raise', nonexistent='raise')
Localize tz-naive index of a Series or DataFrame to target time zone.

This operation localizes the Index. To localize the values in a timezone-naive Series, use Series.dt.tz_localize().

Parameters
- tz [str or tzinfo]
- axis [the axis to localize]
- level [int, str, default None] If axis is a MultiIndex, localize a specific level. Otherwise must be None.
- copy [bool, default True] Also make a copy of the underlying data.
- ambiguous ['infer’, bool-ndarray, ‘NaT’, default ‘raise’] When clocks moved backward due to DST, ambiguous times may arise. For example in Central European Time (UTC+01), when going from 03:00 DST to 02:00 non-DST, 02:30:00 local time occurs both at 00:30:00 UTC and at 01:30:00 UTC. In such a situation, the ambiguous parameter dictates how ambiguous times should be handled.
  - ‘infer’ will attempt to infer fall dst-transition hours based on order
  - bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
  - ‘NaT’ will return NaT where there are ambiguous times
  - ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.
nonexistent [str, default ‘raise’] A nonexistent time does not exist in a particular time-zone where clocks moved forward due to DST. Valid values are:

• ‘shift_forward’ will shift the nonexistent time forward to the closest existing time
• ‘shift_backward’ will shift the nonexistent time backward to the closest existing time
• ‘NaT’ will return NaT where there are nonexistent times
• timedelta objects will shift nonexistent times by the timedelta
• ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

Series or DataFrame Same type as the input.

Raises

TypeError If the TimeSeries is tz-aware and tz is not None.

Examples

Localize local times:

```python
>>> s = pd.Series([1],
                   index=pd.DatetimeIndex(['2018-09-15 01:30:00']))
>>> s.tz_localize('CET')
2018-09-15 01:30:00+02:00 1
dtype: int64
```

Be careful with DST changes. When there is sequential data, pandas can infer the DST time:

```python
>>> s = pd.Series(range(7),
                   index=pd.DatetimeIndex(["2018-10-28 01:30:00",
                                            "2018-10-28 02:00:00",
                                            "2018-10-28 02:30:00",
                                            "2018-10-28 02:00:00",
                                            "2018-10-28 02:30:00",
                                            "2018-10-28 03:00:00",
                                            "2018-10-28 03:30:00"]))
>>> s.tz_localize('CET', ambiguous='infer')
2018-10-28 01:30:00+02:00 0
2018-10-28 02:00:00+02:00 1
2018-10-28 02:30:00+02:00 2
2018-10-28 02:00:00+01:00 3
2018-10-28 02:30:00+01:00 4
2018-10-28 03:00:00+01:00 5
2018-10-28 03:30:00+01:00 6
dtype: int64
```

In some cases, inferring the DST is impossible. In such cases, you can pass an ndarray to the ambiguous parameter to set the DST explicitly
```python
>>> s = pd.Series(range(3),
...                index=pd.DatetimeIndex(['2018-10-28 01:20:00',
...                                         '2018-10-28 02:36:00',
...                                         '2018-10-28 03:46:00']))
>>> s.tz_localize('CET', ambiguous=np.array([True, True, False]))
2018-10-28 01:20:00+02:00 0
2018-10-28 02:36:00+02:00 1
2018-10-28 03:46:00+01:00 2
dtype: int64
```

If the DST transition causes nonexistent times, you can shift these dates forward or backward with a timedelta object or 'shift_forward' or 'shift_backward'.

```python
>>> s = pd.Series(range(2),
...                index=pd.DatetimeIndex(['2015-03-29 02:30:00',
...                                         '2015-03-29 03:30:00']))
>>> s.tz_localize('Europe/Warsaw', nonexistent='shift_forward')
2015-03-29 03:00:00+02:00 0
2015-03-29 03:30:00+02:00 1
dtype: int64
```

```python
>>> s.tz_localize('Europe/Warsaw', nonexistent='shift_backward')
2015-03-29 01:59:59.999999999+01:00 0
2015-03-29 03:30:00+02:00 1
dtype: int64
```

```python
>>> s.tz_localize('Europe/Warsaw', nonexistent=pd.Timedelta('1H'))
2015-03-29 03:30:00+02:00 0
2015-03-29 03:30:00+02:00 1
dtype: int64
```

### pandas.Series.unique

**Series.unique()**

Return unique values of Series object.

Uniques are returned in order of appearance. Hash table-based unique, therefore does NOT sort.

**Returns**

- ndarray or ExtensionArray: The unique values returned as a NumPy array. See Notes.

**See also:**

- `unique`: Top-level unique method for any 1-d array-like object.
- `Index.unique`: Return Index with unique values from an Index object.
Notes

Returns the unique values as a NumPy array. In case of an extension-array backed Series, a new ExtensionArray of that type with just the unique values is returned. This includes

- Categorical
- Period
- Datetime with Timezone
- Interval
- Sparse
- IntegerNA

See Examples section.

Examples

```python
>>> pd.Series([2, 1, 3, 3], name='A').unique()
array([2, 1, 3])

>>> pd.Series([pd.Timestamp('2016-01-01') for _ in range(3)]).unique()
array(['2016-01-01T00:00:00.000000000'], dtype='datetime64[ns]')

>>> pd.Series([pd.Timestamp('2016-01-01', tz='US/Eastern') for _ in range(3)]).unique()  # doctest: +NORMALIZE_WHITESPACE
<DatetimeArray>
['2016-01-01 00:00:00-05:00']
Length: 1, dtype: datetime64[ns, US/Eastern]

An unordered Categorical will return categories in the order of appearance.

```python
>>> pd.Series(pd.Categorical(list('baabc'))).unique()
['b', 'a', 'c']
Categories (3, object): ['b', 'a', 'c']
```

An ordered Categorical preserves the category ordering.

```python
>>> pd.Series(pd.Categorical(list('baabc'), categories=list('abc'), ordered=True)).unique()
['b', 'a', 'c']
Categories (3, object): ['a' < 'b' < 'c']
```

**pandas.Series.unstack**

Series.unstack(level=-1, fill_value=None)

Unstack, also known as pivot, Series with MultiIndex to produce DataFrame.

**Parameters**

- `level` [int, str, or list of these, default last level] Level(s) to unstack, can pass level name.
- `fill_value` [scalar value, default None] Value to use when replacing NaN values.

**Returns**
DataFrame Unstacked Series.

Examples

```python
>>> s = pd.Series([1, 2, 3, 4],
...                index=pd.MultiIndex.from_product([['one', 'two'],
...                                                   ['a', 'b']]))
```

```plaintext
one a 1
     b 2
two a 3
     b 4
dtype: int64
```

```python
>>> s.unstack(level=-1)
     a  b
one 1  2
two 3  4
```

```python
>>> s.unstack(level=0)
     one  two
     a   1  3
     b   2  4
```

pandas.Series.update

`Series.update(other)`

Modify Series in place using values from passed Series.

Uses non-NA values from passed Series to make updates. Aligns on index.

Parameters

- `other` [Series, or object coercible into Series]

Examples

```python
>>> s = pd.Series([1, 2, 3])
>>> s.update(pd.Series([4, 5, 6]))
```

```plaintext
0  4
1  5
2  6
dtype: int64
```

```python
>>> s = pd.Series(['a', 'b', 'c'])
>>> s.update(pd.Series(['d', 'e'], index=[0, 2]))
```

```plaintext
0  d
1  b
2  e
dtype: object
```
If `other` contains NaNs the corresponding values are not updated in the original Series.

```python
>>> s = pd.Series([1, 2, 3])
>>> s.update(pd.Series([4, np.nan, 6]))
>>> s
0 4
1 2
2 6
dtype: int64
```

`other` can also be a non-Series object type that is coercible into a Series

```python
>>> s = pd.Series([1, 2, 3])
>>> s.update([4, np.nan, 6])
>>> s
0 4
1 2
2 6
dtype: int64
```

```python
>>> s = pd.Series([1, 2, 3])
>>> s.update({1: 9})
>>> s
0 1
1 9
2 3
dtype: int64
```

### pandas.Series.value_counts

`Series.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)`

Return a Series containing counts of unique values.

The resulting object will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values by default.

**Parameters**

- `normalize` [bool, default False] If True then the object returned will contain the relative frequencies of the unique values.
- `sort` [bool, default True] Sort by frequencies.
- `ascending` [bool, default False] Sort in ascending order.
- `bins` [int, optional] Rather than count values, group them into half-open bins, a convenience for `pd.cut`, only works with numeric data.
- `dropna` [bool, default True] Don’t include counts of NaN.
Returns
Series

See also:

**Series.count** Number of non-NA elements in a Series.

**DataFrame.count** Number of non-NA elements in a DataFrame.

**DataFrame.value_counts** Equivalent method on DataFrames.

Examples

```python
>>> index = pd.Index([3, 1, 2, 3, 4, np.nan])
>>> index.value_counts()
3.0 2
4.0 1
2.0 1
1.0 1
dtype: int64
```

With `normalize` set to `True`, returns the relative frequency by dividing all values by the sum of values.

```python
>>> s = pd.Series([3, 1, 2, 3, 4, np.nan])
>>> s.value_counts(normalize=True)
3.0 0.4
4.0 0.2
2.0 0.2
1.0 0.2
dtype: float64
```

**bins**

Bins can be useful for going from a continuous variable to a categorical variable; instead of counting unique apparitions of values, divide the index in the specified number of half-open bins.

```python
>>> s.value_counts(bins=3)
(2.0, 3.0] 2
(0.996, 2.0] 2
(3.0, 4.0] 1
dtype: int64
```

**dropna**

With `dropna` set to `False` we can also see NaN index values.

```python
>>> s.value_counts(dropna=False)
3.0 2
NaN 1
4.0 1
2.0 1
1.0 1
dtype: int64
```
**pandas.Series.var**

```
pandas.Series.var(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)
```

Return unbiased variance over requested axis. Normalized by N-1 by default. This can be changed using the ddof argument.

**Parameters**

- **axis** ([index (0)])
- **skipna** (bool, default True) Exclude NA/null values. If an entire row/column is NA, the result will be NA.
- **level** (int or level name, default None) If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.
- **ddof** (int, default 1) Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.
- **numeric_only** (bool, default None) Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**Returns**

scalar or Series (if level specified)

**pandas.Series.view**

```
pandas.Series.view(dtype=None)
```

Create a new view of the Series.

This function will return a new Series with a view of the same underlying values in memory, optionally reinterpreted with a new data type. The new data type must preserve the same size in bytes as to not cause index misalignment.

**Parameters**

- **dtype** (data type) Data type object or one of their string representations.

**Returns**

Series A new Series object as a view of the same data in memory.

**See also:**

numpy.ndarray.view Equivalent numpy function to create a new view of the same data in memory.

**Notes**

Series are instantiated with **dtype=float64** by default. While numpy.ndarray.view() will return a view with the same data type as the original array, Series.view() (without specified dtype) will try using float64 and may fail if the original data type size in bytes is not the same.
Examples

```python
>>> s = pd.Series([-2, -1, 0, 1, 2], dtype='int8')
>>> s
0   -2
1   -1
2    0
3    1
4    2
dtype: int8
```

The 8 bit signed integer representation of -1 is 0b11111111, but the same bytes represent 255 if read as an 8 bit unsigned integer:

```python
>>> us = s.view('uint8')
>>> us
0   254
1   255
2    0
3    1
4    2
dtype: uint8
```

The views share the same underlying values:

```python
>>> us[0] = 128
>>> s
0  -128
1   -1
2    0
3    1
4    2
dtype: int8
```

**pandas.Series.where**

`Series.where(cond, other=nan, inplace=False, axis=None, level=None, errors='raise', try_cast=False)`

Replace values where the condition is False.

**Parameters**

- **cond** [bool Series/DataFrame, array-like, or callable] Where `cond` is True, keep the original value. Where False, replace with corresponding value from `other`. If `cond` is callable, it is computed on the Series/DataFrame and should return boolean Series/DataFrame or array. The callable must not change input Series/DataFrame (though pandas doesn’t check it).

- **other** [scalar, Series/DataFrame, or callable] Entries where `cond` is False are replaced with corresponding value from `other`. If `other` is callable, it is computed on the Series/DataFrame and should return scalar or Series/DataFrame. The callable must not change input Series/DataFrame (though pandas doesn’t check it).

- **inplace** [bool, default False] Whether to perform the operation in place on the data.

- **axis** [int, default None] Alignment axis if needed.

- **level** [int, default None] Alignment level if needed.
**errors** [str, {'raise', 'ignore'}, default ‘raise’] Note that currently this parameter won’t affect the results and will always coerce to a suitable dtype.

- ‘raise’: allow exceptions to be raised.
- ‘ignore’: suppress exceptions. On error return original object.

**try_cast** [bool, default False] Try to cast the result back to the input type (if possible).

**Returns**

Same type as caller

**See also:**

`DataFrame.mask()` Return an object of same shape as self.

**Notes**

The where method is an application of the if-then idiom. For each element in the calling DataFrame, if `cond` is `True` the element is used; otherwise the corresponding element from the DataFrame `other` is used.

The signature for `DataFrame.where()` differs from `numpy.where()`. Roughly `df1.where(m, df2)` is equivalent to `np.where(m, df1, df2)`.

For further details and examples see the `where` documentation in `indexing`.

**Examples**

```python
>>> s = pd.Series(range(5))
>>> s.where(s > 0)
0    NaN
1    1.0
2    2.0
3    3.0
4    4.0
dtype: float64

>>> s.mask(s > 0)
0    0.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64

>>> s.where(s > 1, 10)
0    10
1    10
2     2
3     3
4     4
dtype: int64
```
```python
>>> df = pd.DataFrame(np.arange(10).reshape(-1, 2), columns=['A', 'B'])
>>> df
   A  B
0  0  1
1  2  3
2  4  5
3  6  7
4  8  9

>>> m = df % 3 == 0
>>> df.where(m, -df)
   A  B
0  0 -1
1 -2  3
2 -4 -5
3  6 -7
4 -8  9

>>> df.where(m, -df) == np.where(m, df, -df)
   A  B
0  True True
1  True True
2  True True
3  True True
4  True True

>>> df.where(m, -df) == df.mask(~m, -df)
   A  B
0  True True
1  True True
2  True True
3  True True
4  True True
```

**pandas.Series.xs**

`Series.xs(key, axis=0, level=None, drop_level=True)`

Return cross-section from the Series/DataFrame.

This method takes a `key` argument to select data at a particular level of a MultiIndex.

**Parameters**

- `key` [label or tuple of label] Label contained in the index, or partially in a MultiIndex.
- `axis` [{0 or 'index', 1 or 'columns'}, default 0] Axis to retrieve cross-section on.
- `level` [object, defaults to first n levels (n=1 or len(key))] In case of a key partially contained in a MultiIndex, indicate which levels are used. Levels can be referred by label or position.
- `drop_level` [bool, default True] If False, returns object with same levels as self.

**Returns**

Series or DataFrame Cross-section from the original Series or DataFrame corresponding to the selected index levels.

**See also:**

`DataFrame.loc` Access a group of rows and columns by label(s) or a boolean array.
**DataFrame.iloc** Purely integer-location based indexing for selection by position.

**Notes**

*xs* can not be used to set values.

MultiIndex Slicers is a generic way to get/set values on any level or levels. It is a superset of *xs* functionality, see *MultiIndex Slicers*.

**Examples**

```python
>>> d = {'num_legs': [4, 4, 2, 2],
...      'num_wings': [0, 0, 2, 2],
...      'class': ['mammal', 'mammal', 'mammal', 'bird'],
...      'animal': ['cat', 'dog', 'bat', 'penguin'],
...      'locomotion': ['walks', 'walks', 'flies', 'walks']}
>>> df = pd.DataFrame(data=d)
>>> df = df.set_index(['class', 'animal', 'locomotion'])
>>> df
            num_legs  num_wings
    class animal locomotion
    mammal  cat    walks 4     0
              dog    walks 4     0
              bat    flies 2     2
    bird    penguin walks 2     2
```

Get values at specified index

```python
>>> df.xs('mammal')
            num_legs  num_wings
    animal locomotion
    cat    walks 4     0
    dog    walks 4     0
    bat    flies 2     2
```

Get values at several indexes

```python
>>> df.xs(('mammal', 'dog'))
    locomotion
    walks 4     0
```

Get values at specified index and level

```python
>>> df.xs('cat', level=1)
            num_legs  num_wings
    class locomotion
    mammal walks 4     0
```

Get values at several indexes and levels

```python
>>> df.xs(('bird', 'walks'),
...        level=[0, 'locomotion'])
    num_legs  num_wings
    animal  penguin 2     2
```
Get values at specified column and axis

```python
>>> df.xs('num_wings', axis=1)
class  animal  locomotion
  mammal  cat  walks   0
dog  walks   0
  bat  flies   2
bird  penguin  walks   2
Name: num_wings, dtype: int64
```

### 3.3.2 Attributes

**Axes**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Series.index</code></td>
<td>The index (axis labels) of the Series.</td>
</tr>
<tr>
<td><code>Series.array</code></td>
<td>The ExtensionArray of the data backing this Series or Index.</td>
</tr>
<tr>
<td><code>Series.values</code></td>
<td>Return Series as ndarray or ndarray-like depending on the dtype.</td>
</tr>
<tr>
<td><code>Series.dtype</code></td>
<td>Return the dtype object of the underlying data.</td>
</tr>
<tr>
<td><code>Series.shape</code></td>
<td>Return a tuple of the shape of the underlying data.</td>
</tr>
<tr>
<td><code>Series.nbytes</code></td>
<td>Return the number of bytes in the underlying data.</td>
</tr>
<tr>
<td><code>Series.ndim</code></td>
<td>Number of dimensions of the underlying data, by definition 1.</td>
</tr>
<tr>
<td><code>Series.size</code></td>
<td>Return the number of elements in the underlying data.</td>
</tr>
<tr>
<td><code>Series.T</code></td>
<td>Return the transpose, which is by definition self.</td>
</tr>
<tr>
<td><code>Series.memory_usage</code></td>
<td>Return the memory usage of the Series.</td>
</tr>
<tr>
<td><code>Series.empty</code></td>
<td>Indicator whether DataFrame is empty.</td>
</tr>
<tr>
<td><code>Series.dtypes</code></td>
<td>Return the dtype object of the underlying data.</td>
</tr>
<tr>
<td><code>Series.name</code></td>
<td>Return the name of the Series.</td>
</tr>
</tbody>
</table>

**pandas.Series.empty**

**property** `Series.empty`

Indicator whether DataFrame is empty.

True if DataFrame is entirely empty (no items), meaning any of the axes are of length 0.

**Returns**

`bool` If DataFrame is empty, return True, if not return False.

**See also:**

- `Series.dropna` Return series without null values.
- `DataFrame.dropna` Return DataFrame with labels on given axis omitted where (all or any) data are missing.
Notes

If DataFrame contains only NaNs, it is still not considered empty. See the example below.

Examples

An example of an actual empty DataFrame. Notice the index is empty:

```python
>>> df_empty = pd.DataFrame({'A': []})
>>> df_empty
Empty DataFrame
Columns: [A]
Index: []
>>> df_empty.empty
True
```

If we only have NaNs in our DataFrame, it is not considered empty! We will need to drop the NaNs to make the DataFrame empty:

```python
>>> df = pd.DataFrame({'A': [np.nan]})
>>> df
   A
0  NaN
>>> df.empty
False
>>> df.dropna().empty
True
```

### 3.3.3 Conversion

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Series.astype(dtype[, copy, errors])</code></td>
<td>Cast a pandas object to a specified dtype <code>dtype</code>.</td>
</tr>
<tr>
<td><code>Series.convert_dtypes([infer_objects, ...])</code></td>
<td>Convert columns to best possible dtypes using dtypes supporting <code>pd.NA</code>.</td>
</tr>
<tr>
<td><code>Series.infer_objects()</code></td>
<td>Attempt to infer better dtypes for object columns.</td>
</tr>
<tr>
<td><code>Series.copy([deep])</code></td>
<td>Make a copy of this object’s indices and data.</td>
</tr>
<tr>
<td><code>Series.bool()</code></td>
<td>Return the bool of a single element Series or DataFrame.</td>
</tr>
<tr>
<td><code>Series.to_numpy([dtype, copy, na_value])</code></td>
<td>A NumPy ndarray representing the values in this Series or Index.</td>
</tr>
<tr>
<td><code>Series.to_period([freq, copy])</code></td>
<td>Convert Series from DatetimeIndex to PeriodIndex.</td>
</tr>
<tr>
<td><code>Series.to_timestamp([freq, how, copy])</code></td>
<td>Cast to DatetimeIndex of Timestamps, at <code>beginning</code> of period.</td>
</tr>
<tr>
<td><code>Series.to_list()</code></td>
<td>Return a list of the values.</td>
</tr>
<tr>
<td><code>Series.__array__([dtype])</code></td>
<td>Return the values as a NumPy array.</td>
</tr>
</tbody>
</table>
pandas.Series.__array__

Series.__array__(dtype=None)

Return the values as a NumPy array.

Users should not call this directly. Rather, it is invoked by numpy.array() and numpy.asarray().

Parameters

dtype [str or numpy.dtype, optional] The dtype to use for the resulting NumPy array. By default, the dtype is inferred from the data.

Returns

numpy.ndarray The values in the series converted to a numpy.ndarray with the specified dtype.

See also:
array Create a new array from data.
Series.array Zero-copy view to the array backing the Series.
Series.to_numpy Series method for similar behavior.

Examples

```python
>>> ser = pd.Series([1, 2, 3])
>>> np.asarray(ser)
array([1, 2, 3])
```

For timezone-aware data, the timezones may be retained with dtype='object'

```python
>>> tzser = pd.Series(pd.date_range('2000', periods=2, tz="CET"))
>>> np.asarray(tzser, dtype="object")
array([Timestamp('2000-01-01 00:00:00+0100', tz='CET', freq='D'),
      Timestamp('2000-01-02 00:00:00+0100', tz='CET', freq='D'),
      dtype=object])
```

Or the values may be localized to UTC and the tzinfo discarded with dtype='datetime64[ns]'

```python
>>> np.asarray(tzser, dtype="datetime64[ns]")
array(['1999-12-31T23:00:00.000000000', ...
      dtype='datetime64[ns]'
```

3.3.4 Indexing, iteration

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.get</td>
<td>Get item from object for given key (ex: DataFrame column).</td>
</tr>
<tr>
<td>Series.at</td>
<td>Access a single value for a row/column label pair.</td>
</tr>
<tr>
<td>Series.iat</td>
<td>Access a single value for a row/column pair by integer position.</td>
</tr>
<tr>
<td>Series.loc</td>
<td>Access a group of rows and columns by label(s) or a boolean array.</td>
</tr>
<tr>
<td>Series.iloc</td>
<td>Purely integer-location based indexing for selection by position.</td>
</tr>
<tr>
<td>Series.<strong>iter</strong>()</td>
<td>Return an iterator of the values.</td>
</tr>
</tbody>
</table>

continues on next page
Table 33 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Series.items()</code></td>
<td>Lazily iterate over (index, value) tuples.</td>
</tr>
<tr>
<td><code>Series.iteritems()</code></td>
<td>Lazily iterate over (index, value) tuples.</td>
</tr>
<tr>
<td><code>Series.keys()</code></td>
<td>Return alias for index.</td>
</tr>
<tr>
<td><code>Series.pop(item)</code></td>
<td>Return item and drops from series.</td>
</tr>
<tr>
<td><code>Series.item()</code></td>
<td>Return the first element of the underlying data as a python scalar.</td>
</tr>
<tr>
<td><code>Series.xs(key[, axis, level, drop_level])</code></td>
<td>Return cross-section from the Series/DataFrame.</td>
</tr>
</tbody>
</table>

**`pandas.Series.__iter__`**

`Series.__iter__()`  
Return an iterator of the values.  

These are each a scalar type, which is a Python scalar (for str, int, float) or a pandas scalar (for Timestamp/Timedelta/Interval/Period)  

*Returns*  

iterator

For more information on `.at`, `.iat`, `.loc`, and `.iloc`, see the indexing documentation.

### 3.3.5 Binary operator functions

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Series.add(other[, level, fill_value, axis])</code></td>
<td>Return Addition of series and other, element-wise (binary operator <code>add</code>).</td>
</tr>
<tr>
<td><code>Series.sub(other[, level, fill_value, axis])</code></td>
<td>Return Subtraction of series and other, element-wise (binary operator <code>sub</code>).</td>
</tr>
<tr>
<td><code>Series.mul(other[, level, fill_value, axis])</code></td>
<td>Return Multiplication of series and other, element-wise (binary operator <code>mul</code>).</td>
</tr>
<tr>
<td><code>Series.div(other[, level, fill_value, axis])</code></td>
<td>Return Floating division of series and other, element-wise (binary operator <code>truediv</code>).</td>
</tr>
<tr>
<td><code>Series.truediv(other[, level, fill_value, axis])</code></td>
<td>Return Floating division of series and other, element-wise (binary operator <code>truediv</code>).</td>
</tr>
<tr>
<td><code>Series.floordiv(other[, level, fill_value, axis])</code></td>
<td>Return Integer division of series and other, element-wise (binary operator <code>floordiv</code>).</td>
</tr>
<tr>
<td><code>Series.mod(other[, level, fill_value, axis])</code></td>
<td>Return Modulo of series and other, element-wise (binary operator <code>mod</code>).</td>
</tr>
<tr>
<td><code>Series.pow(other[, level, fill_value, axis])</code></td>
<td>Return Exponential power of series and other, element-wise (binary operator <code>pow</code>).</td>
</tr>
<tr>
<td><code>Series.radd(other[, level, fill_value, axis])</code></td>
<td>Return Addition of series and other, element-wise (binary operator <code>radd</code>).</td>
</tr>
<tr>
<td><code>Series.rsub(other[, level, fill_value, axis])</code></td>
<td>Return Subtraction of series and other, element-wise (binary operator <code>rsub</code>).</td>
</tr>
<tr>
<td><code>Series.rmul(other[, level, fill_value, axis])</code></td>
<td>Return Multiplication of series and other, element-wise (binary operator <code>rmul</code>).</td>
</tr>
<tr>
<td><code>Series.rdiv(other[, level, fill_value, axis])</code></td>
<td>Return Floating division of series and other, element-wise (binary operator <code>rtruediv</code>).</td>
</tr>
<tr>
<td><code>Series.rtruediv(other[, level, fill_value, axis])</code></td>
<td>Return Floating division of series and other, element-wise (binary operator <code>rtruediv</code>).</td>
</tr>
</tbody>
</table>

continues on next page
Table 34 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Series.rfloordiv()</code></td>
<td>Return Integer division of series and other, element-wise (binary operator <code>rfloordiv</code>).</td>
</tr>
<tr>
<td><code>Series.rmod()</code></td>
<td>Return Modulo of series and other, element-wise (binary operator <code>rmod</code>).</td>
</tr>
<tr>
<td><code>Series.rpow()</code></td>
<td>Return Exponential power of series and other, element-wise (binary operator <code>rpow</code>).</td>
</tr>
<tr>
<td><code>Series.combine()</code></td>
<td>Combine the Series with a Series or scalar according to <code>func</code>.</td>
</tr>
<tr>
<td><code>Series.round()</code></td>
<td>Round each value in a Series to the given number of decimals.</td>
</tr>
<tr>
<td><code>Series.lt()</code></td>
<td>Return Less than of series and other, element-wise (binary operator <code>lt</code>).</td>
</tr>
<tr>
<td><code>Series.gt()</code></td>
<td>Return Greater than of series and other, element-wise (binary operator <code>gt</code>).</td>
</tr>
<tr>
<td><code>Series.le()</code></td>
<td>Return Less than or equal to of series and other, element-wise (binary operator <code>le</code>).</td>
</tr>
<tr>
<td><code>Series.ge()</code></td>
<td>Return Greater than or equal to of series and other, element-wise (binary operator <code>ge</code>).</td>
</tr>
<tr>
<td><code>Series.ne()</code></td>
<td>Return Not equal to of series and other, element-wise (binary operator <code>ne</code>).</td>
</tr>
<tr>
<td><code>Series.eq()</code></td>
<td>Return Equal to of series and other, element-wise (binary operator <code>eq</code>).</td>
</tr>
</tbody>
</table>

3.3.6 Function application, GroupBy & window

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Series.apply()</code></td>
<td>Invoke function on values of Series.</td>
</tr>
<tr>
<td><code>Series.agg()</code></td>
<td>Aggregate using one or more operations over the specified axis.</td>
</tr>
<tr>
<td><code>Series.aggregate()</code></td>
<td>Aggregate using one or more operations over the specified axis.</td>
</tr>
<tr>
<td><code>Series.transform()</code></td>
<td>Call <code>func</code> on self producing a Series with transformed values.</td>
</tr>
<tr>
<td><code>Series.map()</code></td>
<td>Map values of Series according to input correspondence.</td>
</tr>
<tr>
<td><code>Series.groupby()</code></td>
<td>Group Series using a mapper or by a Series of columns.</td>
</tr>
<tr>
<td><code>Series.rolling()</code></td>
<td>Provide rolling window calculations.</td>
</tr>
<tr>
<td><code>Series.expanding()</code></td>
<td>Provide expanding transformations.</td>
</tr>
<tr>
<td><code>Series.ewm()</code></td>
<td>Provide exponential weighted (EW) functions.</td>
</tr>
<tr>
<td><code>Series.pipe()</code></td>
<td>Apply <code>func(self, *args, **kwargs)</code>.</td>
</tr>
</tbody>
</table>
### 3.3.7 Computations / descriptive stats

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.abs()</td>
<td>Return a Series/DataFrame with absolute numeric value of each element.</td>
</tr>
<tr>
<td>Series.all([axis, bool_only, skipna, level])</td>
<td>Return whether all elements are True, potentially over an axis.</td>
</tr>
<tr>
<td>Series.any([axis, bool_only, skipna, level])</td>
<td>Return whether any element is True, potentially over an axis.</td>
</tr>
<tr>
<td>Series.autocorr([lag])</td>
<td>Compute the lag-N autocorrelation.</td>
</tr>
<tr>
<td>Series.between(left, right[, inclusive])</td>
<td>Return boolean Series equivalent to left &lt;= series &lt;= right.</td>
</tr>
<tr>
<td>Series.clip([lower, upper, axis, inplace])</td>
<td>Trim values at input threshold(s).</td>
</tr>
<tr>
<td>Series.corr(other[, method, min_periods])</td>
<td>Compute correlation with other Series, excluding missing values.</td>
</tr>
<tr>
<td>Series.count([level])</td>
<td>Return number of non-NA/null observations in the Series.</td>
</tr>
<tr>
<td>Series.cov(other[, min_periods, ddof])</td>
<td>Compute covariance with Series, excluding missing values.</td>
</tr>
<tr>
<td>Series.cummax([axis, skipna])</td>
<td>Return cumulative maximum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td>Series.cummin([axis, skipna])</td>
<td>Return cumulative minimum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td>Series.cumprod([axis, skipna])</td>
<td>Return cumulative product over a DataFrame or Series axis.</td>
</tr>
<tr>
<td>Series.cumsum([axis, skipna])</td>
<td>Return cumulative sum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td>Series.describe([percentiles, include,...])</td>
<td>Generate descriptive statistics.</td>
</tr>
<tr>
<td>Series.diff([periods])</td>
<td>First discrete difference of element.</td>
</tr>
<tr>
<td>Series.factorize([sort, na_sentinel])</td>
<td>Encode the object as an enumerated type or categorical variable.</td>
</tr>
<tr>
<td>Series.kurt([axis, skipna, level, numeric_only])</td>
<td>Return unbiased kurtosis over requested axis.</td>
</tr>
<tr>
<td>Series.mad([axis, skipna, level])</td>
<td>Return the mean absolute deviation of the values for the requested axis.</td>
</tr>
<tr>
<td>Series.max([axis, skipna, level, numeric_only])</td>
<td>Return the maximum of the values for the requested axis.</td>
</tr>
<tr>
<td>Series.mean([axis, skipna, level, numeric_only])</td>
<td>Return the mean of the values for the requested axis.</td>
</tr>
<tr>
<td>Series.median([axis, skipna, level, ...])</td>
<td>Return the median of the values for the requested axis.</td>
</tr>
<tr>
<td>Series.min([axis, skipna, level, numeric_only])</td>
<td>Return the minimum of the values for the requested axis.</td>
</tr>
<tr>
<td>Series.mode([dropna])</td>
<td>Return the mode(s) of the dataset.</td>
</tr>
<tr>
<td>Series.nlargest([n, keep])</td>
<td>Return the largest n elements.</td>
</tr>
<tr>
<td>Series.nsmallest([n, keep])</td>
<td>Return the smallest n elements.</td>
</tr>
<tr>
<td>Series.pct_change([periods, fill_method,...])</td>
<td>Percentage change between the current and a prior element.</td>
</tr>
<tr>
<td>Series.prod([axis, skipna, level, ...])</td>
<td>Return the product of the values for the requested axis.</td>
</tr>
<tr>
<td>Series.quantile([q, interpolation])</td>
<td>Return value at the given quantile.</td>
</tr>
<tr>
<td>Series.rank([axis, method, numeric_only, ...])</td>
<td>Compute numerical data ranks (1 through n) along axis.</td>
</tr>
<tr>
<td>Series.sem([axis, skipna, level, ddof, ...])</td>
<td>Return unbiased standard error of the mean over requested axis.</td>
</tr>
<tr>
<td>Series.skew([axis, skipna, level, numeric_only])</td>
<td>Return unbiased skew over requested axis.</td>
</tr>
<tr>
<td>Series.std([axis, skipna, level, ddof, ...])</td>
<td>Return sample standard deviation over requested axis.</td>
</tr>
<tr>
<td>Series.sum([axis, skipna, level, ...])</td>
<td>Return the sum of the values for the requested axis.</td>
</tr>
<tr>
<td>Series.var([axis, skipna, level, ddof, ...])</td>
<td>Return unbiased variance over requested axis.</td>
</tr>
</tbody>
</table>

continues on next page
<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Series.kurtosis()</code></td>
<td>Return unbiased kurtosis over requested axis.</td>
</tr>
<tr>
<td><code>Series.unique()</code></td>
<td>Return unique values of Series object.</td>
</tr>
<tr>
<td><code>Series.nunique()</code></td>
<td>Return number of unique elements in the object.</td>
</tr>
<tr>
<td><code>Series.is_unique</code></td>
<td>Return boolean if values in the object are unique.</td>
</tr>
<tr>
<td><code>Series.is_monotonic</code></td>
<td>Return boolean if values in the object are monotonically increasing.</td>
</tr>
<tr>
<td><code>Series.is_monotonic_increasing</code></td>
<td>Alias for <code>is_monotonic</code>.</td>
</tr>
<tr>
<td><code>Series.is_monotonic_decreasing</code></td>
<td>Return boolean if values in the object are monotonically decreasing.</td>
</tr>
<tr>
<td><code>Series.value_counts()</code></td>
<td>Return a Series containing counts of unique values.</td>
</tr>
</tbody>
</table>

### 3.3.8 Reindexing / selection / label manipulation

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Series.align()</code></td>
<td>Align two objects on their axes with the specified join method.</td>
</tr>
<tr>
<td><code>Series.drop()</code></td>
<td>Return Series with specified index labels removed.</td>
</tr>
<tr>
<td><code>Series.droplevel()</code></td>
<td>Return DataFrame with requested index / column level(s) removed.</td>
</tr>
<tr>
<td><code>Series.drop_duplicates([keep, inplace])</code></td>
<td>Return Series with duplicate values removed.</td>
</tr>
<tr>
<td><code>Series.duplicated([keep])</code></td>
<td>Indicate duplicate Series values.</td>
</tr>
<tr>
<td><code>Series.equals()</code></td>
<td>Test whether two objects contain the same elements.</td>
</tr>
<tr>
<td><code>Series.first([offset])</code></td>
<td>Select initial periods of time series data based on a date offset.</td>
</tr>
<tr>
<td><code>Series.head([n])</code></td>
<td>Return the first ( n ) rows.</td>
</tr>
<tr>
<td><code>Series.idxmax([axis, skipna])</code></td>
<td>Return the row label of the maximum value.</td>
</tr>
<tr>
<td><code>Series.idxmin([axis, skipna])</code></td>
<td>Return the row label of the minimum value.</td>
</tr>
<tr>
<td><code>Series.isin([values])</code></td>
<td>Whether elements in Series are contained in values.</td>
</tr>
<tr>
<td><code>Series.last([offset])</code></td>
<td>Select final periods of time series data based on a date offset.</td>
</tr>
<tr>
<td><code>Series.reindex([index])</code></td>
<td>Conform Series to new index with optional filling logic.</td>
</tr>
<tr>
<td><code>Series.rename_like([other, method, copy, ...])</code></td>
<td>Return an object with matching indices as other object.</td>
</tr>
<tr>
<td>`Series.rename_axis(**kwargs)```</td>
<td>Alter Series index labels or name.</td>
</tr>
<tr>
<td><code>Series.reset_index([level, drop, name, inplace])</code></td>
<td>Set the name of the axis for the index or columns.</td>
</tr>
<tr>
<td><code>Series.sample([n, frac, replace, weights, ...])</code></td>
<td>Return a random sample of items from an axis of object.</td>
</tr>
<tr>
<td>`Series.set_axis([labels], axis, inplace)```</td>
<td>Assign desired index to given axis.</td>
</tr>
<tr>
<td><code>Series.take(indices[, axis, is_copy])</code></td>
<td>Return the elements in the given positional indices along an axis.</td>
</tr>
<tr>
<td><code>Series.tail([n])</code></td>
<td>Return the last ( n ) rows.</td>
</tr>
<tr>
<td><code>Series.truncate([before, after, axis, copy])</code></td>
<td>Truncate a Series or DataFrame before and after some index value.</td>
</tr>
<tr>
<td><code>Series.where([cond], other, inplace, axis, ...])</code></td>
<td>Replace values where the condition is False.</td>
</tr>
<tr>
<td><code>Series.mask([cond], other, inplace, axis, ...])</code></td>
<td>Replace values where the condition is True.</td>
</tr>
<tr>
<td><code>Series.add_prefix(prefix)</code></td>
<td>Prefix labels with string <code>prefix</code>.</td>
</tr>
<tr>
<td><code>Series.add_suffix(suffix)</code></td>
<td>Suffix labels with string <code>suffix</code>.</td>
</tr>
<tr>
<td><code>Series.filter([items, like, regex, axis])</code></td>
<td>Subset the dataframe rows or columns according to the specified index labels.</td>
</tr>
</tbody>
</table>
3.3.9 Missing data handling

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.backfill(...)</td>
<td>Synonym for DataFrame.fillna() with method='bfill'.</td>
</tr>
<tr>
<td>Series.bfill(...)</td>
<td>Synonym for DataFrame.fillna() with method='bfill'.</td>
</tr>
<tr>
<td>Series.dropna(...)</td>
<td>Return a new Series with missing values removed.</td>
</tr>
<tr>
<td>Series.ffill(...)</td>
<td>Synonym for DataFrame.fillna() with method='ffill'.</td>
</tr>
<tr>
<td>Series.fillna(...)</td>
<td>Fill NA/NaN values using the specified method.</td>
</tr>
<tr>
<td>Series.interpolate(...)</td>
<td>Please note that only method='linear' is supported for DataFrame/Series with a MultiIndex.</td>
</tr>
<tr>
<td>Series.isna()</td>
<td>Detect missing values.</td>
</tr>
<tr>
<td>Series.isnull()</td>
<td>Detect missing values.</td>
</tr>
<tr>
<td>Series.notna()</td>
<td>Detect existing (non-missing) values.</td>
</tr>
<tr>
<td>Series.notnull()</td>
<td>Detect existing (non-missing) values.</td>
</tr>
<tr>
<td>Series.pad(...)</td>
<td>Synonym for DataFrame.fillna() with method='ffill'.</td>
</tr>
<tr>
<td>Series.replace(...)</td>
<td>Replace values given in to_replace with value.</td>
</tr>
</tbody>
</table>

3.3.10 Reshaping, sorting

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.argsort(...)</td>
<td>Return the integer indices that would sort the Series values.</td>
</tr>
<tr>
<td>Series.argmin(...)</td>
<td>Return int position of the smallest value in the Series.</td>
</tr>
<tr>
<td>Series.argmax(...)</td>
<td>Return int position of the largest value in the Series.</td>
</tr>
<tr>
<td>Series.reorder_levels(...)</td>
<td>Rearrange index levels using input order.</td>
</tr>
<tr>
<td>Series.sort_values(...)</td>
<td>Sort by the values.</td>
</tr>
<tr>
<td>Series.sort_index(...)</td>
<td>Sort Series by index labels.</td>
</tr>
<tr>
<td>Series.swaplevel(...)</td>
<td>Swap levels i and j in a MultiIndex.</td>
</tr>
<tr>
<td>Series.unstack(...)</td>
<td>Unstack, also known as pivot, Series with MultiIndex to produce DataFrame.</td>
</tr>
<tr>
<td>Series.explode(...)</td>
<td>Transform each element of a list-like to a row.</td>
</tr>
<tr>
<td>Series.searchsorted(...)</td>
<td>Find indices where elements should be inserted to maintain order.</td>
</tr>
<tr>
<td>Series.ravel(...)</td>
<td>Return the flattened underlying data as an ndarray.</td>
</tr>
<tr>
<td>Series.repeat(...)</td>
<td>Repeat elements of a Series.</td>
</tr>
<tr>
<td>Series.squeeze(...)</td>
<td>Squeeze 1 dimensional axis objects into scalars.</td>
</tr>
<tr>
<td>Series.view(...)</td>
<td>Create a new view of the Series.</td>
</tr>
</tbody>
</table>
3.3.11 Combining / comparing / joining / merging

- `Series.append(to_append[, ignore_index, ...])`: Concatenate two or more Series.
- `Series.compare(other[, align_axis, ...])`: Compare to another Series and show the differences.
- `Series.replace([to_replace, value, inplace, ...])`: Replace values given in `to_replace` with `value`.
- `Series.update(other)`: Modify Series in place using values from passed Series.

3.3.12 Time Series-related

- `Series.asfreq(freq[, method, how, ...])`: Convert TimeSeries to specified frequency.
- `Series.asof(where[, subset])`: Return the last row(s) without any NaNs before `where`.
- `Series.shift([periods, freq, axis, fill_value])`: Shift index by desired number of periods with an optional time `freq`.
- `Series.first_valid_index()`: Return index for first non-NA/null value.
- `Series.last_valid_index()`: Return index for last non-NA/null value.
- `Series.resample(rule[, axis, closed, label, ...])`: Resample time-series data.
- `Series.tz_convert(tz[, axis, level, copy])`: Convert tz-aware axis to target time zone.
- `Series.tz_localize(tz[, axis, level, copy, ...])`: Localize tz-naive index of a Series or DataFrame to target time zone.
- `Series.at_time(time[, asof, axis])`: Select values at particular time of day (e.g., 9:30AM).
- `Series.between_time(start_time, end_time[,...])`: Select values between particular times of the day (e.g., 9:00-9:30 AM).
- `Series.tshift([periods, freq, axis])`: (DEPRECATED) Shift the time index, using the index’s frequency if available.
- `Series.slice_shift([periods, axis])`: Equivalent to `shift` without copying data.

3.3.13 Accessors

Pandas provides dtype-specific methods under various accessors. These are separate namespaces within `Series` that only apply to specific data types.

<table>
<thead>
<tr>
<th>Data Type</th>
<th>Accessor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Datetime, Timedelta, Period</td>
<td><code>dt</code></td>
</tr>
<tr>
<td>String</td>
<td><code>str</code></td>
</tr>
<tr>
<td>Categorical</td>
<td><code>cat</code></td>
</tr>
<tr>
<td>Sparse</td>
<td><code>sparse</code></td>
</tr>
</tbody>
</table>
Datetimelike properties

Series.dt can be used to access the values of the series as datetimelike and return several properties. These can be accessed like `Series.dt.<property>`.

### Datetime properties

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Series.dt.date</code></td>
<td>Returns numpy array of python datetime.date objects (namely, the date part of Timestamps without timezone information).</td>
</tr>
<tr>
<td><code>Series.dt.time</code></td>
<td>Returns numpy array of datetime.time.</td>
</tr>
<tr>
<td><code>Series.dt.timetz</code></td>
<td>Returns numpy array of datetime.time also containing timezone information.</td>
</tr>
<tr>
<td><code>Series.dt.year</code></td>
<td>The year of the datetime.</td>
</tr>
<tr>
<td><code>Series.dt.month</code></td>
<td>The month as January=1, December=12.</td>
</tr>
<tr>
<td><code>Series.dt.day</code></td>
<td>The day of the datetime.</td>
</tr>
<tr>
<td><code>Series.dt.hour</code></td>
<td>The hours of the datetime.</td>
</tr>
<tr>
<td><code>Series.dt.minute</code></td>
<td>The minutes of the datetime.</td>
</tr>
<tr>
<td><code>Series.dt.second</code></td>
<td>The seconds of the datetime.</td>
</tr>
<tr>
<td><code>Series.dt.microsecond</code></td>
<td>The microseconds of the datetime.</td>
</tr>
<tr>
<td><code>Series.dt.nanosecond</code></td>
<td>The nanoseconds of the datetime.</td>
</tr>
<tr>
<td><code>Series.dt.week</code></td>
<td>(DEPRECATED) The week ordinal of the year.</td>
</tr>
<tr>
<td><code>Series.dt.weekofyear</code></td>
<td>(DEPRECATED) The week ordinal of the year.</td>
</tr>
<tr>
<td><code>Series.dt.dayofweek</code></td>
<td>The day of the week with Monday=0, Sunday=6.</td>
</tr>
<tr>
<td><code>Series.dt.weekday</code></td>
<td>The day of the week with Monday=0, Sunday=6.</td>
</tr>
<tr>
<td><code>Series.dt.dayofyear</code></td>
<td>The ordinal day of the year.</td>
</tr>
<tr>
<td><code>Series.dt.quarter</code></td>
<td>The quarter of the date.</td>
</tr>
<tr>
<td><code>Series.dt.is_month_start</code></td>
<td>Indicates whether the date is the first day of the month.</td>
</tr>
<tr>
<td><code>Series.dt.is_month_end</code></td>
<td>Indicates whether the date is the last day of the month.</td>
</tr>
<tr>
<td><code>Series.dt.is_quarter_start</code></td>
<td>Indicator for whether the date is the first day of a quarter.</td>
</tr>
<tr>
<td><code>Series.dt.is_quarter_end</code></td>
<td>Indicator for whether the date is the last day of a quarter.</td>
</tr>
<tr>
<td><code>Series.dt.is_year_start</code></td>
<td>Indicate whether the date is the first day of a year.</td>
</tr>
<tr>
<td><code>Series.dt.is_year_end</code></td>
<td>Indicate whether the date is the last day of the year.</td>
</tr>
<tr>
<td><code>Series.dt.is_leap_year</code></td>
<td>Boolean indicator if the date belongs to a leap year.</td>
</tr>
<tr>
<td><code>Series.dt.daysinmonth</code></td>
<td>The number of days in the month.</td>
</tr>
<tr>
<td><code>Series.dt.days_in_month</code></td>
<td>The number of days in the month.</td>
</tr>
<tr>
<td><code>Series.dt.tz</code></td>
<td>Return timezone, if any.</td>
</tr>
<tr>
<td><code>Series.dt.freq</code></td>
<td>Return the frequency object for this PeriodArray.</td>
</tr>
</tbody>
</table>
pandas.Series.dt.date

Series.dt.date
Returns numpy array of python datetime.date objects (namely, the date part of Timestamps without timezone information).

pandas.Series.dt.time

Series.dt.time
Returns numpy array of datetime.time. The time part of the Timestamps.

pandas.Series.dt.timetz

Series.dt.timetz
Returns numpy array of datetime.time also containing timezone information. The time part of the Timestamps.

pandas.Series.dt.year

Series.dt.year
The year of the datetime.

Examples

```python
>>> datetime_series = pd.Series(
...    pd.date_range("2000-01-01", periods=3, freq="Y")
... )
```

```python
>>> datetime_series
0  2000-12-31
1  2001-12-31
2  2002-12-31
dtype: datetime64[ns]
```

```python
>>> datetime_series.dt.year
0  2000
1  2001
2  2002
dtype: int64
```

pandas.Series.dt.month

Series.dt.month
The month as January=1, December=12.
Examples

```python
>>> datetime_series = pd.Series(
...     pd.date_range("2000-01-01", periods=3, freq="M")
... )
>>> datetime_series
0    2000-01-31
1    2000-02-29
2    2000-03-31
dtype: datetime64[ns]
>>> datetime_series.dt.month
0    1
1    2
2    3
dtype: int64
```

**pandas.Series.dt.day**

Series.dt.day

The day of the datetime.

Examples

```python
>>> datetime_series = pd.Series(
...     pd.date_range("2000-01-01", periods=3, freq="D")
... )
>>> datetime_series
0    2000-01-01
1    2000-01-02
2    2000-01-03
dtype: datetime64[ns]
>>> datetime_series.dt.day
0    1
1    2
2    3
dtype: int64
```
pandas.Series.dt.hour

Series.dt.hour
The hours of the datetime.

**Examples**

```python
>>> datetime_series = pd.Series(
    ...     pd.date_range("2000-01-01", periods=3, freq="h")
    ... )
>>> datetime_series
0 2000-01-01 00:00:00
1 2000-01-01 01:00:00
2 2000-01-01 02:00:00
dtype: datetime64[ns]
>>> datetime_series.dt.hour
0 0
1 1
2 2
dtype: int64
```

pandas.Series.dt.minute

Series.dt.minute
The minutes of the datetime.

**Examples**

```python
>>> datetime_series = pd.Series(
    ...     pd.date_range("2000-01-01", periods=3, freq="T")
    ... )
>>> datetime_series
0 2000-01-01 00:00:00
1 2000-01-01 00:01:00
2 2000-01-01 00:02:00
dtype: datetime64[ns]
>>> datetime_series.dt.minute
0 0
1 1
2 2
dtype: int64
```
pandas.Series.dt.second

Series.dt.second
The seconds of the datetime.

Examples

```python
>>> datetime_series = pd.Series(
    ...     pd.date_range("2000-01-01", periods=3, freq="s")
    ... )
>>> datetime_series
0 2000-01-01 00:00:00
1 2000-01-01 00:00:01
2 2000-01-01 00:00:02
dtype: datetime64[ns]
>>> datetime_series.dt.second
0 0
1 1
2 2
dtype: int64
```

pandas.Series.dt.microsecond

Series.dt.microsecond
The microseconds of the datetime.

Examples

```python
>>> datetime_series = pd.Series(
    ...     pd.date_range("2000-01-01", periods=3, freq="us")
    ... )
>>> datetime_series
0 2000-01-01 00:00:00.000000
1 2000-01-01 00:00:00.000001
2 2000-01-01 00:00:00.000002
dtype: datetime64[ns]
>>> datetime_series.dt.microsecond
0 0
1 1
2 2
dtype: int64
```
**pandas.Series.dt.nanosecond**

Series.dt.nanosecond

The nanoseconds of the datetime.

**Examples**

```python
>>> datetime_series = pd.Series(
    ...    pd.date_range("2000-01-01", periods=3, freq="ns")
    ... )
>>> datetime_series
dataframe
0  2000-01-01 00:00:00.000000000
1  2000-01-01 00:00:00.000000001
2  2000-01-01 00:00:00.000000002
dtype: datetime64[ns]
```

```python
>>> datetime_series.dt.nanosecond
0  0
1  1
2  2
dtype: int64
```

**pandas.Series.dt.week**

Series.dt.week

The week ordinal of the year.

Deprecated since version 1.1.0.

Series.dt.weekofyear and Series.dt.week have been deprecated. Please use Series.dt.isocalendar().week instead.

**pandas.Series.dt.weekofyear**

Series.dt.weekofyear

The week ordinal of the year.

Deprecated since version 1.1.0.

Series.dt.weekofyear and Series.dt.week have been deprecated. Please use Series.dt.isocalendar().week instead.

**pandas.Series.dt.dayofweek**

Series.dt.dayofweek

The day of the week with Monday=0, Sunday=6.

Return the day of the week. It is assumed the week starts on Monday, which is denoted by 0 and ends on Sunday which is denoted by 6. This method is available on both Series with datetime values (using the dt accessor) or DatetimeIndex.

**Returns**

Series or Index Containing integers indicating the day number.

See also:

Series.dt.dayofweek Alias.
Series.dt.weekday Alias.
**Series.dt.day_name** Returns the name of the day of the week.

**Examples**

```python
g = pd.date_range('2016-12-31', '2017-01-08', freq='D').to_series()
g.dt.dayofweek
```

```
2016-12-31 5
2017-01-01 6
2017-01-02 0
2017-01-03 1
2017-01-04 2
2017-01-05 3
2017-01-06 4
2017-01-07 5
2017-01-08 6
Freq: D, dtype: int64
```

**pandas.Series.dt.weekday**

Series.dt.weekday

The day of the week with Monday=0, Sunday=6.

Return the day of the week. It is assumed the week starts on Monday, which is denoted by 0 and ends on Sunday which is denoted by 6. This method is available on both Series with datetime values (using the `dt` accessor) or DatetimeIndex.

**Returns**

Series or Index  Containing integers indicating the day number.

**See also:**

*Series.dt.dayofweek* Alias.
*Series.dt.weekday* Alias.
*Series.dt.day_name* Returns the name of the day of the week.

**Examples**

```python
g = pd.date_range('2016-12-31', '2017-01-08', freq='D').to_series()
g.dt.dayofweek
```

```
2016-12-31 5
2017-01-01 6
2017-01-02 0
2017-01-03 1
2017-01-04 2
2017-01-05 3
2017-01-06 4
2017-01-07 5
2017-01-08 6
Freq: D, dtype: int64
```
pandas.Series.dt.dayofyear

Series.dt.dayofyear
The ordinal day of the year.

pandas.Series.dt.quarter

Series.dt.quarter
The quarter of the date.

pandas.Series.dt.is_month_start

Series.dt.is_month_start
Indicates whether the date is the first day of the month.

Returns

Series or array For Series, returns a Series with boolean values. For DatetimeIndex, returns a boolean array.

See also:

is_month_start Return a boolean indicating whether the date is the first day of the month.

is_month_end Return a boolean indicating whether the date is the last day of the month.

Examples

This method is available on Series with datetime values under the .dt accessor, and directly on DatetimeIndex.

```python
>>> s = pd.Series(pd.date_range("2018-02-27", periods=3))
>>> s
0 2018-02-27
1 2018-02-28
2 2018-03-01
dtype: datetime64[ns]
>>> s.dt.is_month_start
0 False
1 False
2 True
dtype: bool
>>> s.dt.is_month_end
0 False
1 True
2 False
dtype: bool
```

```python
>>> idx = pd.date_range("2018-02-27", periods=3)
>>> idx.is_month_start
array([False, False, True])
>>> idx.is_month_end
array([False, True, False])
```
pandas.Series.dt.is_month_end

Series.dt.is_month_end
Indicates whether the date is the last day of the month.

Returns

Series or array  For Series, returns a Series with boolean values. For DatetimeIndex, returns a boolean array.

See also:

is_month_start  Return a boolean indicating whether the date is the first day of the month.
is_month_end  Return a boolean indicating whether the date is the last day of the month.

Examples

This method is available on Series with datetime values under the .dt accessor, and directly on DatetimeIndex.

```python
>>> s = pd.Series(pd.date_range("2018-02-27", periods=3))
>>> s
0 2018-02-27
1 2018-02-28
2 2018-03-01
dtype: datetime64[ns]
>>> s.dt.is_month_start
0 False
1 False
2 True
dtype: bool
>>> s.dt.is_month_end
0 False
1 True
2 False
dtype: bool
```

```python
>>> idx = pd.date_range("2018-02-27", periods=3)
>>> idx.is_month_start
array([False, False, True])
```

```python
>>> idx.is_month_end
array([False, True, False])
```

pandas.Series.dt.is_quarter_start

Series.dt.is_quarter_start
Indicator for whether the date is the first day of a quarter.

Returns

is_quarter_start  [Series or DatetimeIndex] The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

See also:

quarter  Return the quarter of the date.
is_quarter_end  Similar property for indicating the quarter start.
Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```python
>>> df = pd.DataFrame({'dates': pd.date_range("2017-03-30", ... periods=4)})
>>> df.assign(quarter=df.dates.dt.quarter, ...
   is_quarter_start=df.dates.dt.is_quarter_start)

  dates          quarter  is_quarter_start
0 2017-03-30       1          False
1 2017-03-31       1          False
2 2017-04-01       2           True
3 2017-04-02       2          False
```

```python
>>> idx = pd.date_range('2017-03-30', periods=4)
>>> idx
DatetimeIndex(['2017-03-30', '2017-03-31', '2017-04-01', '2017-04-02'],
              dtype='datetime64[ns]', freq='D')
```

```python
>>> idx.is_quarter_start
array([False, False,   True, False])
```

pandas.Series.dt.is_quarter_end

`Series.dt.is_quarter_end`

Indicator for whether the date is the last day of a quarter.

**Returns**

-is_quarter_end [Series or DatetimeIndex] The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

**See also:**

- **quarter** Return the quarter of the date.
- **is_quarter_start** Similar property indicating the quarter start.

Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```python
>>> df = pd.DataFrame({'dates': pd.date_range("2017-03-30", ... periods=4)})
>>> df.assign(quarter=df.dates.dt.quarter, ...
   is_quarter_end=df.dates.dt.is_quarter_end)

  dates          quarter  is_quarter_end
0 2017-03-30       1          False
1 2017-03-31       1           True
2 2017-04-01       2          False
3 2017-04-02       2          False
```

```python
>>> idx = pd.date_range('2017-03-30', periods=4)
>>> idx
DatetimeIndex(['2017-03-30', '2017-03-31', '2017-04-01', '2017-04-02'],
              dtype='datetime64[ns]', freq='D')
```
pandas.Series.dt.is_year_start

Series.dt.is_year_start
Indicate whether the date is the first day of a year.

Returns

Series or DatetimeIndex  The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

See also:

is_year_end  Similar property indicating the last day of the year.

Examples

This method is available on Series with datetime values under the .dt accessor, and directly on DatetimeIndex.

```python
>>> dates = pd.Series(pd.date_range("2017-12-30", periods=3))
>>> dates
datetime (3): 2017-12-30, 2017-12-31, 2018-01-01
```

```python
>>> dates.dt.is_year_start
0  False
1  False
2  True
dtype: bool
```

```python
>>> idx = pd.date_range("2017-12-30", periods=3)
>>> idx
[timedelta[ns]]: 2017-12-30, 2017-12-31, 2018-01-01
```

```python
>>> idx.is_year_start
array([False, False, True])
```

pandas.Series.dt.is_year_end

Series.dt.is_year_end
Indicate whether the date is the last day of the year.

Returns

Series or DatetimeIndex  The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

See also:

is_year_start  Similar property indicating the start of the year.
Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```python
>>> dates = pd.Series(pd.date_range("2017-12-30", periods=3))
>>> dates
0  2017-12-30
1  2017-12-31
2  2018-01-01
dtype: datetime64[ns]
```

```python
>>> dates.dt.is_year_end
0   False
1    True
2   False
dtype: bool
```

```python
>>> idx = pd.date_range("2017-12-30", periods=3)
>>> idx
DatetimeIndex(['2017-12-30', '2017-12-31', '2018-01-01'],
dtype='datetime64[ns]', freq='D')
```

```python
>>> idx.is_year_end
array([False,  True, False])
```

pandas.Series.dt.is_leap_year

Series.dt.is_leap_year

Boolean indicator if the date belongs to a leap year.

A leap year is a year, which has 366 days (instead of 365) including 29th of February as an intercalary day. Leap years are years which are multiples of four with the exception of years divisible by 100 but not by 400.

Returns

Series or ndarray  Booleans indicating if dates belong to a leap year.

Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```python
>>> idx = pd.date_range("2012-01-01", "2015-01-01", freq="Y")
>>> idx
DatetimeIndex(['2012-12-31', '2013-12-31', '2014-12-31'],
dtype='datetime64[ns]', freq='A-DEC')
```

```python
>>> idx.is_leap_year
array([ True, False, False])
```

```python
>>> dates_series = pd.Series(idx)
>>> dates_series
0  2012-12-31
1  2013-12-31
2  2014-12-31
dtype: datetime64[ns]
```

```python
>>> dates_series.dt.is_leap_year
```

(continues on next page)
pandas: powerful Python data analysis toolkit, Release 1.1.1

0  True
1  False
2  False
dtype: bool

pandas.Series.dt.daysinmonth

Series.dt.daysinmonth
The number of days in the month.

pandas.Series.dt.days_in_month

Series.dt.days_in_month
The number of days in the month.

pandas.Series.dt.tz

Series.dt.tz
Return timezone, if any.

Returns

datetime.tzinfo, pytz.tzinfo.BaseTZInfo, dateutil.tz.tzfile, or None

Returns None when the array is tz-naive.

pandas.Series.dt.freq

Series.dt.freq

Datetime methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.dt.to_period(*args, **kwargs)</td>
<td>Cast to PeriodArray/Index at a particular frequency.</td>
</tr>
<tr>
<td>Series.dt.to_pydatetime()</td>
<td>Return the data as an array of native Python datetime objects.</td>
</tr>
<tr>
<td>Series.dt.tz_localize(*args, **kwargs)</td>
<td>Localize tz-naive Datetime Array/Index to tz-aware Datetime Array/Index.</td>
</tr>
<tr>
<td>Series.dt.tz_convert(*args, **kwargs)</td>
<td>Convert tz-aware Datetime Array/Index from one time zone to another.</td>
</tr>
<tr>
<td>Series.dt.normalize(*args, **kwargs)</td>
<td>Convert times to midnight.</td>
</tr>
<tr>
<td>Series.dt.strftime(*args, **kwargs)</td>
<td>Convert to Index using specified date_format.</td>
</tr>
<tr>
<td>Series.dt.round(*args, **kwargs)</td>
<td>Perform round operation on the data to the specified freq.</td>
</tr>
<tr>
<td>Series.dt.floor(*args, **kwargs)</td>
<td>Perform floor operation on the data to the specified freq.</td>
</tr>
<tr>
<td>Series.dt.ceil(*args, **kwargs)</td>
<td>Perform ceil operation on the data to the specified freq.</td>
</tr>
<tr>
<td>Series.dt.month_name(*args, **kwargs)</td>
<td>Return the month names of the DateTimeIndex with specified locale.</td>
</tr>
</tbody>
</table>

continues on next page
Table 43 – continued from previous page

| Series.dt.day_name(*args, **kwargs) | Return the day names of the DateTimeIndex with specified locale. |

### pandas.Series.dt.to_period

Series.dt.to_period(*args, **kwargs)

Cast to PeriodArray/Index at a particular frequency.

Converts DatetimeArray/Index to PeriodArray/Index.

**Parameters**

- `freq` [str or Offset, optional] One of pandas’ offset strings or an Offset object. Will be inferred by default.

**Returns**

PeriodArray/Index

**Raises**

- ValueError When converting a DatetimeArray/Index with non-regular values, so that a frequency cannot be inferred.

**See also:**

- `PeriodIndex` Immutable ndarray holding ordinal values.
- `DatetimeIndex.to_pydatetime` Return DatetimeIndex as object.

**Examples**

```python
def df = pd.DataFrame("y": [1, 2, 3]), ...
   index=pd.to_datetime(["2000-03-31 00:00:00", ...
   "2000-05-31 00:00:00", ...
   "2000-08-31 00:00:00"])
>>> df.index.to_period("M")
PeriodIndex(["2000-03", "2000-05", "2000-08"],
 dtype='period[M]', freq='M')
```

Infer the daily frequency

```python
>>> idx = pd.date_range("2017-01-01", periods=2)
>>> idx.to_period()
PeriodIndex(["2017-01-01", "2017-01-02"],
 dtype='period[D]', freq='D')
```

### pandas.Series.dt.to_pydatetime

Series.dt.to_pydatetime()

Return the data as an array of native Python datetime objects.

Timezone information is retained if present.

**Warning:** Python’s datetime uses microsecond resolution, which is lower than pandas (nanosecond). The values are truncated.
Returns

numpy.ndarray Object dtype array containing native Python datetime objects.

See also:

datetime.datetime Standard library value for a datetime.

Examples

```python
>>> s = pd.Series(pd.date_range('20180310', periods=2))
```

```python
>>> s
0 2018-03-10
1 2018-03-11
dtype: datetime64[ns]
```

```python
>>> s.dt.to_pydatetime()
array([datetime.datetime(2018, 3, 10, 0, 0),
       datetime.datetime(2018, 3, 11, 0, 0)], dtype=object)
```

Pandas’ nanosecond precision is truncated to microseconds.

```python
>>> s = pd.Series(pd.date_range('20180310', periods=2, freq='ns'))
```

```python
>>> s
0 2018-03-10 00:00:00.000000000
1 2018-03-10 00:00:00.000000001
dtype: datetime64[ns]
```

```python
>>> s.dt.to_pydatetime()
array([datetime.datetime(2018, 3, 10, 0, 0),
       datetime.datetime(2018, 3, 10, 0, 0)], dtype=object)
```

pandas.Series.dt.tz_localize

Series.dt.tz_localize(*args, **kwargs)

Localize tz-naive Datetime Array/Index to tz-aware Datetime Array/Index.

This method takes a time zone (tz) naive Datetime Array/Index object and makes this time zone aware. It does
not move the time to another time zone. Time zone localization helps to switch from time zone aware to time
zone unaware objects.

Parameters

- tz [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone to convert timestamps to. Passing
  None will remove the time zone information preserving local time.

- ambiguous ['infer', 'NaT', bool array, default 'raise'] When clocks moved backward due to
  DST, ambiguous times may arise. For example in Central European Time (UTC+01),
  when going from 03:00 DST to 02:00 non-DST, 02:30:00 local time occurs both at
  00:30:00 UTC and at 01:30:00 UTC. In such a situation, the ambiguous parameter
  dictates how ambiguous times should be handled.

  - ‘infer’ will attempt to infer fall dst-transition hours based on order
  - bool-ndarray where True signifies a DST time, False signifies a non-DST time (note
    that this flag is only applicable for ambiguous times)
  - ‘NaT’ will return NaT where there are ambiguous times
• ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

nonexistent  [‘shift_forward’, ‘shift_backward’, ‘NaT’, timedelta, default ‘raise’] A non-existent time does not exist in a particular timezone where clocks moved forward due to DST.

• ‘shift_forward’ will shift the nonexistent time forward to the closest existing time
• ‘shift_backward’ will shift the nonexistent time backward to the closest existing time
• ‘NaT’ will return NaT where there are nonexistent times
• timedelta objects will shift nonexistent times by the timedelta
• ‘raise’ will raise a NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

Same type as self  Array/Index converted to the specified time zone.

Raises

TypeError  If the Datetime Array/Index is tz-aware and tz is not None.

See also:

DatetimeIndex.tz_convert  Convert tz-aware DatetimeIndex from one time zone to another.

Examples

```python
>>> tz_naive = pd.date_range('2018-03-01 09:00', periods=3)
>>> tz_naive
DatetimeIndex(['2018-03-01 09:00:00', '2018-03-02 09:00:00',
              '2018-03-03 09:00:00'], dtype='datetime64[ns]', freq='D')

Localize DatetimeIndex in US/Eastern time zone:

```
In some cases, inferring the DST is impossible. In such cases, you can pass an ndarray to the ambiguous parameter to set the DST explicitly

```python
>>> s = pd.to_datetime(pd.Series(['2018-10-28 01:20:00',
                               ...
                               '2018-10-28 02:36:00',
                               ...
                               '2018-10-28 03:46:00']))
```

```python
>>> s.dt.tz_localize('CET', ambiguous=np.array([True, True, False]))
```

If the DST transition causes nonexistent times, you can shift these dates forward or backwards with a timedelta object or 'shift_forward' or 'shift_backwards'.

```python
>>> s = pd.to_datetime(pd.Series(['2015-03-29 02:30:00',
                               ...
                               '2015-03-29 03:30:00']))
```

```python
>>> s.dt.tz_localize('Europe/Warsaw', nonexistent='shift_forward')
```

```python
>>> s.dt.tz_localize('Europe/Warsaw', nonexistent='shift_backward')
```

```python
>>> s.dt.tz_localize('Europe/Warsaw', nonexistent=pd.Timedelta('1H'))
```
**pandas.Series.dt.tz_convert**

Series.dt.tz_convert(*args, **kwargs)
Convert tz-aware Datetime Array/Index from one time zone to another.

**Parameters**

- `tz` [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone for time. Corresponding timestamps would be converted to this time zone of the Datetime Array/Index. A `tz` of None will convert to UTC and remove the timezone information.

**Returns**

Array or Index

**Raises**

TypeError If Datetime Array/Index is tz-naive.

**See also:**

- DatetimeIndex.tz
  A timezone that has a variable offset from UTC.
- DatetimeIndex.tz_localize
  Localize tz-naive DatetimeIndex to a given time zone, or remove timezone from a tz-aware DatetimeIndex.

**Examples**

With the `tz` parameter, we can change the DatetimeIndex to other time zones:

```python
>>> dti = pd.date_range(start='2014-08-01 09:00',
                      freq='H', periods=3, tz='Europe/Berlin')
```

```python
>>> dti
DatetimeIndex(['2014-08-01 09:00:00+02:00',
               '2014-08-01 10:00:00+02:00',
               '2014-08-01 11:00:00+02:00'],
              dtype='datetime64[ns, Europe/Berlin]',
              freq='H')
```

```python
>>> dti.tz_convert('US/Central')
DatetimeIndex(['2014-08-01 02:00:00-05:00',
               '2014-08-01 03:00:00-05:00',
               '2014-08-01 04:00:00-05:00'],
              dtype='datetime64[ns, US/Central]',
              freq='H')
```

With the `tz=None`, we can remove the timezone (after converting to UTC if necessary):

```python
>>> dti = pd.date_range(start='2014-08-01 09:00',
                      freq='H', periods=3, tz='Europe/Berlin')
```

```python
>>> dti
DatetimeIndex(['2014-08-01 09:00:00+02:00',
               '2014-08-01 10:00:00+02:00',
               '2014-08-01 11:00:00+02:00'],
              dtype='datetime64[ns, Europe/Berlin]',
              freq='H')
```

```python
>>> dti.tz_convert(None)
DatetimeIndex(['2014-08-01 07:00:00',
               '2014-08-01 08:00:00',
               '2014-08-01 09:00:00'],
              dtype='datetime64[ns]',
              freq='H')
```

(continues on next page)
pandas.Series.dt.normalize

Series.dt.normalize(*args, **kwargs)
Convert times to midnight.

The time component of the date-time is converted to midnight i.e. 00:00:00. This is useful in cases, when the
time does not matter. Length is unaltered. The timezones are unaffected.

This method is available on Series with datetime values under the .dt accessor, and directly on Datetime
Array/Index.

Returns

DatetimeArray, DatetimeIndex or Series  The same type as the original data. Series will
have the same name and index. DatetimeIndex will have the same name.

See also:
floor  Floor the datetimes to the specified freq.
ceil   Ceil the datetimes to the specified freq.
round  Round the datetimes to the specified freq.

Examples

```python
>>> idx = pd.date_range(start='2014-08-01 10:00', freq='H',
                      periods=3, tz='Asia/Calcutta')
```

```python
>>> idx
DatetimeIndex(['2014-08-01 10:00:00+05:30',
                '2014-08-01 11:00:00+05:30',
                '2014-08-01 12:00:00+05:30'],
               dtype='datetime64[ns, Asia/Calcutta]', freq='H')
```

```python
>>> idx.normalize()
DatetimeIndex(['2014-08-01 00:00:00+05:30',
                '2014-08-01 00:00:00+05:30',
                '2014-08-01 00:00:00+05:30'],
               dtype='datetime64[ns, Asia/Calcutta]', freq=None)
```

pandas.Series.dt.strftime

Series.dt.strftime(*args, **kwargs)
Convert to Index using specified date_format.

Return an Index of formatted strings specified by date_format, which supports the same string format as the
python standard library. Details of the string format can be found in python string format doc.

Parameters

date_format  [str] Date format string (e.g. “%Y-%m-%d”).

Returns

ndarray  NumPy ndarray of formatted strings.

See also:
to_datetime Convert the given argument to datetime.

DatetimeIndex.normalize Return DatetimeIndex with times to midnight.

DatetimeIndex.round Round the DatetimeIndex to the specified freq.

DatetimeIndex.floor Floor the DatetimeIndex to the specified freq.

Examples

```python
>>> rng = pd.date_range(pd.Timestamp("2018-03-10 09:00"),
...     periods=3, freq='s')
>>> rng.strftime('%B %d, %Y, %r')
Index(['March 10, 2018, 09:00:00 AM', 'March 10, 2018, 09:00:01 AM',
    'March 10, 2018, 09:00:02 AM'],
    dtype='object')
```

pandas.Series.dt.round

`Series.dt.round(*args, **kwargs)`

Perform round operation on the data to the specified `freq`.

Parameters

- `freq` [str or Offset] The frequency level to round the index to. Must be a fixed frequency like ‘S’ (second) not ‘ME’ (month end). See `frequency aliases` for a list of possible `freq` values.

- `ambiguous` ['infer', bool-ndarray, ‘NaT’, default ‘raise’] Only relevant for DatetimeIndex:
  - ‘infer’ will attempt to infer fall dst-transition hours based on order
  - bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
  - ‘NaT’ will return NaT where there are ambiguous times
  - ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

- `nonexistent` ['shift_forward’, ‘shift_backward’, ‘NaT’, timedelta, default ‘raise’] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.
  - ‘shift_forward’ will shift the nonexistent time forward to the closest existing time
  - ‘shift_backward’ will shift the nonexistent time backward to the closest existing time
  - ‘NaT’ will return NaT where there are nonexistent times
  - timedelta objects will shift nonexistent times by the timedelta
  - ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

- DatetimeIndex, TimedeltaIndex, or Series Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

Raises
ValueError if the freq cannot be converted.

Examples

DatetimeIndex

```python
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00', '2018-01-01 12:01:00'],
              dtype='datetime64[ns]', freq='T')
```

```python
>>> rng.round('H')
DatetimeIndex(['2018-01-01 12:00:00', '2018-01-01 12:00:00', '2018-01-01 12:00:00'],
              dtype='datetime64[ns]', freq=None)
```

Series

```python
>>> pd.Series(rng).dt.round("H")
0 2018-01-01 12:00:00
1 2018-01-01 12:00:00
2 2018-01-01 12:00:00
dtype: datetime64[ns]
```

pandas.Series.dt.floor

Series.dt.floor(*args, **kwargs)

Perform floor operation on the data to the specified freq.

Parameters

freq [str or Offset] The frequency level to floor the index to. Must be a fixed frequency like ‘S’ (second) not ‘ME’ (month end). See frequency aliases for a list of possible freq values.

ambiguous ['infer’, bool-ndarray, ‘NaT’, default ‘raise’] Only relevant for DatetimeIndex:

• ‘infer’ will attempt to infer fall dst-transition hours based on order
• bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
• ‘NaT’ will return NaT where there are ambiguous times
• ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

nonexistent ['shift_forward’, ‘shift_backward’, ‘NaT’, timedelta, default ‘raise’] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

• ‘shift_forward’ will shift the nonexistent time forward to the closest existing time
• ‘shift_backward’ will shift the nonexistent time backward to the closest existing time
• ‘NaT’ will return NaT where there are nonexistent times
• timedelta objects will shift nonexistent times by the timedelta
pandas: powerful Python data analysis toolkit, Release 1.1.1

- ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

DatetimeIndex, TimedeltaIndex, or Series  Index of the same type for a DatetimeIndex or
TimedeltaIndex, or a Series with the same index for a Series.

Raises

ValueError if the freq cannot be converted.

Examples

DatetimeIndex

```python
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'], dtype='datetime64[ns]', freq='T')
>>> rng.floor('H')
DatetimeIndex(['2018-01-01 11:00:00', '2018-01-01 12:00:00',
               '2018-01-01 12:00:00'], dtype='datetime64[ns]', freq=None)
```

Series

```python
>>> pd.Series(rng).dt.floor("H")
0  2018-01-01 11:00:00
1  2018-01-01 12:00:00
2  2018-01-01 12:00:00
dtype: datetime64[ns]
```

pandas.Series.dt.ceil

Series.dt.ceil(*args, **kwargs)

Perform ceil operation on the data to the specified freq.

Parameters

freq [str or Offset] The frequency level to ceil the index to. Must be a fixed frequency like
‘S’ (second) not ‘ME’ (month end). See frequency aliases for a list of possible freq
values.

ambiguous ['infer', bool-ndarray, 'NaT', default ‘raise’] Only relevant for DatetimeIndex:
- ‘infer’ will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time
  (note that this flag is only applicable for ambiguous times)
- ‘NaT’ will return NaT where there are ambiguous times
- ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.
nonexistent ['shift_forward', 'shift_backward', 'NaT', timedelta, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- 'shift_forward' will shift the nonexistent time forward to the closest existing time
- 'shift_backward' will shift the nonexistent time backward to the closest existing time
- 'NaT' will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- 'raise' will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

DatetimeIndex, TimedeltaIndex, or Series Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

Raises

ValueError if the freq cannot be converted.

Examples

DatetimeIndex

```python
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
              dtype='datetime64[ns]', freq='T')
```

```python
>>> rng.ceil('H')
DatetimeIndex(['2018-01-01 12:00:00', '2018-01-01 12:00:00',
               '2018-01-01 13:00:00'],
              dtype='datetime64[ns]', freq=None)
```

Series

```python
>>> pd.Series(rng).dt.ceil("H")
0  2018-01-01 12:00:00
1  2018-01-01 12:00:00
2  2018-01-01 13:00:00
dtype: datetime64[ns]
```

pandas.Series.dt.month_name

Series.dt.month_name(*args, **kwargs)

Return the month names of the DateTimeIndex with specified locale.

New in version 0.23.0.

Parameters

- locale [str, optional] Locale determining the language in which to return the month name. Default is English locale.

Returns
Index  Index of month names.

Examples

```python
>>> idx = pd.date_range(start='2018-01', freq='M', periods=3)
>>> idx
DatetimeIndex(['2018-01-31', '2018-02-28', '2018-03-31'],
   dtype='datetime64[ns]', freq='M')
>>> idx.month_name()
Index(['January', 'February', 'March'], dtype='object')
```

**pandas.Series.dt.day_name**

Series.dt.day_name(*args, **kwargs)

Return the day names of the DateTimeIndex with specified locale.

New in version 0.23.0.

Parameters

locale  [str, optional] Locale determining the language in which to return the day name. Default is English locale.

Returns

Index  Index of day names.

Examples

```python
>>> idx = pd.date_range(start='2018-01-01', freq='D', periods=3)
>>> idx
DatetimeIndex(['2018-01-01', '2018-01-02', '2018-01-03'],
   dtype='datetime64[ns]', freq='D')
>>> idx.day_name()
Index(['Monday', 'Tuesday', 'Wednesday'], dtype='object')
```

**Period properties**

Series.dt.qyear

Series.dt.start_time

Series.dt.end_time
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.Series.dt.qyear

Series.dt.qyear

pandas.Series.dt.start_time

Series.dt.start_time

pandas.Series.dt.end_time

Series.dt.end_time

Timedelta properties

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.dt.days</td>
<td>Number of days for each element.</td>
</tr>
<tr>
<td>Series.dt.seconds</td>
<td>Number of seconds (&gt;= 0 and less than 1 day) for each element.</td>
</tr>
<tr>
<td>Series.dt.microseconds</td>
<td>Number of microseconds (&gt;= 0 and less than 1 second) for each element.</td>
</tr>
<tr>
<td>Series.dt.nanoseconds</td>
<td>Number of nanoseconds (&gt;= 0 and less than 1 microsecond) for each element.</td>
</tr>
<tr>
<td>Series.dt.components</td>
<td>Return a Dataframe of the components of the Timedeltas.</td>
</tr>
</tbody>
</table>

pandas.Series.dt.days

Series.dt.days
  Number of days for each element.

pandas.Series.dt.seconds

Series.dt.seconds
  Number of seconds (>= 0 and less than 1 day) for each element.

pandas.Series.dt.microseconds

Series.dt.microseconds
  Number of microseconds (>= 0 and less than 1 second) for each element.
pandas.Series.dt.nanoseconds

Series.dt.nanoseconds
Number of nanoseconds (>= 0 and less than 1 microsecond) for each element.

pandas.Series.dt.components

Series.dt.components
Return a Dataframe of the components of the Timedeltas.

Returns
DataFrame

Examples
>>> s = pd.Series(pd.to_timedelta(np.arange(5), unit='s'))
>>> s
0 0 days 00:00:00
1 0 days 00:00:01
2 0 days 00:00:02
3 0 days 00:00:03
4 0 days 00:00:04
dtype: timedelta64[ns]

>>> s.dt.components
    days   hours   minutes   seconds  milliseconds  microseconds  nanoseconds
0      0       0         0         0              0             0             0
1      0       0         0         1              0             0             0
2      0       0         0         2              0             0             0
3      0       0         0         3              0             0             0
4      0       0         0         4              0             0             0

Timedelta methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.dt.to_pytimedelta()</td>
<td>Return an array of native datetime.timedelta objects.</td>
</tr>
<tr>
<td>Series.dt.total_seconds(*args, **kwargs)</td>
<td>Return total duration of each element expressed in seconds.</td>
</tr>
</tbody>
</table>

pandas.Series.dt.to_pytimedelta

Series.dt.to_pytimedelta()
Return an array of native datetime.timedelta objects.

Python’s standard datetime library uses a different representation timedelta’s. This method converts a Series of pandas Timedeltas to datetime.timedelta format with the same length as the original Series.

Returns
numpy.ndarray Array of 1D containing data with datetime.timedelta type.

See also:
datetime.timedelta

3.3. Series
Examples

```python
>>> s = pd.Series(pd.to_timedelta(np.arange(5), unit="d"))
>>> s
0 0 days
1 1 days
2 2 days
3 3 days
4 4 days
dtype: timedelta64[ns]

>>> s.dt.to_pytimedelta()
array([datetime.timedelta(0), datetime.timedelta(days=1),
       datetime.timedelta(days=2), datetime.timedelta(days=3),
       datetime.timedelta(days=4)], dtype=object)
```

**pandas.Series.dt.total_seconds**

Series.dt.total_seconds(*args, **kwargs)

Return total duration of each element expressed in seconds.

This method is available directly on TimedeltaArray, TimedeltaIndex and on Series containing timedelta values under the .dt namespace.

**Returns**

seconds [[ndarray, Float64Index, Series]] When the calling object is a TimedeltaArray, the return type is ndarray. When the calling object is a TimedeltaIndex, the return type is a Float64Index. When the calling object is a Series, the return type is Series of type float64 whose index is the same as the original.

See also:

datetime.timedelta.total_seconds Standard library version of this method.
TimedeltaIndex.components Return a DataFrame with components of each Timedelta.

Examples

Series

```python
>>> s = pd.Series(pd.to_timedelta(np.arange(5), unit='d'))
>>> s
0 0 days
1 1 days
2 2 days
3 3 days
4 4 days
dtype: timedelta64[ns]

>>> s.dt.total_seconds()
0 0.0
1 86400.0
2 172800.0
3 259200.0
4 345600.0
dtype: float64
```
TimedeltaIndex

```python
>>> idx = pd.to_timedelta(np.arange(5), unit='d')
>>> idx
TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'],
               dtype='timedelta64[ns]', freq=None)

>>> idx.total_seconds()
Float64Index([0.0, 86400.0, 172800.0, 259200.0, 345600.0],
              dtype='float64')
```

String handling

Series.str can be used to access the values of the series as strings and apply several methods to it. These can be accessed like `Series.str.<function/property>.

```python
Series.str.capitalize(*args, **kwars) Convert strings in the Series/Index to be capitalized.
Series.str.casefold(*args, **kwars) Convert strings in the Series/Index to be casefolded.
Series.str.cat(*args, **kwars) Concatenate strings in the Series/Index with given separator.
Series.str.center(*args, **kwars) Pad left and right side of strings in the Series/Index.
Series.str.contains(*args, **kwars) Test if pattern or regex is contained within a string of a Series or Index.
Series.str.count(*args, **kwars) Count occurrences of pattern in each string of the Series/Index.
Series.str.decode(encoding[, errors]) Decode character string in the Series/Index using indicated encoding.
Series.str.encode(*args, **kwargs) Encode character string in the Series/Index using indicated encoding.
Series.str.endswith(*args, **kwargs) Test if the end of each string element matches a pattern.
Series.str.extract(*args, **kwargs) Extract capture groups in the regex pat as columns in a DataFrame.
Series.str.extractall(*args, **kwargs) Extract capture groups in the regex pat as columns in DataFrame.
Series.str.find(*args, **kwargs) Return lowest indexes in each strings in the Series/Index.
Series.str.findall(*args, **kwargs) Find all occurrences of pattern or regular expression in the Series/Index.
Series.str.get(i) Extract element from each component at specified position.
Series.str.index(*args, **kwargs) Return lowest indexes in each string in Series/Index.
Series.str.join(*args, **kwargs) Join lists contained as elements in the Series/Index with passed delimiter.
Series.str.len(*args, **kwargs) Compute the length of each element in the Series/Index.
Series.str.ljust(*args, **kwargs) Pad right side of strings in the Series/Index.
Series.str.lower(*args, **kwargs) Convert strings in the Series/Index to lowercase.
Series.str.lstrip(*args, **kwargs) Remove leading characters.
Series.str.match(*args, **kwargs) Determine if each string starts with a match of a regular expression.
Series.str.normalize(*args, **kwargs) Return the Unicode normal form for the strings in the Series/Index.
```
<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Series.str.pad(*args, **kwargs)</code></td>
<td>Pad strings in the Series/Index up to width.</td>
</tr>
<tr>
<td><code>Series.str.partition(*args, **kwargs)</code></td>
<td>Split the string at the first occurrence of <code>sep</code>.</td>
</tr>
<tr>
<td><code>Series.str.repeat(*args, **kwargs)</code></td>
<td>Duplicate each string in the Series or Index.</td>
</tr>
<tr>
<td><code>Series.str.replace(*args, **kwargs)</code></td>
<td>Replace each occurrence of pattern/regex in the Series/Index.</td>
</tr>
<tr>
<td><code>Series.str.rfind(*args, **kwargs)</code></td>
<td>Return highest indexes in each strings in the Series/Index.</td>
</tr>
<tr>
<td><code>Series.str.rindex(*args, **kwargs)</code></td>
<td>Return highest indexes in each string in Series/Index.</td>
</tr>
<tr>
<td><code>Series.str.rjust(*args, **kwargs)</code></td>
<td>Pad left side of strings in the Series/Index.</td>
</tr>
<tr>
<td><code>Series.str.rpartition(*args, **kwargs)</code></td>
<td>Split the string at the last occurrence of <code>sep</code>.</td>
</tr>
<tr>
<td><code>Series.str.rstrip(*args, **kwargs)</code></td>
<td>Remove trailing characters.</td>
</tr>
<tr>
<td><code>Series.str.slice(*start, stop, step*)</code></td>
<td>Slice substrings from each element in the Series or Index.</td>
</tr>
<tr>
<td><code>Series.str.slice_replace(*args, **kwargs)</code></td>
<td>Replace a positional slice of a string with another value.</td>
</tr>
<tr>
<td><code>Series.str.split(*args, **kwargs)</code></td>
<td>Split strings around given separator/delimiter.</td>
</tr>
<tr>
<td><code>Series.str.rsplit(*args, **kwargs)</code></td>
<td>Split strings around given separator/delimiter.</td>
</tr>
<tr>
<td><code>Series.str.startswith(*args, **kwargs)</code></td>
<td>Test if the start of each string element matches a pattern.</td>
</tr>
<tr>
<td><code>Series.str.strip(*args, **kwargs)</code></td>
<td>Remove leading and trailing characters.</td>
</tr>
<tr>
<td><code>Series.str.swapcase(*args, **kwargs)</code></td>
<td>Convert strings in the Series/Index to be swapcased.</td>
</tr>
<tr>
<td><code>Series.str.title(*args, **kwargs)</code></td>
<td>Convert strings in the Series/Index to titlecase.</td>
</tr>
<tr>
<td><code>Series.str.translate(*args, **kwargs)</code></td>
<td>Map all characters in the string through the given mapping table.</td>
</tr>
<tr>
<td><code>Series.str.upper(*args, **kwargs)</code></td>
<td>Convert characters in the Series/Index to uppercase.</td>
</tr>
<tr>
<td><code>Series.str.wrap(*args, **kwargs)</code></td>
<td>Wrap strings in Series/Index at specified line width.</td>
</tr>
<tr>
<td><code>Series.str.zfill(*args, **kwargs)</code></td>
<td>Pad strings in the Series/Index by prepending ‘0’ characters.</td>
</tr>
<tr>
<td><code>Series.str.isalnum(*args, **kwargs)</code></td>
<td>Check whether all characters in each string are alphanumeric.</td>
</tr>
<tr>
<td><code>Series.str.isalpha(*args, **kwargs)</code></td>
<td>Check whether all characters in each string are alphabetic.</td>
</tr>
<tr>
<td><code>Series.str.isdigit(*args, **kwargs)</code></td>
<td>Check whether all characters in each string are digits.</td>
</tr>
<tr>
<td><code>Series.str.isspace(*args, **kwargs)</code></td>
<td>Check whether all characters in each string are whitespace.</td>
</tr>
<tr>
<td><code>Series.str.islower(*args, **kwargs)</code></td>
<td>Check whether all characters in each string are lowercase.</td>
</tr>
<tr>
<td><code>Series.str.isupper(*args, **kwargs)</code></td>
<td>Check whether all characters in each string are uppercase.</td>
</tr>
<tr>
<td><code>Series.str.istitle(*args, **kwargs)</code></td>
<td>Check whether all characters in each string are titlecase.</td>
</tr>
<tr>
<td><code>Series.str.isnumeric(*args, **kwargs)</code></td>
<td>Check whether all characters in each string are numeric.</td>
</tr>
<tr>
<td><code>Series.str.isdecimal(*args, **kwargs)</code></td>
<td>Check whether all characters in each string are decimal.</td>
</tr>
<tr>
<td><code>Series.str.get_dummies(*args, **kwargs)</code></td>
<td>Return DataFrame of dummy/indicator variables for Series.</td>
</tr>
</tbody>
</table>
pandas.Series.str.capitalize

Series.str.capitalize(*args, **kwargs)
Convert strings in the Series/Index to be capitalized.

Equivalent to str.capitalize().

Returns
Series or Index of object

See also:
Series.str.lower  Converts all characters to lowercase.
Series.str.upper  Converts all characters to uppercase.
Series.str.title  Converts first character of each word to uppercase and remaining to lowercase.
Series.str.capitalize  Converts first character to uppercase and remaining to lowercase.
Series.str.swapcase  Converts uppercase to lowercase and lowercase to uppercase.
Series.str.casefold  Removes all case distinctions in the string.

Examples

```python
>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])

>>> s
0    lower
1  CAPITALS
2    this is a sentence
3       SwApCaSe
dtype: object

>>> s.str.lower()
0    lower
1  capitals
2    this is a sentence
3       swapcase
dtype: object

>>> s.str.upper()
0   LOWER
1  CAPITALS
2  THIS IS A SENTENCE
3     SWAPCASE
dtype: object

>>> s.str.title()
0   Lower
1  Capitals
2  This Is A Sentence
3       Swapcase
dtype: object

>>> s.str.capitalize()
0   Lower
1  Capitals
2  This is a sentence
3       Swapcase
dtype: object
```
pandas.Series.str.swapcase

Series.str.swapcase()  
Convert uppercase to lowercase and lowercase to uppercase.

Series or Index of object

Examples

```python
>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])
>>> s
0   lower
1  CAPITALS
2  this is a sentence
3     SwApCaSe
dtype: object

>>> s.str.swapcase()
0    LOWER
1  capitals
2  THIS IS A SENTENCE
3     sWaFCaSE
dtype: object
```

pandas.Series.str.casefold

Series.str.casefold(*args, **kwargs)
  
Convert strings in the Series/Index to be casefolded.

New in version 0.25.0.

Equivalent to str.casefold().

Returns
  
Series or Index of object

See also:

Series.str.lower Converts all characters to lowercase.
Series.str.upper Converts all characters to uppercase.
Series.str.title Converts first character of each word to uppercase and remaining to lowercase.
Series.str.capitalize Converts first character to uppercase and remaining to lowercase.
Series.str.swapcase Converts uppercase to lowercase and lowercase to uppercase.
Series.str.casefold Removes all case distinctions in the string.

Examples

```python
>>> s.str.swapcase()
0    LOWER
1  capitals
2  THIS IS A SENTENCE
3     sWaFCaSE

>>> s.str.lower()
0   lower
1  capitals
2  this is a sentence
3     swapcase
dtype: object

>>> s.str.upper()
0    LOWER
1  CAPITALS
2  THIS IS A SENTENCE
3     SWAPCASE
dtype: object

>>> s.str.title()
0    Lower
(continues on next page)```
1 Capitals
2 This Is A Sentence
3 Swapcase
dtype: object

```python
>>> s.str.capitalize()
0 Lower
1 Capitals
2 This is a sentence
3 Swapcase
dtype: object
```

```python
>>> s.str.swapcase()
0 LOWER
1 capitals
2 THIS IS A SENTENCE
3 sWaPcAsE
dtype: object
```

**pandas.Series.str.cat**

`Series.str.cat(*args, **kwargs)`
Concatenate strings in the Series/Index with given separator.

If `others` is specified, this function concatenates the Series/Index and elements of `others` element-wise. If `others` is not passed, then all values in the Series/Index are concatenated into a single string with a given `sep`.

**Parameters**

- **others** [Series, Index, DataFrame, np.ndarray or list-like] Series, Index, DataFrame, np.ndarray (one- or two-dimensional) and other list-likes of strings must have the same length as the calling Series/Index, with the exception of indexed objects (i.e. Series/Index/DataFrame) if `join` is not None.

  If `others` is a list-like that contains a combination of Series, Index or np.ndarray (1-dim), then all elements will be unpacked and must satisfy the above criteria individually.

  If `others` is None, the method returns the concatenation of all strings in the calling Series/Index.

- **sep** [str, default ''] The separator between the different elements/columns. By default the empty string '' is used.

- **na_rep** [str or None, default None] Representation that is inserted for all missing values:
  - If `na_rep` is None, and `others` is None, missing values in the Series/Index are omitted from the result.
  - If `na_rep` is None, and `others` is not None, a row containing a missing value in any of the columns (before concatenation) will have a missing value in the result.

- **join** [‘left’, ‘right’, ‘outer’, ‘inner’], default ‘left’] Determines the join-style between the calling Series/Index and any Series/Index/DataFrame in `others` (objects without an index need to match the length of the calling Series/Index). To disable alignment, use `.values` on any Series/Index/DataFrame in `others`.

  New in version 0.23.0.

  Changed in version 1.0.0: Changed default of `join` from None to ‘left’.

```
```
Returns

*str, Series or Index*  If `others` is None, `str` is returned, otherwise a `Series/Index` (same type as caller) of objects is returned.

See also:

- **split** Split each string in the Series/Index.
- **join** Join lists contained as elements in the Series/Index.

Examples

When not passing `others`, all values are concatenated into a single string:

```python
>>> s = pd.Series(['a', 'b', np.nan, 'd'])
>>> s.str.cat(sep=' ')
'a b d'
```

By default, NA values in the Series are ignored. Using `na_rep`, they can be given a representation:

```python
>>> s.str.cat(sep=' ', na_rep='?')
'a b ? d'
```

If `others` is specified, corresponding values are concatenated with the separator. Result will be a Series of strings.

```python
>>> s.str.cat(['A', 'B', 'C', 'D'], sep=','
0 a,A
1 b,B
2 NaN
3 d,D
dtype: object
```

Missing values will remain missing in the result, but can again be represented using `na_rep`

```python
>>> s.str.cat(['A', 'B', 'C', 'D'], sep=' ', na_rep='--')
0 aA
1 bB
2 --C
3 dD
dtype: object
```

If `sep` is not specified, the values are concatenated without separation.

```python
>>> s.str.cat(['A', 'B', 'C', 'D'], na_rep='--')
0 aA
1 bB
2 --C
3 dD
dtype: object
```

Series with different indexes can be aligned before concatenation. The `join`-keyword works as in other methods.

```python
>>> t = pd.Series(['d', 'a', 'e', 'c'], index=[3, 0, 4, 2])
>>> s.str.cat(t, join='left', na_rep='--')
0 aa
1 b--
2 --c
3 dd
```

(continues on next page)
```python
dtype: object
>>> s.str.cat(t, join='outer', na_rep='-')
0   aa
1   b-
2   -c
3   dd
4   -e
dtype: object

>>> s.str.cat(t, join='inner', na_rep='-')
0   aa
2   -c
3   dd
dtype: object

>>> s.str.cat(t, join='right', na_rep='-')
3   dd
0   aa
4   -e
2   -c
dtype: object
```

For more examples, see [here](#).

### pandas.Series.str.center

**Series.str.center(*args, **kwargs)**

Pad left and right side of strings in the Series/Index.

Equivalent to `str.center()`.

**Parameters**

- `width` [int] Minimum width of resulting string; additional characters will be filled with `fillchar`.
- `fillchar` [str] Additional character for filling, default is whitespace.

**Returns**

- `filled` [Series/Index of objects.]

### pandas.Series.str.contains

**Series.str.contains(*args, **kwargs)**

Test if pattern or regex is contained within a string of a Series or Index.

Return boolean Series or Index based on whether a given pattern or regex is contained within a string of a Series or Index.

**Parameters**

- `pat` [str] Character sequence or regular expression.
- `case` [bool, default True] If True, case sensitive.
- `flags` [int, default 0 (no flags)] Flags to pass through to the re module, e.g. re.IGNORECASE.
- `na` [default NaN] Fill value for missing values.
regex [bool, default True] If True, assumes the pat is a regular expression.

If False, treats the pat as a literal string.

Returns

Series or Index of boolean values A Series or Index of boolean values indicating whether
the given pattern is contained within the string of each element of the Series or Index.

See also:

match Analogous, but stricter, relying on re.match instead of re.search.
Series.str.startswith Test if the start of each string element matches a pattern.
Series.str.endswith Same as startswith, but tests the end of string.

Examples

Returning a Series of booleans using only a literal pattern.

```python
>>> s1 = pd.Series(['Mouse', 'dog', 'house and parrot', '23', np.NaN])
>>> s1.str.contains('og', regex=False)
0    False
1     True
2    False
3    False
4    NaN
dtype: object
```

Returning an Index of booleans using only a literal pattern.

```python
>>> ind = pd.Index(['Mouse', 'dog', 'house and parrot', '23.0', np.NaN])
>>> ind.str.contains('23', regex=False)
Index([False, False, False, True, nan], dtype='object')
```

Specifying case sensitivity using case.

```python
>>> s1.str.contains('oG', case=True, regex=True)
0    False
1    False
2    False
3    False
4    NaN
dtype: object
```

Specifying na to be False instead of NaN replaces NaN values with False. If Series or Index does not contain NaN values the resultant dtype will be bool, otherwise, an object dtype.

```python
>>> s1.str.contains('og', na=False, regex=True)
0    False
1     True
2    False
3    False
4    False
dtype: bool
```

Returning ‘house’ or ‘dog’ when either expression occurs in a string.
>>> s1.str.contains('house|dog', regex=True)
0    False
1     True
2     True
3    False
4    NaN
dtype: object

Ignoring case sensitivity using flags with regex.

>>> import re

>>> s1.str.contains('PARROT', flags=re.IGNORECASE, regex=True)
0    False
1    False
2     True
3    False
4    NaN
dtype: object

Returning any digit using regular expression.

>>> s1.str.contains('\d', regex=True)
0    False
1    False
2    False
3     True
4    NaN
dtype: object

Ensure pat is a not a literal pattern when regex is set to True. Note in the following example one might expect only s2[1] and s2[3] to return True. However, '\.0' as a regex matches any character followed by a 0.

>>> s2 = pd.Series(['40', '40.0', '41', '41.0', '35'])
>>> s2.str.contains('.0', regex=True)
0     True
1     True
2    False
3     True
4    False
dtype: bool

**pandas.Series.str.count**

Series.str.count(*args, **kwargs)

Count occurrences of pattern in each string of the Series/Index.

This function is used to count the number of times a particular regex pattern is repeated in each of the string elements of the Series.

- **Parameters**
  - pat [str] Valid regular expression.
  - flags [int, default 0, meaning no flags] Flags for the re module. For a complete list, see here.
  - **kwargs** For compatibility with other string methods. Not used.

- **Returns**
Series or Index  Same type as the calling object containing the integer counts.

See also:
- re  Standard library module for regular expressions.
- str.count  Standard library version, without regular expression support.

Notes
Some characters need to be escaped when passing in pat. eg. ‘$’ has a special meaning in regex and must be escaped when finding this literal character.

Examples

```python
>>> s = pd.Series(['A', 'B', 'Aaba', 'Baca', np.nan, 'CABA', 'cat'])
>>> s.str.count('a')
0    0.0
1    0.0
2    2.0
3    2.0
4    NaN
5    0.0
6    1.0
dtype: float64
```

Escape ' $ ' to find the literal dollar sign.

```python
>>> s = pd.Series(['$', 'B', 'Aab$', '$$ca', 'C$B$', 'cat'])
>>> s.str.count('\$')
0    1
1    0
2    1
3    2
4    2
5    0
dtype: int64
```

This is also available on Index

```python
>>> pd.Index(['A', 'A', 'Aaba', 'cat']).str.count('a')
Int64Index([0, 0, 2, 1], dtype='int64')
```

pandas.Series.str.decode

Series.str.decode(encoding, errors='strict')
Decode character string in the Series/Index using indicated encoding.

Equivalent to str.decode() in python2 and bytes.decode() in python3.

Parameters
- encoding  [str]
- errors  [str, optional]

Returns
Series or Index
pandas.Series.str.encode

Series.str.encode(*args, **kwargs)
Encode character string in the Series/Index using indicated encoding.

Equivalent to str.encode().

Parameters
- encoding [str]
- errors [str, optional]

Returns
- encoded [Series/Index of objects]

pandas.Series.str.endswith

Series.str.endswith(*args, **kwargs)
Test if the end of each string element matches a pattern.

Equivalent to str.endswith().

Parameters
- pat [str] Character sequence. Regular expressions are not accepted.
- na [object, default NaN] Object shown if element tested is not a string.

Returns
- Series or Index of bool A Series of booleans indicating whether the given pattern matches
the end of each string element.

See also:
- str.endswith Python standard library string method.
- Series.str.startswith Same as endswith, but tests the start of string.
- Series.str.contains Tests if string element contains a pattern.

Examples

```python
>>> s = pd.Series(['bat', 'bear', 'caT', np.nan])
>>> s
0  bat
1  bear
2  caT
3  NaN
dtype: object

>>> s.str.endswith('t')
0   True
1  False
2  False
3   NaN
dtype: object
```

Specifying `na` to be `False` instead of `NaN`. 
>>> s.str.endswith('t', na=False)
0    True  
1      False
2     False
3     False
dtype: bool

**pandas.Series.str.extract**

Series.str.extract(*args, **kwargs)

Extract capture groups in the regex pat as columns in a DataFrame.

For each subject string in the Series, extract groups from the first match of regular expression pat.

**Parameters**

- **pat** [str] Regular expression pattern with capturing groups.
- **flags** [int, default 0 (no flags)] Flags from the re module, e.g. re.IGNORECASE, that modify regular expression matching for things like case, spaces, etc. For more details, see re.
- **expand** [bool, default True] If True, return DataFrame with one column per capture group. If False, return a Series/Index if there is one capture group or DataFrame if there are multiple capture groups.

**Returns**

- **DataFrame or Series or Index** A DataFrame with one row for each subject string, and one column for each group. Any capture group names in regular expression pat will be used for column names; otherwise capture group numbers will be used. The dtype of each result column is always object, even when no match is found. If expand=False and pat has only one capture group, then return a Series (if subject is a Series) or Index (if subject is an Index).

**See also:**

extractall Returns all matches (not just the first match).

**Examples**

A pattern with two groups will return a DataFrame with two columns. Non-matches will be NaN.

```python
>>> s = pd.Series(['a1', 'b2', 'c3'])
>>> s.str.extract(r'([ab])(\d)')
   0  1
0 a 1
1 b 2
2 NaN NaN
```

A pattern may contain optional groups.

```python
>>> s.str.extract(r'([ab])?(\d)')
   0  1
0 a 1
1 b 2
2 NaN NaN
```

Named groups will become column names in the result.
A pattern with one group will return a DataFrame with one column if expand=True.

```
>>> s.str.extract(r'(?P<letter>[ab])(?P<digit>\d)')
   letter digit
0    a     1
1    b     2
2  NaN   NaN
```

A pattern with one group will return a Series if expand=False.

```
>>> s.str.extract(r'([ab])(\d)', expand=False)
0  1
1  2
2  NaN
dtype: object
```

**pandas.Series.str.extractall**

Series.str.extractall(*args, **kwargs)

Extract capture groups in the regex pat as columns in DataFrame.

For each subject string in the Series, extract groups from all matches of regular expression pat. When each subject string in the Series has exactly one match, extractall(pat).xs(0, level='match') is the same as extract(pat).

**Parameters**

- **pat** [str] Regular expression pattern with capturing groups.
- **flags** [int, default 0 (no flags)] A re module flag, for example re.IGNORECASE. These allow to modify regular expression matching for things like case, spaces, etc. Multiple flags can be combined with the bitwise OR operator, for example re.IGNORECASE | re.MULTILINE.

**Returns**

DataFrame A DataFrame with one row for each match, and one column for each group. Its rows have a MultiIndex with first levels that come from the subject Series. The last level is named 'match' and indexes the matches in each item of the Series. Any capture group names in regular expression pat will be used for column names; otherwise capture group numbers will be used.

**See also:**

- extract Returns first match only (not all matches).
Examples

A pattern with one group will return a DataFrame with one column. Indices with no matches will not appear in the result.

```python
>>> s = pd.Series(["a1a2", "b1", "c1"], index=["A", "B", "C"])
>>> s.str.extractall(r"\[ab\](\d)")
match
0     A 0
1     1  2
B 0  1
```

Capture group names are used for column names of the result.

```python
>>> s.str.extractall(r"\[ab\](?P<digit>\d)")
digit
match
0    A 0
1    1  2
B 0  1
```

A pattern with two groups will return a DataFrame with two columns.

```python
>>> s.str.extractall(r"(?P<letter>[ab])(?P<digit>\d)")
letter digit
match
A 0    a  1
1      a  2
B 0    b  1
```

Optional groups that do not match are NaN in the result.

```python
>>> s.str.extractall(r"(?P<letter>[ab])?(?P<digit>\d)")
letter digit
match
A 0    a  1
1      a  2
B 0    b  1
C 0  NaN  1
```

`pandas.Series.str.find`

`Series.str.find(*args, **kwargs)`

Return lowest indexes in each strings in the Series/Index.

Each of returned indexes corresponds to the position where the substring is fully contained between [start:end]. Return -1 on failure. Equivalent to standard `str.find()`.

Parameters

- `sub` [str] Substring being searched.
- `start` [int] Left edge index.
- `end` [int] Right edge index.

Returns
Series or Index of int.

See also:

**rfind** Return highest indexes in each strings.

### pandas.Series.str.findall

**pandas.Series.str.findall**(*args, **kwargs*)

Find all occurrences of pattern or regular expression in the Series/Index.

Equivalent to applying `re.findall()` to all the elements in the Series/Index.

**Parameters**

- `pat` [str] Pattern or regular expression.
- `flags` [int, default 0] Flags from `re` module, e.g. `re.IGNORECASE` (default is 0, which means no flags).

**Returns**

*Series/Index of lists of strings* All non-overlapping matches of pattern or regular expression in each string of this Series/Index.

See also:

- `count` Count occurrences of pattern or regular expression in each string of the Series/Index.
- `extractall` For each string in the Series, extract groups from all matches of regular expression and return a DataFrame with one row for each match and one column for each group.
- `re.findall` The equivalent `re` function to all non-overlapping matches of pattern or regular expression in string, as a list of strings.

### Examples

```python
>>> s = pd.Series(['Lion', 'Monkey', 'Rabbit'])

The search for the pattern ‘Monkey’ returns one match:

```python
gbgeg
s.str.findall('Monkey')
```

```
0    []
1   ['Monkey']
2    []
dtype: object
```

On the other hand, the search for the pattern ‘MONKEY’ doesn’t return any match:

```python
gbgeg
s.str.findall('MONKEY')
```

```
0    []
1    []
2    []
dtype: object
```

Flags can be added to the pattern or regular expression. For instance, to find the pattern ‘MONKEY’ ignoring the case:

```python
>>> import re
>>> s.str.findall('MONKEY', flags=re.IGNORECASE)
```

```
0    []
```
When the pattern matches more than one string in the Series, all matches are returned:

```python
>>> s.str.findall('on')
0    [on]
1    [on]
2     []
dtype: object
```

Regular expressions are supported too. For instance, the search for all the strings ending with the word ‘on’ is shown next:

```python
>>> s.str.findall('on$')
0    [on]
1     []
2     []
dtype: object
```

If the pattern is found more than once in the same string, then a list of multiple strings is returned:

```python
>>> s.str.findall('b')
0     []
1     []
2    [b, b]
dtype: object
```

### pandas.Series.str.get

**Series.str.get(i)**

Extract element from each component at specified position.

Extract element from lists, tuples, or strings in each element in the Series/Index.

**Parameters**

- **i** [int] Position of element to extract.

**Returns**

Series or Index

**Examples**

```python
>>> s = pd.Series(['String',
...                 (1, 2, 3),
...                 ['a', 'b', 'c'],
...                 123,
...                 -456,
...                 {1: 'Hello', 2: 'World'}])
>>> s
0    String
1    (1, 2, 3)
2    [a, b, c]
3    123
4    -456
5    {1: 'Hello', 2: 'World'}
```

```python
(continues on next page)```
```
2       [a, b, c]
3          123
4          -456
5    {1: 'Hello', '2': 'World'}
dtype: object
```

```
>>> s.str.get(1)
0   t
1   2
2   b
3  NaN
4  NaN
5  Hello
dtype: object
```

```
>>> s.str.get(-1)
0   g
1   3
2   c
3  NaN
4  NaN
5   None
dtype: object
```

```
pandas.Series.str.index
```

Series.str.index(*args, **kwargs)

Return lowest indexes in each string in Series/Index.

Each of the returned indexes corresponds to the position where the substring is fully contained between [start:end]. This is the same as str.find except instead of returning -1, it raises a ValueError when the substring is not found. Equivalent to standard str.index.

Parameters

- **sub** [str] Substring being searched.
- **start** [int] Left edge index.
- **end** [int] Right edge index.

Returns

Series or Index of object

See also:

- **rindex** Return highest indexes in each strings.
**pandas.Series.str.join**

Series.str.join(*args, **kwargs)

Join lists contained as elements in the Series/Index with passed delimiter.

If the elements of a Series are lists themselves, join the content of these lists using the delimiter passed to the function. This function is an equivalent to `str.join()`.

**Parameters**

- `sep` [str] Delimiter to use between list entries.

**Returns**

- **Series/Index:** object The list entries concatenated by intervening occurrences of the delimiter.

**Raises**

- `AttributeError` If the supplied Series contains neither strings nor lists.

**See also:**

- `str.join` Standard library version of this method.
- `Series.str.split` Split strings around given separator/delimiter.

**Notes**

If any of the list items is not a string object, the result of the join will be `NaN`.

**Examples**

Example with a list that contains non-string elements.

```python
>>> s = pd.Series([['lion', 'elephant', 'zebra'],
                 ... [1.1, 2.2, 3.3],
                 ... ['cat', np.nan, 'dog'],
                 ... ['cow', 4.5, 'goat'],
                 ... ['duck', ['swan', 'fish'], 'guppy']])
```

Join all lists using a `-`. The lists containing object(s) of types other than str will produce a NaN.

```python
>>> s.str.join('-')
0    lion-elephant-zebra
1     NaN
2     NaN
3     NaN
4     NaN
dtype: object
```
pandas.Series.str.len

Series.str.len(*args, **kwargs)
Compute the length of each element in the Series/Index.

The element may be a sequence (such as a string, tuple or list) or a collection (such as a dictionary).

Returns

Series or Index of int A Series or Index of integer values indicating the length of each element in the Series or Index.

See also:

str.len Python built-in function returning the length of an object.
Series.size Returns the length of the Series.

Examples

Returns the length (number of characters) in a string. Returns the number of entries for dictionaries, lists or tuples.

```python
>>> s = pd.Series(['dog', '', 5, ('foo': 'bar'), [2, 3, 5, 7], ('one', 'two', 'three')])
>>> s
0   dog
1    
2    5
3   {'foo': 'bar'}
4  [2, 3, 5, 7]
5   (one, two, three)
dtype: object
>>> s.str.len()
0  3.0
1  0.0
2  NaN
3  1.0
4  4.0
5  3.0
dtype: float64
```

pandas.Series.str.ljust

Series.str.ljust(*args, **kwargs)
Pad right side of strings in the Series/Index.

Equivalent to str.ljust().

Parameters

- **width** [int] Minimum width of resulting string; additional characters will be filled with fillchar.
- **fillchar** [str] Additional character for filling, default is whitespace.

Returns
Series.str.lower

Series.str.lower(*args, **kwargs)

Convert strings in the Series/Index to lowercase.

Equivalent to str.lower().

Returns

Series or Index of object

See also:

Series.str.lower Converts all characters to lowercase.
Series.str.upper Converts all characters to uppercase.
Series.str.title Converts first character of each word to uppercase and remaining to lowercase.
Series.str.capitalize Converts first character to uppercase and remaining to lowercase.
Series.str.swapcase Converts uppercase to lowercase and lowercase to uppercase.
Series.str.casefold Removes all case distinctions in the string.

Examples

```python
>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])
>>> s
0     lower
1    CAPITALS
2   this is a sentence
3   SwApCaSe
dtype: object

>>> s.str.lower()  #Converts all characters to lowercase.
0     lower
1    capitals
2   this is a sentence
3   swapcase
dtype: object

>>> s.str.upper()  #Converts all characters to uppercase.
0      LOWER
1    CAPITALS
2  THIS IS A SENTENCE
3   SWAPCASE
dtype: object

>>> s.str.title()  #Converts first character of each word to uppercase and remaining to lowercase.
0     Lower
1    Capitals
2   This Is A Sentence
3   Swapcase
dtype: object

>>> s.str.capitalize()  #Converts first character to uppercase and remaining to lowercase.
0     Lower
1    Capitals
```
```python
>>> s = pd.Series(['1. Ant.', '2. Bee!
', '3. Cat?	', np.nan])
>>> s
0   1. Ant.
1  2. Bee!
2   3. Cat?
3     NaN
dtype: object
```

```python
>>> s.str.strip()
0   1. Ant.
1  2. Bee!
2   3. Cat?
3     NaN
dtype: object
```

```python
>>> s = pd.Series(['1. Ant.', '2. Bee!
', '3. Cat?	', np.nan])
>>> s
0   1. Ant.
1  2. Bee!
2   3. Cat?
3     NaN
dtype: object
```

```python
>>> s.str.lstrip('123.')
0   Ant.
1  Bee!
2   Cat?
3     NaN
dtype: object
```

```python
>>> s = pd.Series(['1. Ant.', '2. Bee!
', '3. Cat?	', np.nan])
>>> s
0   1. Ant.
1  2. Bee!
2   3. Cat?
3     NaN
dtype: object
```

```python
>>> s.str.lstrip('I23.')
0   Ant.
1  Bee!
```

---

**pandas.Series.str.lstrip**

`Series.str.lstrip(*args, **kwargs)`

Remove leading characters.

Strip whitespaces (including newlines) or a set of specified characters from each string in the Series/Index from left side. Equivalent to `str.lstrip()`.

**Parameters**

- `to_strip` [str or None, default None] Specifying the set of characters to be removed. All combinations of this set of characters will be stripped. If None then whitespaces are removed.

**Returns**

Series or Index of object

**See also:**

- `Series.str.strip` Remove leading and trailing characters in Series/Index.
- `Series.str.lstrip` Remove leading characters in Series/Index.
- `Series.str.rstrip` Remove trailing characters in Series/Index.

**Examples**

```python
>>> s = pd.Series(['1. Ant. ', '2. Bee!
', '3. Cat?	', np.nan])
>>> s
0   1. Ant. 
1   2. Bee!
2   3. Cat?
3     NaN
dtype: object
```

```python
>>> s.str.strip()
0   1. Ant. 
1   2. Bee!
2   3. Cat?
3     NaN
dtype: object
```

```python
>>> s = pd.Series(['1. Ant. ', '2. Bee!
', '3. Cat?	', np.nan])
>>> s
0   1. Ant. 
1   2. Bee!
2   3. Cat?
3     NaN
dtype: object
```

```python
>>> s.str.lstrip('123.')
0   Ant. 
1   Bee!
2   Cat?
3     NaN
dtype: object
```

---

3.3. Series 1311
pandas.Series.str.match

Series.str.match(*args, **kwargs)

Determine if each string starts with a match of a regular expression.

Parameters:

- **pat** [str] Character sequence or regular expression.
- **case** [bool, default True] If True, case sensitive.
- **flags** [int, default 0 (no flags)] Regex module flags, e.g. re.IGNORECASE.
- **na** [default NaN] Fill value for missing values.

Returns:

Series/array of boolean values

See also:

fullmatch  Stricter matching that requires the entire string to match.
contains   Analogous, but less strict, relying on re.search instead of re.match.
extract    Extract matched groups.

pandas.Series.str.normalize

Series.str.normalize(*args, **kwargs)

Return the Unicode normal form for the strings in the Series/Index.

For more information on the forms, see the unicodedata.normalize().

Parameters:


Returns:

normalized [Series/Index of objects]
pandas.Series.str.pad

Series.str.pad(*args, **kwargs)

Pad strings in the Series/Index up to width.

Parameters

- **width** [int] Minimum width of resulting string; additional characters will be filled with character defined in fillchar.
- **side** [{'left', 'right', 'both'}, default 'left'] Side from which to fill resulting string.
- **fillchar** [str, default ' '] Additional character for filling, default is whitespace.

Returns

Series or Index of object  Returns Series or Index with minimum number of char in object.

See also:

- **Series.str.rjust** Fills the left side of strings with an arbitrary character. Equivalent to Series.str.pad(side='left').
- **Series.str.ljust** Fills the right side of strings with an arbitrary character. Equivalent to Series.str.pad(side='right').
- **Series.str.center** Fills both sides of strings with an arbitrary character. Equivalent to Series.str.pad(side='both').
- **Series.str.zfill** Pad strings in the Series/Index by prepending '0' character. Equivalent to Series.str.pad(side='left', fillchar='0').

Examples

```python
>>> s = pd.Series(['caribou', 'tiger'])
>>> s
0  caribou
1   tiger
dtype: object

>>> s.str.pad(width=10)
0  caribou
1   tiger
dtype: object

>>> s.str.pad(width=10, side='right', fillchar='-')
0  caribou---
1 ---tiger---
dtype: object

>>> s.str.pad(width=10, side='both', fillchar='-')
0  -caribou--
1   --tiger---
dtype: object
```
pandas.Series.str.partition

Series.str.partition(*args, **kwargs)
Split the string at the first occurrence of sep.

This method splits the string at the first occurrence of sep, and returns 3 elements containing the part before the separator, the separator itself, and the part after the separator. If the separator is not found, return 3 elements containing the string itself, followed by two empty strings.

Parameters

- sep [str, default whitespace] String to split on.
- expand [bool, default True] If True, return DataFrame/MultiIndex expanding dimensionality. If False, return Series/Index.

Returns

DataFrame/MultiIndex or Series/Index of objects

See also:

- rpartition Split the string at the last occurrence of sep.
- Series.str.split Split strings around given separators.
- str.partition Standard library version.

Examples

```python
>>> s = pd.Series(['Linda van der Berg', 'George Pitt-Rivers'])
>>> s
0   Linda van der Berg
1   George Pitt-Rivers
dtype: object

>>> s.str.partition()
   0   1   2
0  Linda  van der Berg
1  George Pitt-Rivers

To partition by the last space instead of the first one:

```python
>>> s.str.rpartition()
   0   1   2
0  Linda  van der Berg
1  George Pitt-Rivers
```

To partition by something different than a space:

```python
>>> s.str.partition('-')
   0   1   2
0  Linda  van der Berg
1  George Pitt - Rivers
```

To return a Series containing tuples instead of a DataFrame:

```python
>>> s.str.partition('-', expand=False)
   0   1   2
0 (Linda van der Berg, , )
1 (George Pitt, -, Rivers)
dtype: object
```
Also available on indices:

```python
>>> idx = pd.Index(['X 123', 'Y 999'])
>>> idx
Index(['X 123', 'Y 999'], dtype='object')
```

Which will create a MultiIndex:

```python
>>> idx.str.partition()
MultiIndex([('X', ' ', '123'), ('Y', ' ', '999')],
           )
```

Or an index with tuples with `expand=False`:

```python
>>> idx.str.partition(expand=False)
Index([('X', ' ', '123'), ('Y', ' ', '999')], dtype='object')
```

**pandas.Series.str.repeat**

`Series.str.repeat(*args, **kwargs)`

Duplicate each string in the Series or Index.

**Parameters**

- `repeats` [int or sequence of int] Same value for all (int) or different value per (sequence).

**Returns**

- `Series or Index of object` Series or Index of repeated string objects specified by input parameter repeats.

**Examples**

```python
>>> s = pd.Series(['a', 'b', 'c'])
>>> s
0    a
1    b
2    c
dtype: object

Single int repeats string in Series

```python
>>> s.str.repeat(repeats=2)
0   aa
1   bb
2   cc
dtype: object
```

Sequence of int repeats corresponding string in Series

```python
>>> s.str.repeat(repeats=[1, 2, 3])
0    a
1   bb
2  ccc
dtype: object
```
pandas.Series.str.replace

Series.str.replace(*args, **kwargs)
Replace each occurrence of pattern/regex in the Series/Index.

Equivalent to str.replace() or re.sub(), depending on the regex value.

**Parameters**

- **pat** [str or compiled regex] String can be a character sequence or regular expression.
- **repl** [str or callable] Replacement string or a callable. The callable is passed the regex match object and must return a replacement string to be used. See re.sub().
- **n** [int, default -1 (all)] Number of replacements to make from start.
- **case** [bool, default None] Determines if replace is case sensitive:
  - If True, case sensitive (the default if pat is a string)
  - Set to False for case insensitive
  - Cannot be set if pat is a compiled regex.
- **flags** [int, default 0 (no flags)] Regex module flags, e.g. re.IGNORECASE. Cannot be set if pat is a compiled regex.
- **regex** [bool, default True] Determines if assumes the passed-in pattern is a regular expression:
  - If True, assumes the passed-in pattern is a regular expression.
  - If False, treats the pattern as a literal string
  - Cannot be set to False if pat is a compiled regex or repl is a callable.

New in version 0.23.0.

**Returns**

Series or Index of object A copy of the object with all matching occurrences of pat replaced by repl.

**Raises**

- **ValueError**
  - if regex is False and repl is a callable or pat is a compiled regex
  - if pat is a compiled regex and case or flags is set

**Notes**

When pat is a compiled regex, all flags should be included in the compiled regex. Use of case, flags, or regex=False with a compiled regex will raise an error.
Examples

When `pat` is a string and `regex` is True (the default), the given `pat` is compiled as a regex. When `repl` is a string, it replaces matching regex patterns as with `re.sub()`. NaN value(s) in the Series are left as is:

```python
>>> pd.Series(['foo', 'fuz', np.nan]).str.replace('f.', 'ba', regex=True)
0 bao
1 baz
2 NaN
dtype: object
```

When `pat` is a string and `regex` is False, every `pat` is replaced with `repl` as with `str.replace()`:

```python
>>> pd.Series(['f.o', 'fuz', np.nan]).str.replace('f.', 'ba', regex=False)
0 bao
1 fuz
2 NaN
dtype: object
```

When `repl` is a callable, it is called on every `pat` using `re.sub()`. The callable should expect one positional argument (a regex object) and return a string.

To get the idea:

```python
>>> pd.Series(['foo', 'fuz', np.nan]).str.replace('f', repr)
0 <re.Match object; span=(0, 1), match='f'>oo
1 <re.Match object; span=(0, 1), match='f'>uz
2 NaN
dtype: object
```

Reverse every lowercase alphabetic word:

```python
>>> repl = lambda m: m.group(0)[::-1]
>>> pd.Series(['foo 123', 'bar baz', np.nan]).str.replace(r'[a-z]+', repl)
0 oof 123
1 rab zab
2 NaN
dtype: object
```

Using regex groups (extract second group and swap case):

```python
>>> pat = r"(?P<one>[a-zA-Z]) (?P<two>[a-zA-Z]) (?P<three>[a-zA-Z])"
>>> repl = lambda m: m.group('two').swapcase()
>>> pd.Series(['One Two Three', 'Foo Bar Baz']).str.replace(pat, repl)
0 tWO
1 bAR
dtype: object
```

Using a compiled regex with flags

```python
>>> import re
>>> regex_pat = re.compile(r'FUZ', flags=re.IGNORECASE)
>>> pd.Series(['foo', 'fuz', np.nan]).str.replace(regex_pat, 'bar')
0 foo
1 bar
2 NaN
dtype: object
```
pandas.Series.str.rfind

Series.str.rfind(*args, **kwargs)
Return highest indexes in each strings in the Series/Index.
Each of returned indexes corresponds to the position where the substring is fully contained between [start:end].
Return -1 on failure. Equivalent to standard str.rfind().

Parameters
- sub [str] Substring being searched.
- start [int] Left edge index.
- end [int] Right edge index.

Returns
Series or Index of int.

See also:
find Return lowest indexes in each strings.

pandas.Series.str.rindex

Series.str.rindex(*args, **kwargs)
Return highest indexes in each string in Series/Index.
Each of the returned indexes corresponds to the position where the substring is fully contained between [start:end]. This is the same as str.rfind except instead of returning -1, it raises a ValueError when the substring is not found. Equivalent to standard str.rindex.

Parameters
- sub [str] Substring being searched.
- start [int] Left edge index.
- end [int] Right edge index.

Returns
Series or Index of object

See also:
index Return lowest indexes in each strings.

pandas.Series.str.rjust

Series.str.rjust(*args, **kwargs)
Pad left side of strings in the Series/Index.
Equivalent to str.rjust().

Parameters
- width [int] Minimum width of resulting string; additional characters will be filled with fillchar.

fillchar [str] Additional character for filling, default is whitespace.

Returns
filled [Series/Index of objects.]
**pandas.Series.str.rpartition**

Series.str.rpartition(*args, **kwargs)

Split the string at the last occurrence of `sep`.

This method splits the string at the last occurrence of `sep`, and returns 3 elements containing the part before the separator, the separator itself, and the part after the separator. If the separator is not found, return 3 elements containing two empty strings, followed by the string itself.

**Parameters**

- `sep` [str, default whitespace] String to split on.
- `expand` [bool, default True] If True, return DataFrame/MultiIndex expanding dimensionality. If False, return Series/Index.

**Returns**

DataFrame/MultiIndex or Series/Index of objects

See also:

- `partition` Split the string at the first occurrence of `sep`.
- `Series.str.split` Split strings around given separators.
- `str.partition` Standard library version.

**Examples**

```python
>>> s = pd.Series(['Linda van der Berg', 'George Pitt-Rivers'])
>>> s
0   Linda van der Berg
1   George Pitt-Rivers
dtype: object

>>> s.str.partition()
   0    1    2
0  Linda  van  Berg
1  George Pitt-Rivers

To partition by the last space instead of the first one:

```python
>>> s.str.rpartition()
   0   1   2
0  Linda   van   Berg
1  George  Pitt-Rivers
```  

To partition by something different than a space:

```python
>>> s.str.partition('-')
   0   1   2
0  Linda van der Berg
1  George  Pitt-Rivers
```

To return a Series containing tuples instead of a DataFrame:

```python
>>> s.str.partition('-', expand=False)
   0       1       2
0 (Linda van der Berg, , )
1 (George Pitt, -, Rivers)
```

```
3.3. Series 1319
```
Also available on indices:

```python
>>> idx = pd.Index(['X 123', 'Y 999'])
>>> idx
Index(['X 123', 'Y 999'], dtype='object')
```

Which will create a MultiIndex:

```python
>>> idx.str.partition()
MultiIndex([(X', ' ', '123'),
            ('Y', ' ', '999')],
           )
```

Or an index with tuples with `expand=False`:

```python
>>> idx.str.partition(expand=False)
Index([(X', ' ', '123'), (Y', ' ', '999')], dtype='object')
```

### pandas.Series.str.rstrip

Series.str.rstrip(*args, **kwargs)

Remove trailing characters.

Strip whitespaces (including newlines) or a set of specified characters from each string in the Series/Index from right side. Equivalent to `str.rstrip()`.

**Parameters**

- `to_strip` [str or None, default None] Specifying the set of characters to be removed. All combinations of this set of characters will be stripped. If None then whitespaces are removed.

**Returns**

Series or Index of object

**See also:**

- `Series.str.strip` Remove leading and trailing characters in Series/Index.
- `Series.str.lstrip` Remove leading characters in Series/Index.
- `Series.str.rstrip` Remove trailing characters in Series/Index.

**Examples**

```python
>>> s = pd.Series(['1. Ant. ', '2. Bee!
', '3. Cat?\t', np.nan])
>>> s
0     1. Ant.
1     2. Bee!
2     3. Cat?
3         NaN
dtype: object

>>> s.str.strip()
0     1. Ant.
1     2. Bee!
2     3. Cat?
3         NaN
dtype: object
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

>>> s.str.lstrip('123.')</div><div class="highlight"><span class="n">0</span>  Ant.
1  Bee!
2  Cat?
3  NaN
<code class="highlighted">dtype</code>: <span class="n">object</span><br/></div>

>>> s.str.rstrip('.!? 
\t')
0  1. Ant
1  2. Bee
2  3. Cat
3  NaN<code class="highlighted"><br/></code><br/>

>>> s.str.strip('123.!? 
\t')
0  Ant
1  Bee
2  Cat
3  NaN<code class="highlighted"><br/></code><br/>

**pandas.Series.str.slice**

Series.str.slice(<code class="highlighted">start=None, stop=None, step=None</code>)

Slice substrings from each element in the Series or Index.

**Parameters**

- **start** [int, optional] Start position for slice operation.
- **stop** [int, optional] Stop position for slice operation.
- **step** [int, optional] Step size for slice operation.

**Returns**

Series or Index of object Series or Index from sliced substring from original string object.

**See also:**

- **Series.str.slice_replace** Replace a slice with a string.
- **Series.str.get** Return element at position. Equivalent to `Series.str.slice(start=i, stop=i+1)` with `i` being the position.

**Examples**

```python
>>> s = pd.Series(['koala', 'fox', 'chameleon'])
```

```python
>>> s
0  koala
1  fox
2  chameleon
<code class="highlighted"></code><br/>
dtype: <span class="n">object</span><br/>
```

```python
>>> s.str.slice(start=1)
0  oala
1  ox
```

(continues on next page)
pandas: powerful Python data analysis toolkit, Release 1.1.1

(continued from previous page)

2  hameleon
dtype: object

>>> s.str.slice(start=-1)
 0  a
 1  x
 2  n
dtype: object

>>> s.str.slice(stop=2)
 0  ko
 1  fo
 2  ch
dtype: object

>>> s.str.slice(step=2)
 0  kaa
 1  fx
 2  caeen
dtype: object

>>> s.str.slice(start=0, stop=5, step=3)
 0  kl
 1  f
 2  cm
dtype: object

equivalent behaviour to:

>>> s.str[0:5:3]
 0  kl
 1  f
 2  cm
dtype: object

pandas.Series.str.slice_replace

Series.str.slice_replace(*args, **kwargs)
Replace a positional slice of a string with another value.

Parameters

- **start** [int, optional] Left index position to use for the slice. If not specified (None), the slice is unbounded on the left, i.e. slice from the start of the string.
- **stop** [int, optional] Right index position to use for the slice. If not specified (None), the slice is unbounded on the right, i.e. slice until the end of the string.
- **repl** [str, optional] String for replacement. If not specified (None), the sliced region is replaced with an empty string.

Returns

Series or Index Same type as the original object.

See also:

Series.str.slice Just slicing without replacement.
Examples

```python
>>> s = pd.Series(['a', 'ab', 'abc', 'abdc', 'abcde'])
>>> s
0    a
1   ab
2   abc
3  abdc
4  abcde
dtype: object
```

Specify just `start`, meaning replace `start` until the end of the string with `repl`.

```python
>>> s.str.slice_replace(start=1, repl='X')
0    aX
1   aX
2   aX
3   aX
4   aX
dtype: object
```

Specify just `stop`, meaning the start of the string to `stop` is replaced with `repl`, and the rest of the string is included.

```python
>>> s.str.slice_replace(stop=2, repl='X')
0   X
1   Xc
2   Xdc
3   Xdc
4   Xdc
dtype: object
```

Specify `start` and `stop`, meaning the slice from `start` to `stop` is replaced with `repl`. Everything before or after `start` and `stop` is included as is.

```python
>>> s.str.slice_replace(start=1, stop=3, repl='X')
0    aX
1   aX
2   aX
3   aXc
4   aXdc
dtype: object
```

**pandas.Series.str.split**

`Series.str.split(*args, **kwargs)`

Split strings around given separator/delimiter.

Splits the string in the Series/Index from the beginning, at the specified delimiter string. Equivalent to `str.split()`.

**Parameters**

- `pat` [str, optional] String or regular expression to split on. If not specified, split on whitespace.
- `n` [int, default -1 (all)] Limit number of splits in output. None, 0 and -1 will be interpreted as return all splits.
expand [bool, default False] Expand the split strings into separate columns.

- If True, return DataFrame/MultiIndex expanding dimensionality.
- If False, return Series/Index, containing lists of strings.

Returns

Series, Index, DataFrame or MultiIndex  Type matches caller unless expand=True (see Notes).

See also:

Series.str.split  Split strings around given separator/delimiter.
Series.str.rsplit  Splits string around given separator/delimiter, starting from the right.
Series.str.join  Join lists contained as elements in the Series/Index with passed delimiter.
str.split  Standard library version for split.
str.rsplit  Standard library version for rsplit.

Notes

The handling of the $n$ keyword depends on the number of found splits:

- If found splits > $n$, make first $n$ splits only
- If found splits <= $n$, make all splits
- If for a certain row the number of found splits < $n$, append None for padding up to $n$ if expand=True

If using expand=True, Series and Index callers return DataFrame and MultiIndex objects, respectively.

Examples

```python
>>> s = pd.Series(
...     [
...         "this is a regular sentence",
...         "https://docs.python.org/3/tutorial/index.html",
...         np.nan
...     ]
... )
>>> s
0  this is a regular sentence
1  https://docs.python.org/3/tutorial/index.html
2      NaN
dtype: object

In the default setting, the string is split by whitespace.

```python
>>> s.str.split()
0  [this, is, a, regular, sentence]
1  [https://docs.python.org/3/tutorial/index.html]
2      NaN
dtype: object
```

Without the $n$ parameter, the outputs of rsplit and split are identical.

```python
>>> s.str.rsplit()
0  [this, is, a, regular, sentence]
1  [https://docs.python.org/3/tutorial/index.html]
2      NaN
dtype: object
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

The n parameter can be used to limit the number of splits on the delimiter. The outputs of split and rsplit are
different.
>>> s.str.split(n=2)
0
[this, is, a regular sentence]
1
[https://docs.python.org/3/tutorial/index.html]
2
NaN
dtype: object
>>> s.str.rsplit(n=2)
0
[this is a, regular, sentence]
1
[https://docs.python.org/3/tutorial/index.html]
2
NaN
dtype: object

The pat parameter can be used to split by other characters.
>>> s.str.split(pat="/")
0
[this is a regular sentence]
1
[https:, , docs.python.org, 3, tutorial, index...
2
NaN
dtype: object

When using expand=True, the split elements will expand out into separate columns. If NaN is present, it is
propagated throughout the columns during the split.
>>> s.str.split(expand=True)
0
1
2

0
this
https://docs.python.org/3/tutorial/index.html
NaN

1
is
None
NaN

2
a
None
NaN

3
regular
None
NaN

4
sentence
None
NaN

For slightly more complex use cases like splitting the html document name from a url, a combination of parameter settings can be used.
>>> s.str.rsplit("/", n=1, expand=True)
0
1
0
this is a regular sentence
None
1 https://docs.python.org/3/tutorial index.html
2
NaN
NaN

Remember to escape special characters when explicitly using regular expressions.
>>> s = pd.Series(["1+1=2"])
>>> s
0
1+1=2
dtype: object
>>> s.str.split(r"\+|=", expand=True)
0
1
2
0
1
1
2

3.3. Series

1325


pandas.Series.str.rsplit

Series.str.rsplit (*args, **kwargs)

Split strings around given separator/delimiter.

Splits the string in the Series/Index from the end, at the specified delimiter string. Equivalent to str.rsplited().

Parameters

- **pat** [str, optional] String or regular expression to split on. If not specified, split on whitespace.
- **n** [int, default -1 (all)] Limit number of splits in output. None, 0 and -1 will be interpreted as return all splits.
- **expand** [bool, default False] Expand the split strings into separate columns.
  - If True, return DataFrame/MultiIndex expanding dimensionality.
  - If False, return Series/Index, containing lists of strings.

Returns

Series, Index, DataFrame or MultiIndex Type matches caller unless expand=True (see Notes).

See also:

- Series.str.split Split strings around given separator/delimiter.
- Series.str.rsplit Splits string around given separator/delimiter, starting from the right.
- Series.str.join Join lists contained as elements in the Series/Index with passed delimiter.
- str.split Standard library version for split.
- str.rsplit Standard library version for rsplit.

Notes

The handling of the n keyword depends on the number of found splits:
- If found splits > n, make first n splits only
- If found splits <= n, make all splits
- If for a certain row the number of found splits < n, append None for padding up to n if expand=True

If using expand=True, Series and Index callers return DataFrame and MultiIndex objects, respectively.

Examples

```python
>>> s = pd.Series(
...     [  
...         "this is a regular sentence",
...         "https://docs.python.org/3/tutorial/index.html",
...         np.nan
...     ]
... )
```

```python
>>> s
0 this is a regular sentence  
1 https://docs.python.org/3/tutorial/index.html  
2         NaN
```

dtype: object

In the default setting, the string is split by whitespace.
Without the \textit{n} parameter, the outputs of \textit{rsplit} and \textit{split} are identical.

The \textit{n} parameter can be used to limit the number of splits on the delimiter. The outputs of \textit{split} and \textit{rsplit} are different.

The \textit{pat} parameter can be used to split by other characters.

When using \texttt{expand=True}, the split elements will expand out into separate columns. If NaN is present, it is propagated throughout the columns during the split.

For slightly more complex use cases like splitting the html document name from a url, a combination of parameter settings can be used.

Remember to escape special characters when explicitly using regular expressions.
>>> s = pd.Series(["1+1=2"])  
>>> s  
0 1+1=2  
dtype: object  
>>> s.str.split(r"\+|=", expand=True)  
0 1 2  
1 1 2

### pandas.Series.str.startswith

Series.str.startswith(*args, **kwargs)  
Test if the start of each string element matches a pattern.

Equivalent to str.startswith().

Parameters

- **pat** [str] Character sequence. Regular expressions are not accepted.
- **na** [object, default NaN] Object shown if element tested is not a string.

Returns

Series or Index of bool A Series of booleans indicating whether the given pattern matches the start of each string element.

See also:

- [str.startswith](https://docs.python.org/3/library/stdtypes.html#str.startswith) Python standard library string method.

#### Examples

```python
>>> s = pd.Series(["bat", 'Bear', 'cat', np.nan])
```

```python
>>> s  
0 bat  
1 Bear  
2 cat  
3 NaN  
dtype: object
```

```python
>>> s.str.startswith('b')  
0 True  
1 False  
2 False  
3 NaN  
dtype: object
```

Specifying `na` to be `False` instead of `NaN`.

```python
>>> s.str.startswith('b', na=False)  
0 True  
1 False  
2 False  
3 False  
dtype: bool
```
**pandas.Series.str.strip**

```python
def str.strip(*args, **kwargs)
```

Remove leading and trailing characters.

Strip whitespaces (including newlines) or a set of specified characters from each string in the Series/Index from left and right sides. Equivalent to `str.strip()`.

**Parameters**

- `to_strip` [str or None, default None] Specifying the set of characters to be removed. All combinations of this set of characters will be stripped. If None then whitespaces are removed.

**Returns**

Series or Index of object

**See also:**

- `Series.str.strip` Remove leading and trailing characters in Series/Index.
- `Series.str.lstrip` Remove leading characters in Series/Index.
- `Series.str.rstrip` Remove trailing characters in Series/Index.

**Examples**

```python
>>> s = pd.Series(['1. Ant. ', '2. Bee!
', '3. Cat?	', np.nan])
>>> s
0    1. Ant.
1    2. Bee!
2    3. Cat?
3     NaN
dtype: object

>>> s.str.strip()
0    1. Ant.
1    2. Bee!
2    3. Cat?
3     NaN
dtype: object

>>> s.str.lstrip('123.')
0    Ant.
1    Bee!
2    Cat?
3     NaN
dtype: object

>>> s.str.rstrip('.!?\n\t')
0    1. Ant
1    2. Bee
2    3. Cat
3     NaN
dtype: object

>>> s.str.strip('123.?!\n\t')
0    Ant
(continues on next page)
pandas.Series.str.swapcase

Series.str.swapcase(*args, **kwargs)
Convert strings in the Series/Index to be swapcased.

Equivalent to str.swapcase().

Returns
Series or Index of object

See also:
Series.str.lower Converts all characters to lowercase.
Series.str.upper Converts all characters to uppercase.
Series.str.title Converts first character of each word to uppercase and remaining to lowercase.
Series.str.capitalize Converts first character to uppercase and remaining to lowercase.
Series.str.swapcase Converts uppercase to lowercase and lowercase to uppercase.
Series.str.casefold Removes all case distinctions in the string.

Examples

```python
>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])
>>> s
0        lower
1    CAPITALS
2  this is a sentence
3     SwApCaSe
dtype: object

>>> s.str.lower()
0        lower
1    capitals
2  this is a sentence
3     swapcase
dtype: object

>>> s.str.upper()
0     LOWER
1    CAPITALS
2  THIS IS A SENTENCE
3       SWAPCASE
dtype: object

>>> s.str.title()
0     Lower
1   Capitals
2  This Is A Sentence
3         Swapcase
dtype: object
```
pandas.Series.str.title

Series.str.title(*args, **kwargs)

Convert strings in the Series/Index to titlecase.

Equivalent to str.title().

Returns

Series or Index of object

See also:

Series.str.lower Converts all characters to lowercase.
Series.str.upper Converts all characters to uppercase.
Series.str.title Converts first character of each word to uppercase and remaining to lowercase.
Series.str.capitalize Converts first character to uppercase and remaining to lowercase.
Series.str.swapcase Converts uppercase to lowercase and lowercase to uppercase.
Series.str.casefold Removes all case distinctions in the string.

Examples

```python
>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])
>>> s
0    lower
1  CAPITALS
2  this is a sentence
3    SwApCaSe
dtype: object
```

```python
>>> s.str.lower()  
0    lower
1  capitals
2  this is a sentence
3    swapcase
dtype: object
```

```python
>>> s.str.upper()  
0    LOWER
1  CAPITALS
2  THIS IS A SENTENCE
```

(continues on next page)
3    SWAPCASE
   dtype: object

>>> s.str.title()
0       Lower
1      Capitals
2  This Is A Sentence
3      Swapcase
   dtype: object

>>> s.str.capitalize()
0       Lower
1      Capitals
2  This is a sentence
3      Swapcase
   dtype: object

>>> s.str.swapcase()
0       LOWER
1   capitals
2  THIS IS A SENTENCE
3   sWaPcAsE
   dtype: object

pandas.Series.str.translate

Series.str.translate(*args, **kwargs)
Map all characters in the string through the given mapping table.

Equivalent to standard str.translate().

Parameters
    table [dict] Table is a mapping of Unicode ordinals to Unicode ordinals, strings, or None. Unmapped characters are left untouched. Characters mapped to None are deleted. str.maketrans() is a helper function for making translation tables.

Returns
    Series or Index

pandas.Series.str.upper

Series.str.upper(*args, **kwargs)
Convert strings in the Series/Index to uppercase.

Equivalent to str.upper().

Returns
    Series or Index of object

See also:
    Series.str.lower Converts all characters to lowercase.
    Series.str.upper Converts all characters to uppercase.
    Series.str.title Converts first character of each word to uppercase and remaining to lowercase.
**Series.str.capitalize** Converts first character to uppercase and remaining to lowercase.
**Series.str.swapcase** Converts uppercase to lowercase and lowercase to uppercase.
**Series.str.casefold** Removes all case distinctions in the string.

### Examples

```python
>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])
>>> s
0  lower
1  CAPITALS
2  this is a sentence
3  SwApCaSe
dtype: object

>>> s.str.lower()  
0  lower
1  capitals
2  this is a sentence
3  swapcase
dtype: object

>>> s.str.upper()  
0  LOWER
1  CAPITALS
2  THIS IS A SENTENCE
3  SWAPCASE
dtype: object

>>> s.str.title()  
0  Lower
1  Capitals
2  This Is A Sentence
3  Swapcase
dtype: object

>>> s.str.capitalize()  
0  Lower
1  Capitals
2  This is a sentence
3  Swapcase
dtype: object

>>> s.str.swapcase()  
0  LOWER
1  capitals
2  THIS IS A SENTENCE
3  sWaPcAsE
dtype: object
```
pandas.Series.str.wrap

Series.str.wrap(*args, **kwargs)
Wrap strings in Series/Index at specified line width.
This method has the same keyword parameters and defaults as textwrap.TextWrapper.

Parameters

width [int] Maximum line width.
expand_tabs [bool, optional] If True, tab characters will be expanded to spaces (default: True).
replace_whitespace [bool, optional] If True, each whitespace character (as defined by string.whitespace) remaining after tab expansion will be replaced by a single space (default: True).
drop_whitespace [bool, optional] If True, whitespace that, after wrapping, happens to end up at the beginning or end of a line is dropped (default: True).
break_long_words [bool, optional] If True, then words longer than width will be broken in order to ensure that no lines are longer than width. If it is false, long words will not be broken, and some lines may be longer than width (default: True).
break_on_hyphens [bool, optional] If True, wrapping will occur preferably on whitespace and right after hyphens in compound words, as it is customary in English. If false, only whitespaces will be considered as potentially good places for line breaks, but you need to set break_long_words to false if you want truly inseparable words (default: True).

Returns

Series or Index

Notes

Internally, this method uses a textwrap.TextWrapper instance with default settings. To achieve behavior matching R’s stringr library str_wrap function, use the arguments:

- expand_tabs = False
- replace_whitespace = True
- drop_whitespace = True
- break_long_words = False
- break_on_hyphens = False

Examples

```python
>>> s = pd.Series(['line to be wrapped', 'another line to be wrapped'])
>>> s.str.wrap(12)
0    line to be\n     wrapped
1    another line\n     to be\n     wrapped
dtype: object
```
### pandas.Series.str.zfill

**Series.str.zfill(*args, **kwargs)**

Pad strings in the Series/Index by prepending ‘0’ characters.

Strings in the Series/Index are padded with ‘0’ characters on the left of the string to reach a total string length `width`. Strings in the Series/Index with length greater or equal to `width` are unchanged.

**Parameters**

- `width` [int] Minimum length of resulting string; strings with length less than `width` be prepended with ‘0’ characters.

**Returns**

Series/Index of objects.

**See also:**

- `Series.str.rjust` Fills the left side of strings with an arbitrary character.
- `Series.str.ljust` Fills the right side of strings with an arbitrary character.
- `Series.str.pad` Fills the specified sides of strings with an arbitrary character.
- `Series.str.center` Fills both sides of strings with an arbitrary character.

**Notes**

Differs from `str.zfill()` which has special handling for ‘+/−’ in the string.

**Examples**

```python
>>> s = pd.Series(['-1', '1', '1000', 10, np.nan])
>>> s
0   -1
1    1
2  1000
3    10
4   NaN
dtype: object
```

Note that 10 and NaN are not strings, therefore they are converted to NaN. The minus sign in ‘−1’ is treated as a regular character and the zero is added to the left of it (`str.zfill()` would have moved it to the left). 1000 remains unchanged as it is longer than `width`.

```python
>>> s.str.zfill(3)
0   0-1
1   001
2  1000
3   NaN
4   NaN
dtype: object
```
pandas.Series.str.isalnum

Series.str.isalnum(*args, **kwargs)
Check whether all characters in each string are alphanumeric.
This is equivalent to running the Python string method str.isalnum() for each element of the Series/Index. If a string has zero characters, False is returned for that check.

Returns
Series or Index of bool Series or Index of boolean values with the same length as the original Series/Index.

See also:
Series.str.isalpha Check whether all characters are alphabetic.
Series.str.isnumeric Check whether all characters are numeric.
Series.str.isalnum Check whether all characters are alphanumeric.
Series.str.isdigit Check whether all characters are digits.
Series.str.isdecimal Check whether all characters are decimal.
Series.str.isspace Check whether all characters are whitespace.
Series.str.islower Check whether all characters are lowercase.
Series.str.isupper Check whether all characters are uppercase.
Series.str.istitle Check whether all characters are titlecase.

Examples

Checks for Alphabetic and Numeric Characters

```python
>>> s1 = pd.Series(['one', 'one1', '1', ''])

>>> s1.str.isalpha()
0   True
1  False
2  False
3  False
dtype: bool

>>> s1.str.isnumeric()
0  False
1  False
2   True
3  False
dtype: bool

>>> s1.str.isalnum()
0   True
1   True
2   True
3  False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```python
>>> s2 = pd.Series(['A B', '1.5', '3,000'])
>>> s2.str.isalnum()
```
(continues on next page)
More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```python
>>> s3 = pd.Series(['23', '3', '', ''])
```

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```python
>>> s3.str.isdecimal()
0    True
1    False
2    False
3    False
dtype: bool
```

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```python
>>> s3.str.isdigit()
0    True
1    True
2    False
3    False
dtype: bool
```

The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```python
>>> s3.str.isnumeric()
0    True
1    True
2    True
3    False
dtype: bool
```

Checks for Whitespace

```python
>>> s4 = pd.Series([' ', '	\r\n ', ''])
```  

```python
>>> s4.str.isspace()
0    True
1    True
2    False
dtype: bool
```

Checks for Character Case

```python
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
```  

```python
>>> s5.str.islower()
0    True
1    False
```

(continues on next page)
The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```python
>>> s5.str.istitle()
0    False
1      True
2    False
3    False
dtype: bool
```

**pandas.Series.str.isalpha**

`Series.str.isalpha(*args, **kwargs)`

Check whether all characters in each string are alphabetic.

This is equivalent to running the Python string method `str.isalpha()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.

**Returns**

Series or Index of bool Series or Index of boolean values with the same length as the original Series/Index.

**See also:**

- `Series.str.isalpha` Check whether all characters are alphabetic.
- `Series.str.isnumeric` Check whether all characters are numeric.
- `Series.str.isalnum` Check whether all characters are alphanumeric.
- `Series.str.isdigit` Check whether all characters are digits.
- `Series.str.isdecimal` Check whether all characters are decimal.
- `Series.str.isspace` Check whether all characters are whitespace.
- `Series.str.islower` Check whether all characters are lowercase.
- `Series.str.isupper` Check whether all characters are uppercase.
- `Series.str.istitle` Check whether all characters are titlecase.
Examples

Checks for Alphabetic and Numeric Characters

```python
g1 = pd.Series(['one', 'one1', '1', ''])
```

```python
>>> g1.str.isalpha()
0    True
1   False
2   False
3   False
dtype: bool
```

```python
>>> g1.str.isnumeric()
0   False
1   False
2    True
3   False
dtype: bool
```

```python
>>> g1.str.isalnum()
0    True
1    True
2    True
3   False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```python
g2 = pd.Series(['A B', '1.5', '3,000'])
```

```python
>>> g2.str.isalnum()
0  False
1  False
2  False
dtype: bool
```

More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```python
g3 = pd.Series(['23', '3', '', ''])
```

The `g3.str.isdecimal` method checks for characters used to form numbers in base 10.

```python
>>> g3.str.isdecimal()
0    True
1   False
2   False
3   False
dtype: bool
```

The `g3.str.isdigit` method is the same as `g3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```python
>>> g3.str.isdigit()
0    True
```

(continues on next page)
The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```python
>>> s3.str.isnumeric()
dtype: bool
```

Checks for Whitespace

```python
>>> s4 = pd.Series([' ', '	\r\n ', ''])
>>> s4.str.isspace()
daatype: bool
```

Checks for Character Case

```python
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
>>> s5.str.islower()
daype: bool
```

```python
>>> s5.str.isupper()
daype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```python
>>> s5.str.istitle()
daype: bool
```
pandas.Series.str.isdigit

Series.str.isdigit(*args, **kwargs)
Check whether all characters in each string are digits.

This is equivalent to running the Python string method `str.isdigit()` for each element of the Series/Index. If a string has zero characters, False is returned for that check.

Returns

Series or Index of bool Series or Index of boolean values with the same length as the original Series/Index.

See also:

Series.str.isalpha Check whether all characters are alphabetic.
Series.str.isnumeric Check whether all characters are numeric.
Series.str.isalnum Check whether all characters are alphanumeric.
Series.str.isdigit Check whether all characters are digits.
Series.str.isdecimal Check whether all characters are decimal.
Series.str.isspace Check whether all characters are whitespace.
Series.str.islower Check whether all characters are lowercase.
Series.str.isupper Check whether all characters are uppercase.
Series.str.istitle Check whether all characters are titlecase.

Examples

Checks for Alphabetic and Numeric Characters

>>> s1 = pd.Series(['one', 'one1', '1', ''])

>>> s1.str.isalpha()
0    True
1   False
2   False
3   False
dtype: bool

>>> s1.str.isnumeric()
0   False
1   False
2    True
3   False
dtype: bool

>>> s1.str.isalnum()
0    True
1    True
2    True
3   False
dtype: bool

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

>>> s2 = pd.Series(['A B', '1.5', '3,000'])

>>> s2.str.isalnum()
(continues on next page)
More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```python
s3 = pd.Series(['23', '³', '', ''])
```

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```python
s3.str.isdecimal()
```

0    True
1    False
2    False
3    False
dtype: bool

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```python
s3.str.isdigit()
```

0    True
1    True
2    False
3    False
dtype: bool

The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```python
s3.str.isnumeric()
```

0    True
1    True
2    True
3    False
dtype: bool

Checks for Whitespace

```python
s4 = pd.Series([' ', '	\r\n', ''])
```

```python
s4.str.isspace()
```

0    True
1    True
2    False
dtype: bool

Checks for Character Case

```python
s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
```

```python
s5.str.islower()
```

0    True
1    False
The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```python
>>> s5.str.istitle()
0    False
1     True
2    False
3    False
dtype: bool
```

### pandas.Series.str.isspace

**Series.str.isspace(***args, **kwargs**

Check whether all characters in each string are whitespace.

This is equivalent to running the Python string method `str.isspace()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.

**Returns**

Series or Index of bool Series or Index of boolean values with the same length as the original Series/Index.

**See also:**

- `Series.str.isalpha` Check whether all characters are alphabetic.
- `Series.str.isnumeric` Check whether all characters are numeric.
- `Series.str.isalnum` Check whether all characters are alphanumeric.
- `Series.str.isdigit` Check whether all characters are digits.
- `Series.str.isdecimal` Check whether all characters are decimal.
- `Series.str.isspace` Check whether all characters are whitespace.
- `Series.str.islower` Check whether all characters are lowercase.
- `Series.str.isupper` Check whether all characters are uppercase.
- `Series.str.istitle` Check whether all characters are titlecase.
Examples

Checks for Alphabetic and Numeric Characters

```python
>>> s1 = pd.Series(['one', 'one1', '1', ''])

>>> s1.str.isalpha()
0   True
1  False
2  False
3  False
dtype: bool

>>> s1.str.isnumeric()
0   False
1  False
2   True
3  False
dtype: bool

>>> s1.str.isalnum()
0   True
1   True
2   True
3  False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```python
>>> s2 = pd.Series(['A B', '1.5', '3,000'])

>>> s2.str.isalnum()
0  False
1  False
2  False
dtype: bool
```

More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```python
>>> s3 = pd.Series(['23', '²', '', ''])

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```python
>>> s3.str.isdecimal()
0   True
1  False
2  False
3  False
dtype: bool
```

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```python
>>> s3.str.isdigit()
0   True
```

(continues on next page)
The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```python
>>> s3.str.isnumeric()
0    True
1    True
2    True
3    False
dtype: bool
```

Checks for Whitespace

```python
>>> s4 = pd.Series([' ', '	\n ', ''])
>>> s4.str.isspace()
0    True
1    True
2    False
dtype: bool
```

Checks for Character Case

```python
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])

>>> s5.str.islower()
0    True
1    False
2    False
3    False
dtype: bool

>>> s5.str.isupper()
0    False
1    False
2    True
3    False
dtype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```python
>>> s5.str.istitle()
0    False
1    True
2    False
3    False
dtype: bool
```
**pandas.Series.str.islower**

Series.str.islower(*args, **kwargs)

Check whether all characters in each string are lowercase.

This is equivalent to running the Python string method `str.islower()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.

**Returns**

Series or Index of bool  
Series or Index of boolean values with the same length as the original Series/Index.

**See also:**

- `Series.str.isalpha` Check whether all characters are alphabetic.
- `Series.str.isnumeric` Check whether all characters are numeric.
- `Series.str.isalnum` Check whether all characters are alphanumeric.
- `Series.str.isdigit` Check whether all characters are digits.
- `Series.str.isdecimal` Check whether all characters are decimal.
- `Series.str.isspace` Check whether all characters are whitespace.
- `Series.str.islower` Check whether all characters are lowercase.
- `Series.str.isupper` Check whether all characters are uppercase.
- `Series.str.istitle` Check whether all characters are titlecase.

**Examples**

**Checks for Alphabetic and Numeric Characters**

```python
>>> s1 = pd.Series(['one', 'one1', '1', ''])

>>> s1.str.isalpha()
0   True
1   False
2   False
3   False
dtype: bool

>>> s1.str.isnumeric()
0   False
1   False
2   True
3   False
dtype: bool

>>> s1.str.isalnum()
0   True
1   True
2   True
3   False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```python
>>> s2 = pd.Series(['A B', '1.5', '3,000'])

>>> s2.str.isalnum()
0   False
1   False
2   False
```

(continues on next page)
More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```python
>>> s3 = pd.Series(['23', '3', '', ''])
```

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```python
>>> s3.str.isdecimal()
0    True
1    False
2    False
3    False
dtype: bool
```

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```python
>>> s3.str.isdigit()
0    True
1    True
2    False
3    False
dtype: bool
```

The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```python
>>> s3.str.isnumeric()
0    True
1    True
2    True
3    False
dtype: bool
```

Checks for Whitespace

```python
>>> s4 = pd.Series([' ', '	\n ', ''])
>>> s4.str.isspace()
0    True
1    True
2    False
dtype: bool
```

Checks for Character Case

```python
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
>>> s5.str.islower()
0    True
1    False
```

(continues on next page)
2    False
3    False
dtype: bool

```python
>>> s5.str.isupper()
0    False
1    False
2    True
3    False
dtype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```python
>>> s5.str.istitle()
0    False
1    True
2    False
3    False
dtype: bool
```

### pandas.Series.str.isupper

`Series.str.isupper(*args, **kwargs)`

Check whether all characters in each string are uppercase.

This is equivalent to running the Python string method `str.isupper()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.

**Returns**

Series or Index of bool  Series or Index of boolean values with the same length as the original Series/Index.

**See also:**

- `Series.str.isalpha`  Check whether all characters are alphabetic.
- `Series.str.isnumeric`  Check whether all characters are numeric.
- `Series.str.isalnum`  Check whether all characters are alphanumeric.
- `Series.str.isdigit`  Check whether all characters are digits.
- `Series.str.isdecimal`  Check whether all characters are decimal.
- `Series.str.isspace`  Check whether all characters are whitespace.
- `Series.str.islower`  Check whether all characters are lowercase.
- `Series.str.isupper`  Check whether all characters are uppercase.
- `Series.str.istitle`  Check whether all characters are titlecase.
Examples

Checks for Alphabetic and Numeric Characters

```python
>>> s1 = pd.Series(['one', 'one1', '1', ''])

>>> s1.str.isalpha()
0    True
1    False
2    False
3    False
dtype: bool

>>> s1.str.isnumeric()
0    False
1    False
2    True
3    False
dtype: bool

>>> s1.str.isalnum()
0    True
1    True
2    True
3    False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumerical check.

```python
>>> s2 = pd.Series(['A B', '1.5', '3,000'])

>>> s2.str.isalnum()
0    False
1    False
2    False
dtype: bool
```

More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```python
>>> s3 = pd.Series(['23', '3', '', ''])

The s3.str.isdecimal method checks for characters used to form numbers in base 10.

```python
>>> s3.str.isdecimal()
0    True
1    False
2    False
3    False
dtype: bool
```

The s.str.isdigit method is the same as s3.str.isdecimal but also includes special digits, like superscripted and subscripted digits in unicode.

```python
>>> s3.str.isdigit()
0    True
```
The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```python
>>> s3.str.isnumeric()
0    True
1    True
2    True
3    False
dtype: bool
```

### Checks for Whitespace

```python
>>> s4 = pd.Series([' ', '	\n ', ''])
>>> s4.str.isspace()
0    True
1    True
2    False
dtype: bool
```

### Checks for Character Case

```python
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
>>> s5.str.islower()
0    True
1    False
2    False
3    False
dtype: bool
```

```python
>>> s5.str.isupper()
0    False
1    False
2    True
3    False
dtype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```python
>>> s5.str.istitle()
0    False
1    True
2    False
3    False
dtype: bool
```
pandas.Series.str.istitle

Series.str.istitle(*args, **kwargs)
Check whether all characters in each string are titlecase.

This is equivalent to running the Python string method str.istitle() for each element of the Series/Index. If a string has zero characters, False is returned for that check.

Returns

Series or Index of bool Series or Index of boolean values with the same length as the original Series/Index.

See also:

Series.str.isalpha Check whether all characters are alphabetic.
Series.str.isnumeric Check whether all characters are numeric.
Series.str.isalnum Check whether all characters are alphanumeric.
Series.str.isdigit Check whether all characters are digits.
Series.str.isdecimal Check whether all characters are decimal.
Series.str.isspace Check whether all characters are whitespace.
Series.str.islower Check whether all characters are lowercase.
Series.str.isupper Check whether all characters are uppercase.
Series.str.istitle Check whether all characters are titlecase.

Examples

Checks for Alphabetic and Numeric Characters

```python
>>> s1 = pd.Series(['one', 'one1', '1', ''])

>>> s1.str.isalpha()
0   True
1  False
2  False
3  False
   dtype: bool

>>> s1.str.isnumeric()
0  False
1  False
2   True
3  False
   dtype: bool

>>> s1.str.isalnum()
0   True
1   True
2   True
3  False
   dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```python
>>> s2 = pd.Series(['A B', '1.5', '3,000'])

>>> s2.str.isalnum()
(continues on next page)"
More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```python
>>> s3 = pd.Series(['23', '3', '', ''])
```

The `s.str.isdecimal` method checks for characters used to form numbers in base 10.

```python
>>> s3.str.isdecimal()
0    True
1    False
2    False
3    False
dtype: bool
```

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```python
>>> s3.str.isdigit()
0    True
1    True
2    False
3    False
dtype: bool
```

The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```python
>>> s3.str.isnumeric()
0    True
1    True
2    True
3    False
dtype: bool
```

Checks for Whitespace

```python
>>> s4 = pd.Series([' ', '	\r\n ', ''])
>>> s4.str.isspace()
0    True
1    True
2    False
dtype: bool
```

Checks for Character Case

```python
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
>>> s5.str.islower()
0    True
1    False
```

(continues on next page)
s5.str.isupper()
0 False
1 False
2 True
3 False
dtype: bool

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be any sequence of non-numeric characters separated by whitespace characters.

s5.str.istitle()
0 False
1 True
2 False
3 False
dtype: bool

**pandas.Series.str.isnumeric**

`Series.str.isnumeric(*args, **kwargs)`

Check whether all characters in each string are numeric.

This is equivalent to running the Python string method `str.isnumeric()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.

**Returns**

Series or Index of boolean values with the same length as the original Series/Index.

**See also:**

- `Series.str.isalpha`: Check whether all characters are alphabetic.
- `Series.str.isnumeric`: Check whether all characters are numeric.
- `Series.str.isalnum`: Check whether all characters are alphanumeric.
- `Series.str.isdigit`: Check whether all characters are digits.
- `Series.str.isdecimal`: Check whether all characters are decimal.
- `Series.str.isspace`: Check whether all characters are whitespace.
- `Series.str.islower`: Check whether all characters are lowercase.
- `Series.str.isupper`: Check whether all characters are uppercase.
- `Series.str.istitle`: Check whether all characters are titlecase.
Examples

Checks for Alphabetic and Numeric Characters

```python
>>> s1 = pd.Series(['one', 'one1', '1', ''])
>>> s1.str.isalpha()
0    True
1   False
2   False
3   False
dtype: bool

>>> s1.str.isnumeric()
0   False
1   False
2    True
3   False
dtype: bool

>>> s1.str.isalnum()
0    True
1    True
2    True
3   False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```python
>>> s2 = pd.Series(['A B', '1.5', '3,000'])
>>> s2.str.isalnum()
0   False
1   False
2   False
dtype: bool
```

More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```python
>>> s3 = pd.Series(['23', '3', '', ''])
The s3.str.isdecimal method checks for characters used to form numbers in base 10.

```python
>>> s3.str.isdecimal()
0    True
1   False
2   False
3   False
dtype: bool
```

The s.str.isdigit method is the same as s3.str.isdecimal but also includes special digits, like superscripted and subscripted digits in unicode.

```python
>>> s3.str.isdigit()
0    True
```
The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```python
>>> s3.str.isnumeric()
0    True
1    True
2    True
3    False
dtype: bool
```

Checks for Whitespace

```python
>>> s4 = pd.Series([' ', '	\n ', ''])
>>> s4.str.isspace()
0    True
1    True
2    False
dtype: bool
```

Checks for Character Case

```python
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
```

```python
>>> s5.str.islower()
0    True
1    False
2    False
3    False
dtype: bool
```

```python
>>> s5.str.isupper()
0    False
1    False
2    True
3    False
dtype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```python
>>> s5.str.istitle()
0    False
1    True
2    False
3    False
dtype: bool
```
pandas.Series.str.isdecimal

Series.str.isdecimal(*args, **kwargs)
    Check whether all characters in each string are decimal.
    This is equivalent to running the Python string method str.isdecimal() for each element of the Series/Index. If a string has zero characters, False is returned for that check.

    Returns
    Series or Index of bool Series or Index of boolean values with the same length as the original Series/Index.

See also:
    Series.str.isalpha Check whether all characters are alphabetic.
    Series.str.isnumeric Check whether all characters are numeric.
    Series.str.isalnum Check whether all characters are alphanumeric.
    Series.str.isdigit Check whether all characters are digits.
    Series.str.isdecimal Check whether all characters are decimal.
    Series.str.isspace Check whether all characters are whitespace.
    Series.str.islower Check whether all characters are lowercase.
    Series.str.isupper Check whether all characters are uppercase.
    Series.str.istitle Check whether all characters are titlecase.

Examples

Checks for Alphabetic and Numeric Characters

>>> s1 = pd.Series(['one', 'one1', '1', ''])

>>> s1.str.isalpha()
0    True
1   False
2   False
3   False
dtype: bool

>>> s1.str.isnumeric()
0   False
1   False
2    True
3   False
dtype: bool

>>> s1.str.isalnum()
0    True
1    True
2    True
3   False
dtype: bool

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

>>> s2 = pd.Series(['A B', '1.5', '3,000'])
>>> s2.str.isalnum()
0    False
1    False
2    False
... (continues on next page)
More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```python
>>> s3 = pd.Series(['23', '3', '', ''])

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```python
>>> s3.str.isdecimal()
0   True
1   False
2   False
3   False
dtype: bool
```

The `s3.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```python
>>> s3.str.isdigit()
0   True
1   True
2   False
3   False
dtype: bool
```

The `s3.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```python
>>> s3.str.isnumeric()
0   True
1   True
2   True
3   False
dtype: bool
```

Checks for Whitespace

```python
>>> s4 = pd.Series([' ', '	\n ', ''])
>>> s4.str.isspace()
0   True
1   True
2   False
dtype: bool
```

Checks for Character Case

```python
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])

```python
>>> s5.str.islower()
0   True
1   False
dtype: bool
```
The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```python
>>> s5.str.istitle()
0   False
1    True
2   False
3   False
dtype: bool
```

### pandas.Series.str.get_dummies

`Series.str.get_dummies(*args, **kwargs)`

Return DataFrame of dummy/indicator variables for Series.

Each string in Series is split by sep and returned as a DataFrame of dummy/indicator variables.

**Parameters**

- `sep` [str, default “|”] String to split on.

**Returns**

DataFrame Dummy variables corresponding to values of the Series.

**See also:**

- `get_dummies` Convert categorical variable into dummy/indicator variables.

**Examples**

```python
>>> pd.Series(['a|b', 'a', 'a|c']).str.get_dummies()
   a  b  c
0  1  1  0
1  1  0  0
2  1  0  1

>>> pd.Series(['a|b', np.nan, 'a|c']).str.get_dummies()
   a  b  c
0  1  1  0
1  0  0  0
2  1  0  1
```
Categorical accessor

Categorical-dtype specific methods and attributes are available under the `Series.cat` accessor.

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Series.cat.categories</code></td>
<td>The categories of this categorical.</td>
</tr>
<tr>
<td><code>Series.cat.ordered</code></td>
<td>Whether the categories have an ordered relationship.</td>
</tr>
<tr>
<td><code>Series.cat.codes</code></td>
<td>Return Series of codes as well as the index.</td>
</tr>
</tbody>
</table>

**pandas.Series.cat.categories**

The categories of this categorical.

Setting assigns new values to each category (effectively a rename of each individual category).

The assigned value has to be a list-like object. All items must be unique and the number of items in the new categories must be the same as the number of items in the old categories.

Assigning to `categories` is an inplace operation!

**Raises**

- `ValueError` If the new categories do not validate as categories or if the number of new categories is unequal the number of old categories

**See also:**

- `rename_categories` Rename categories.
- `reorder_categories` Reorder categories.
- `add_categories` Add new categories.
- `remove_categories` Remove the specified categories.
- `remove_unused_categories` Remove categories which are not used.
- `set_categories` Set the categories to the specified ones.

**pandas.Series.cat.ordered**

Whether the categories have an ordered relationship.

**pandas.Series.cat.codes**

Return Series of codes as well as the index.

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Series.cat.rename_categories</code></td>
<td>Rename categories.</td>
</tr>
<tr>
<td><code>Series.cat.reorder_categories</code></td>
<td>Reorder categories as specified in new_categories.</td>
</tr>
<tr>
<td><code>Series.cat.add_categories</code></td>
<td>Add new categories.</td>
</tr>
<tr>
<td><code>Series.cat.remove_categories</code></td>
<td>Remove the specified categories.</td>
</tr>
<tr>
<td><code>Series.cat.remove_unused_categories</code></td>
<td>Remove categories which are not used.</td>
</tr>
</tbody>
</table>

continues on next page
pandas: powerful Python data analysis toolkit, Release 1.1.1

Table 49 – continued from previous page

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.cat.set_categories(*args, **kwargs)</td>
<td>Set the categories to the specified new_categories.</td>
</tr>
<tr>
<td>Series.cat.as_ordered(*args, **kwargs)</td>
<td>Set the Categorical to be ordered.</td>
</tr>
<tr>
<td>Series.cat.as_unordered(*args, **kwargs)</td>
<td>Set the Categorical to be unordered.</td>
</tr>
</tbody>
</table>

**pandas.Series.cat.rename_categories**

Series.cat.rename_categories(*args, **kwargs)

Rename categories.

Parameters

  new_categories [list-like, dict-like or callable] New categories which will replace old categories.
    - list-like: all items must be unique and the number of items in the new categories must match the existing number of categories.
    - dict-like: specifies a mapping from old categories to new. Categories not contained in the mapping are passed through and extra categories in the mapping are ignored.
    - callable : a callable that is called on all items in the old categories and whose return values comprise the new categories.

  inplace [bool, default False] Whether or not to rename the categories inplace or return a copy of this categorical with renamed categories.

Returns

  cat [Categorical or None] With inplace=False, the new categorical is returned. With inplace=True, there is no return value.

Raises

  ValueError If new categories are list-like and do not have the same number of items than the current categories or do not validate as categories

See also:

  reorder_categories Reorder categories.
  add_categories Add new categories.
  remove_categories Remove the specified categories.
  remove_unused_categories Remove categories which are not used.
  set_categories Set the categories to the specified ones.

Examples

```python
>>> c = pd.Categorical(['a', 'a', 'b'])
>>> c.rename_categories([0, 1])
[0, 0, 1]
Categories (2, int64): [0, 1]
```

For dict-like new_categories, extra keys are ignored and categories not in the dictionary are passed through

```python
>>> c.rename_categories({'a': 'A', 'c': 'C'})
['A', 'A', 'b']
Categories (2, object): ['A', 'b']
```
You may also provide a callable to create the new categories

```python
>>> c.rename_categories(lambda x: x.upper())
['A', 'A', 'B']
Categories (2, object): ['A', 'B']
```

### pandas.Series.cat.reorder_categories

`Series.cat.reorder_categories(*args, **kwargs)`

Reorder categories as specified in new_categories.

- **new_categories** need to include all old categories and no new category items.

**Parameters**

- **new_categories** [Index-like] The categories in new order.
- **ordered** [bool, optional] Whether or not the categorical is treated as a ordered categorical.
  If not given, do not change the ordered information.
- **inplace** [bool, default False] Whether or not to reorder the categories inplace or return a copy of this categorical with reordered categories.

**Returns**

- **cat** [Categorical with reordered categories or None if inplace.]

**Raises**

- **ValueError** If the new categories do not contain all old category items or any new ones.

See also:

- **rename_categories** Rename categories.
- **add_categories** Add new categories.
- **remove_categories** Remove the specified categories.
- **remove_unused_categories** Remove categories which are not used.
- **set_categories** Set the categories to the specified ones.

### pandas.Series.cat.add_categories

`Series.cat.add_categories(*args, **kwargs)`

Add new categories.

- **new_categories** will be included at the last/highest place in the categories and will be unused directly after this call.

**Parameters**

- **new_categories** [category or list-like of category] The new categories to be included.
- **inplace** [bool, default False] Whether or not to add the categories inplace or return a copy of this categorical with added categories.

**Returns**

- **cat** [Categorical with new categories added or None if inplace.]

**Raises**

- **ValueError** If the new categories include old categories or do not validate as categories.

See also:
rename_categories Rename categories.
reorder_categories Reorder categories.
remove_categories Remove the specified categories.
remove_unused_categories Remove categories which are not used.
set_categories Set the categories to the specified ones.

pandas.Series.cat.remove_categories

Series.cat.remove_categories(*args, **kwargs)
Remove the specified categories.

removals must be included in the old categories. Values which were in the removed categories will be set to NaN.

Parameters

removals [category or list of categories] The categories which should be removed.
inplace [bool, default False] Whether or not to remove the categories inplace or return a copy of this categorical with removed categories.

Returns

cat [Categorical with removed categories or None if inplace.]

Raises

ValueError If the removals are not contained in the categories

See also:

rename_categories Rename categories.
reorder_categories Reorder categories.
add_categories Add new categories.
remove_unused_categories Remove categories which are not used.
set_categories Set the categories to the specified ones.

pandas.Series.cat.remove_unused_categories

Series.cat.remove_unused_categories(*args, **kwargs)
Remove categories which are not used.

Parameters

inplace [bool, default False] Whether or not to drop unused categories inplace or return a copy of this categorical with unused categories dropped.

Returns

cat [Categorical with unused categories dropped or None if inplace.]

See also:

rename_categories Rename categories.
reorder_categories Reorder categories.
add_categories Add new categories.
remove_categories Remove the specified categories.
set_categories Set the categories to the specified ones.
pandas.Series.cat.set_categories

Series.cat.set_categories(*args, **kwargs)
Set the categories to the specified new_categories.

new_categories can include new categories (which will result in unused categories) or remove old categories (which results in values set to NaN). If rename==True, the categories will simple be renamed (less or more items than in old categories will result in values set to NaN or in unused categories respectively).

This method can be used to perform more than one action of adding, removing, and reordering simultaneously and is therefore faster than performing the individual steps via the more specialised methods.

On the other hand this methods does not do checks (e.g., whether the old categories are included in the new categories on a reorder), which can result in surprising changes, for example when using special string dtypes, which does not considers a S1 string equal to a single char python string.

Parameters

- new_categories [Index-like] The categories in new order.
- ordered [bool, default False] Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.
- rename [bool, default False] Whether or not the new_categories should be considered as a rename of the old categories or as reordered categories.
- inplace [bool, default False] Whether or not to reorder the categories in-place or return a copy of this categorical with reordered categories.

Returns

Categorical with reordered categories or None if inplace.

Raises

ValueError If new_categories does not validate as categories

See also:

rename_categories Rename categories.
reorder_categories Reorder categories.
add_categories Add new categories.
remove_categories Remove the specified categories.
remove_unused_categories Remove categories which are not used.

pandas.Series.cat.as_ordered

Series.cat.as_ordered(*args, **kwargs)
Set the Categorical to be ordered.

Parameters

- inplace [bool, default False] Whether or not to set the ordered attribute in-place or return a copy of this categorical with ordered set to True.

Returns

Categorical Ordered Categorical.
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.Series.cat.as_unordered

Series.cat.as_unordered(*args, **kwargs)
Set the Categorical to be unordered.

Parameters
inplace [bool, default False] Whether or not to set the ordered attribute in-place or return a copy of this categorical with ordered set to False.

Returns
Categorical Unordered Categorical.

Sparse accessor

Sparse-dtype specific methods and attributes are provided under the Series.sparse accessor.

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.sparse.npoints</td>
<td>The number of non-fill_value points.</td>
</tr>
<tr>
<td>Series.sparse.density</td>
<td>The percent of non-fill_value points, as decimal.</td>
</tr>
<tr>
<td>Series.sparse.fill_value</td>
<td>Elements in data that are fill_value are not stored.</td>
</tr>
<tr>
<td>Series.sparse.sp_values</td>
<td>An ndarray containing the non-fill_value values.</td>
</tr>
</tbody>
</table>

pandas.Series.sparse.npoints

Series.sparse.npoints
The number of non-fill_value points.

Examples

```python
>>> s = SparseArray([0, 0, 1, 1, 1], fill_value=0)
>>> s.npoints
3
```

pandas.Series.sparse.density

Series.sparse.density
The percent of non-fill_value points, as decimal.

Examples

```python
>>> s = SparseArray([0, 0, 1, 1, 1], fill_value=0)
>>> s.density
0.6
```
**pandas.Series.sparse.fill_value**

Series.sparse.fill_value

Elements in data that are fill_value are not stored.

For memory savings, this should be the most common value in the array.

**pandas.Series.sparse.sp_values**

Series.sparse.sp_values

An ndarray containing the non-fill_value values.

**Examples**

```python
>>> s = SparseArray([0, 0, 1, 0, 2], fill_value=0)
>>> s.sp_values
array([1, 2])
```

**Series.sparse.from_coo(A, dense_index=False)**

Create a Series with sparse values from a scipy.sparse.coo_matrix.

**Parameters**

- **A** [scipy.sparse.coo_matrix]
- **dense_index** [bool, default False] If False (default), the SparseSeries index consists of only the coords of the non-null entries of the original coo_matrix. If True, the SparseSeries index consists of the full sorted (row, col) coordinates of the coo_matrix.

**Returns**

- **s** [Series] A Series with sparse values.

**Examples**

```python
>>> from scipy import sparse

>>> A = sparse.coo_matrix(
...     ([3.0, 1.0, 2.0], ([1, 0, 0], [0, 2, 3])), shape=(3, 4)
... )
>>> A
<3x4 sparse matrix of type '<class 'numpy.float64'>'>
with 3 stored elements in COOrdinate format>
```
```python
>>> A.todense()
matrix([[0., 0., 1., 2.],
        [3., 0., 0., 0.],
        [0., 0., 0., 0.]])
```

```python
>>> ss = pd.Series.sparse.from_coo(A)
>>> ss
0  2  1.0
  3  2.0
1  0  3.0
dtype: Sparse[float64, nan]
```

### `pandas.Series.sparse.to_coo`

`Series.sparse.to_coo(row_levels=0, column_levels=1, sort_labels=False)`

Create a scipy.sparse.coo_matrix from a Series with MultiIndex.

Use `row_levels` and `column_levels` to determine the row and column coordinates respectively. `row_levels` and `column_levels` are the names (labels) or numbers of the levels. `{row_levels, column_levels}` must be a partition of the MultiIndex level names (or numbers).

**Parameters**

- `row_levels` [tuple/list]
- `column_levels` [tuple/list]
- `sort_labels` [bool, default False] Sort the row and column labels before forming the sparse matrix.

**Returns**

- `y` [scipy.sparse.coo_matrix]
- `rows` [list (row labels)]
- `columns` [list (column labels)]

**Examples**

```python
>>> s = pd.Series([3.0, np.nan, 1.0, 3.0, np.nan, np.nan])
>>> s.index = pd.MultiIndex.from_tuples(...
...   [ ...
...     (1, 2, "a", 0),
...     (1, 2, "a", 1),
...     (1, 1, "b", 0),
...     (1, 1, "b", 1),
...     (2, 1, "b", 0),
...     (2, 1, "b", 1)
...   ],
...   names=["A", "B", "C", "D"],
... )
>>> s
A  B  C  D
1  2  a  0  3.0
   1  NaN
   1  b  0  1.0
(continues on next page)
```
1 3.0
2 1 b 0 NaN
   1 NaN
dtype: float64

>>> ss = s.astype("Sparse")
>>> ss
A   B   C   D
1  2 a  0  3.0
   1   NaN
1 b  0  1.0
   1   NaN
2  1 b  0  NaN
   1   NaN
dtype: Sparse[float64, nan]

>>> A, rows, columns = ss.sparse.to_coo(
...   row_levels=["A", "B"], column_levels=["C", "D"], sort_labels=True
...)

>>> A
<3x4 sparse matrix of type '<class 'numpy.float64'>'
with 3 stored elements in COOrdinate format>

>>> A.todense()
matrix([[0., 0., 1., 3.],
        [3., 0., 0., 0.],
        [0., 0., 0., 0.]])

>>> rows
[(1, 1), (1, 2), (2, 1)]

>>> columns
[('a', 0), ('a', 1), ('b', 0), ('b', 1)]

**Metadata**

*Series.attrs* is a dictionary for storing global metadata for this Series.

**Warning:** *Series.attrs* is considered experimental and may change without warning.

*Series.attrs* Dictionary of global attributes on this object.
3.3.14 Plotting

Series.plot is both a callable method and a namespace attribute for specific plotting methods of the form Series.plot.<kind>.

Series.plot(kind, ax, figsize, . . .) Series plotting accessor and method

Series.plot.area(x, y) Draw a stacked area plot.
Series.plot.bar(x, y) Vertical bar plot.
Series.plot.barch(x, y) Make a horizontal bar plot.
Series.plot.box(by) Make a box plot of the DataFrame columns.
Series.plot.density(bw_method, ind) Generate Kernel Density Estimate plot using Gaussian kernels.
Series.plot.hist(by, bins) Draw one histogram of the DataFrame’s columns.
Series.plot.kde(bw_method, ind) Generate Kernel Density Estimate plot using Gaussian kernels.
Series.plot.line(x, y) Plot Series or DataFrame as lines.
Series.plot.pie(**kwargs) Generate a pie plot.

pandas.Series.plot.area

Series.plot.area(x=None, y=None, **kwargs)
  Draw a stacked area plot.

  An area plot displays quantitative data visually. This function wraps the matplotlib area function.

  Parameters
  
  x [label or position, optional] Coordinates for the X axis. By default uses the index.
  y [label or position, optional] Column to plot. By default uses all columns.
  stacked [bool, default True] Area plots are stacked by default. Set to False to create a unstacked plot.
  **kwargs Additional keyword arguments are documented in DataFrame.plot().

  Returns
  
  matplotlib.axes.Axes or numpy.ndarray Area plot, or array of area plots if subplots is True.

  See also:
  
  DataFrame.plot Make plots of DataFrame using matplotlib / pylab.

Examples

Draw an area plot based on basic business metrics:

>>> df = pd.DataFrame({'
...     'sales': [3, 2, 3, 9, 10, 6],
...     'signups': [5, 5, 6, 12, 14, 13],
...     'visits': [20, 42, 28, 62, 81, 50],
... }, index=pd.date_range(start='2018/01/01', end='2018/07/01',
...     freq='M'))

>>> ax = df.plot.area()
Area plots are stacked by default. To produce an unstacked plot, pass `stacked=False`:

```python
>>> ax = df.plot.area(stacked=False)
```

Draw an area plot for a single column:

```python
>>> ax = df.plot.area(y='sales')
```

Draw with a different `x`:

```python
>>> df = pd.DataFrame({
...     'sales': [3, 2, 3],
...     'visits': [20, 42, 28],
...     'day': [1, 2, 3],
... })
>>> ax = df.plot.area(x='day')
```
3.3. Series
pandas.Series.plot.bar

Series.plot.bar(x=None, y=None, **kwargs)

Vertical bar plot.

A bar plot is a plot that presents categorical data with rectangular bars with lengths proportional to the values that they represent. A bar plot shows comparisons among discrete categories. One axis of the plot shows the specific categories being compared, and the other axis represents a measured value.

Parameters

x [label or position, optional] Allows plotting of one column versus another. If not specified, the index of the DataFrame is used.

y [label or position, optional] Allows plotting of one column versus another. If not specified, all numerical columns are used.

color [str, array_like, or dict, optional] The color for each of the DataFrame's columns. Possible values are:

- A single color string referred to by name, RGB or RGBA code, for instance 'red' or '#a98d19'.
- A sequence of color strings referred to by name, RGB or RGBA code, which will be used for each column recursively. For instance ['green', 'yellow'] each column's bar will be filled in green or yellow, alternatively.
- A dict of the form {column name: [color], so that each column will be colored accordingly. For example, if your columns are called a and b, then passing {'a': 'green', 'b': 'red'} will color bars for column a in green and bars for column b in red.

New in version 1.1.0.

**kwargs Additional keyword arguments are documented in DataFrame.plot().

Returns

matplotlib.axes.Axes or np.ndarray of them An ndarray is returned with one matplotlib.axes.Axes per column when subplots=True.

See also:

DataFrame.plot.barh Horizontal bar plot.
DataFrame.plot Make plots of a DataFrame.
matplotlib.pyplot.bar Make a bar plot with matplotlib.

Examples

Basic plot.

```python
>>> df = pd.DataFrame({'lab': ['A', 'B', 'C'], 'val': [10, 30, 20]})
>>> ax = df.plot.bar(x='lab', y='val', rot=0)
```

Plot a whole dataframe to a bar plot. Each column is assigned a distinct color, and each row is nested in a group along the horizontal axis.

```python
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]
>>> index = ['snail', 'pig', 'elephant',...
  'rabbit', 'giraffe', 'coyote', 'horse']
```

(continues on next page)
>>> df = pd.DataFrame({'speed': speed,
...                    'lifespan': lifespan}, index=index)

>>> ax = df.plot.bar(rot=0)

Plot stacked bar charts for the DataFrame

>>> ax = df.plot.bar(stacked=True)

Instead of nesting, the figure can be split by column with subplots=True. In this case, a numpy.ndarray of matplotlib.axes.Axes are returned.

>>> axes = df.plot.bar(rot=0, subplots=True)

If you don’t like the default colours, you can specify how you’d like each column to be colored.

```python
def plot_bar(subplots=True, color=None):
    ax = df.plot.bar(subplots=subplots, color=color)
    legend(loc=2)
```

Plot a single column.
pandas.Series.plot.bar

Series.plot.barh(x=None, y=None, **kwargs)

Make a horizontal bar plot.

A horizontal bar plot is a plot that presents quantitative data with rectangular bars with lengths proportional to the values that they represent. A bar plot shows comparisons among discrete categories. One axis of the plot shows the specific categories being compared, and the other axis represents a measured value.

Parameters

- x [label or position, optional] Allows plotting of one column versus another. If not specified, the index of the DataFrame is used.
- y [label or position, optional] Allows plotting of one column versus another. If not specified, all numerical columns are used.
- color [str, array_like, or dict, optional] The color for each of the DataFrame’s columns. Possible values are:
• A single color string referred to by name, RGB or RGBA code, for instance ‘red’ or ‘#a98d19’.

• A sequence of color strings referred to by name, RGB or RGBA code, which will be used for each column recursively. For instance ['green', 'yellow'] each column’s bar will be filled in green or yellow, alternatively.

• A dict of the form {column name: color}, so that each column will be colored accordingly. For example, if your columns are called a and b, then passing {'a': 'green', 'b': 'red'} will color bars for column a in green and bars for column b in red.

New in version 1.1.0.

**kwargs Additional keyword arguments are documented in DataFrame.plot().

Returns

matplotlib.axes.Axes or np.ndarray of them An ndarray is returned with one matplotlib.axes.Axes per column when subplots=True.

See also:

DataFrame.plot.bar Vertical bar plot.

DataFrame.plot Make plots of DataFrame using matplotlib.

matplotlib.axes.Axes.bar Plot a vertical bar plot using matplotlib.

Examples

Basic example

>>> df = pd.DataFrame({'lab': ['A', 'B', 'C'], 'val': [10, 30, 20]})
>>> ax = df.plot.barh(x='lab', y='val')

Plot a whole DataFrame to a horizontal bar plot

>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]
>>> index = ['snail', 'pig', 'elephant', ...
         'rabbit', 'giraffe', 'coyote', 'horse']
>>> df = pd.DataFrame({'speed': speed, ...
         'lifespan': lifespan}, index=index)
>>> ax = df.plot.barh()
pandas: powerful Python data analysis toolkit, Release 1.1.1

3.3. Series

3.3. Series

3.3. Series
Plot DataFrame versus the desired column

```python
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]
>>> index = ['snail', 'pig', 'elephant',
...    'rabbit', 'giraffe', 'coyote', 'horse']
>>> df = pd.DataFrame({'speed': speed,
...    'lifespan': lifespan}, index=index)
>>> ax = df.plot.barh(x='lifespan')
```
pandas.Series.plot.box

Series.plot.box(by=None, **kwargs)

Make a box plot of the DataFrame columns.

A box plot is a method for graphically depicting groups of numerical data through their quartiles. The box extends from the Q1 to Q3 quartile values of the data, with a line at the median (Q2). The whiskers extend from the edges of box to show the range of the data. The position of the whiskers is set by default to 1.5*IQR (IQR = Q3 - Q1) from the edges of the box. Outlier points are those past the end of the whiskers.

For further details see Wikipedia’s entry for boxplot.

A consideration when using this chart is that the box and the whiskers can overlap, which is very common when plotting small sets of data.

Parameters

- **by** [str or sequence] Column in the DataFrame to group by.
- **kwargs** Additional keywords are documented in DataFrame.plot().

Returns

- matplotlib.axes.Axes or numpy.ndarray of them

See also:

- DataFrame.boxplot Another method to draw a box plot.
- Series.plot.box Draw a box plot from a Series object.
- matplotlib.pyplot.boxplot Draw a box plot in matplotlib.

Examples

Draw a box plot from a DataFrame with four columns of randomly generated data.

```python
>>> data = np.random.randn(25, 4)
>>> df = pd.DataFrame(data, columns=list('ABCD'))
>>> ax = df.plot.box()
```

pandas.Series.plot.density

Series.plot.density(bw_method=None, ind=None, **kwargs)

Generate Kernel Density Estimate plot using Gaussian kernels.

In statistics, kernel density estimation (KDE) is a non-parametric way to estimate the probability density function (PDF) of a random variable. This function uses Gaussian kernels and includes automatic bandwidth determination.

Parameters

- **bw_method** [str, scalar or callable, optional] The method used to calculate the estimator bandwidth. This can be ‘scott’, ‘silverman’, a scalar constant or a callable. If None (default), ‘scott’ is used. See scipy.stats.gaussian_kde for more information.
- **ind** [NumPy array or int, optional] Evaluation points for the estimated PDF. If None (default), 1000 equally spaced points are used. If ind is a NumPy array, the KDE is evaluated at the points passed. If ind is an integer, ind number of equally spaced points are used.
- **kwargs** Additional keyword arguments are documented in pandas.%(this-datatype)s.plot().
Returns

matplotlib.axes.Axes or numpy.ndarray of them

See also:

scipy.stats.gaussian_kde Representation of a kernel-density estimate using Gaussian kernels. This is the function used internally to estimate the PDF.

Examples

Given a Series of points randomly sampled from an unknown distribution, estimate its PDF using KDE with automatic bandwidth determination and plot the results, evaluating them at 1000 equally spaced points (default):

```python
>>> s = pd.Series([1, 2, 2.5, 3, 3.5, 4, 5])
>>> ax = s.plot.kde()
```

![Graph of estimated density function]

A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

```python
>>> ax = s.plot.kde(bw_method=0.3)
>>> ax = s.plot.kde(bw_method=3)
```

Finally, the ind parameter determines the evaluation points for the plot of the estimated PDF:
For DataFrame, it works in the same way:

```python
>>> df = pd.DataFrame(
...   {'x': [1, 2, 2.5, 3, 3.5, 4, 5],
...    'y': [4, 4, 4.5, 5, 5.5, 6, 6]},
...)
>>> ax = df.plot.kde()
```

A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

```python
>>> ax = df.plot.kde(bw_method=0.3)

>>> ax = df.plot.kde(bw_method=3)
```

Finally, the `ind` parameter determines the evaluation points for the plot of the estimated PDF:

```python
>>> ax = df.plot.kde(ind=[1, 2, 3, 4, 5, 6])
```
3.3. Series
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.Series.plot.hist

Series.plot.hist(by=None, bins=10, **kwargs)

Draw one histogram of the DataFrame’s columns.

A histogram is a representation of the distribution of data. This function groups the values of all given Series in the DataFrame into bins and draws all bins in one matplotlib.axes.Axes. This is useful when the DataFrame’s Series are in a similar scale.

Parameters

by [str or sequence, optional] Column in the DataFrame to group by.
bins [int, default 10] Number of histogram bins to be used.

**kwargs Additional keyword arguments are documented in DataFrame.plot().

Returns

class:matplotlib.AxesSubplot Return a histogram plot.

See also:

DataFrame.hist Draw histograms per DataFrame’s Series.
Series.hist Draw a histogram with Series’ data.

Examples

When we draw a dice 6000 times, we expect to get each value around 1000 times. But when we draw two dices and sum the result, the distribution is going to be quite different. A histogram illustrates those distributions.

```python
>>> df = pd.DataFrame(...
...     np.random.randint(1, 7, 6000),
...     columns = ['one'])
>>> df['two'] = df['one'] + np.random.randint(1, 7, 6000)
>>> ax = df.plot.hist(bins=12, alpha=0.5)
```

pandas.Series.plot.kde

Series.plot.kde(bw_method=None, ind=None, **kwargs)

Generate Kernel Density Estimate plot using Gaussian kernels.

In statistics, kernel density estimation (KDE) is a non-parametric way to estimate the probability density function (PDF) of a random variable. This function uses Gaussian kernels and includes automatic bandwidth determination.

Parameters

bw_method [str, scalar or callable, optional] The method used to calculate the estimator bandwidth. This can be ‘scott’, ‘silverman’, a scalar constant or a callable. If None (default), ‘scott’ is used. See scipy.stats.gaussian_kde for more information.

ind [NumPy array or int, optional] Evaluation points for the estimated PDF. If None (default), 1000 equally spaced points are used. If ind is a NumPy array, the KDE is evaluated at the points passed. If ind is an integer, ind number of equally spaced points are used.

**kwargs Additional keyword arguments are documented in pandas.%(this-datatype)s.plot().

Returns

1398 Chapter 3. API reference
matplotlib.axes.Axes or numpy.ndarray of them

See also:

scipy.stats.gaussian_kde Representation of a kernel-density estimate using Gaussian kernels. This is the function used internally to estimate the PDF.

Examples

Given a Series of points randomly sampled from an unknown distribution, estimate its PDF using KDE with automatic bandwidth determination and plot the results, evaluating them at 1000 equally spaced points (default):

```python
>>> s = pd.Series([1, 2, 2.5, 3, 3.5, 4, 5])
>>> ax = s.plot.kde()
```

A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

```python
>>> ax = s.plot.kde(bw_method=0.3)
>>> ax = s.plot.kde(bw_method=3)
```

Finally, the `ind` parameter determines the evaluation points for the plot of the estimated PDF:
3.3. Series
For DataFrame, it works in the same way:

```python
>>> df = pd.DataFrame({
...     'x': [1, 2, 2.5, 3, 3.5, 4, 5],
...     'y': [4, 4, 4.5, 5, 5.5, 6, 6],
... })
>>> ax = df.plot.kde()
```

A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

```python
>>> ax = df.plot.kde(bw_method=0.3)

>>> ax = df.plot.kde(bw_method=3)
```

Finally, the `ind` parameter determines the evaluation points for the plot of the estimated PDF:

```python
>>> ax = df.plot.kde(ind=[1, 2, 3, 4, 5])
```
**pandas.Series.plot.line**

Series.plot.line(x=None, y=None, **kwargs)

Plot Series or DataFrame as lines.

This function is useful to plot lines using DataFrame’s values as coordinates.

**Parameters**

- **x** [label or position, optional] Allows plotting of one column versus another. If not specified, the index of the DataFrame is used.
- **y** [label or position, optional] Allows plotting of one column versus another. If not specified, all numerical columns are used.
- **color** [str, array_like, or dict, optional] The color for each of the DataFrame’s columns. Possible values are:
  - A single color string referred to by name, RGB or RGBA code, for instance ‘red’ or ‘#a98d19’.
  - A sequence of color strings referred to by name, RGB or RGBA code, which will be used for each column recursively. For instance ['green', 'yellow'] each column’s line will be filled in green or yellow, alternatively.
  - A dict of the form {column name: color}, so that each column will be colored accordingly. For example, if your columns are called `a` and `b`, then passing {'a': 'green', 'b': 'red'} will color lines for column `a` in green and lines for column `b` in red.

New in version 1.1.0.

**kwargs** Additional keyword arguments are documented in `DataFrame.plot()`.

**Returns**

- `matplotlib.axes.Axes` or `np.ndarray` of them An ndarray is returned with one `matplotlib.axes.Axes` per column when subplots=True.

See also:

- `matplotlib.pyplot.plot` Plot y versus x as lines and/or markers.

**Examples**

```python
>>> s = pd.Series([1, 3, 2])
>>> s.plot.line()
```

The following example shows the populations for some animals over the years.

```python
>>> df = pd.DataFrame(
...     {'pig': [20, 18, 489, 675, 1776],
...      'horse': [4, 25, 281, 600, 1900],
```

```python
>>> lines = df.plot.line()  # An example with subplots, so an array of axes is returned.
```

```python
>>> axes = df.plot.line(subplots=True)
```

```python
>>> type(axes)
<class 'numpy.ndarray'>
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

Let’s repeat the same example, but specifying colors for each column (in this case, for each animal).
>>> axes = df.plot.line(
...
subplots=True, color={"pig": "pink", "horse": "#742802"}
... )

The following example shows the relationship between both populations.
>>> lines = df.plot.line(x='pig', y='horse')

pandas.Series.plot.pie
Series.plot.pie(**kwargs)
Generate a pie plot.
A pie plot is a proportional representation of the numerical data in a column. This function wraps
matplotlib.pyplot.pie() for the specified column.
If no column reference is passed and
subplots=True a pie plot is drawn for each numerical column independently.
Parameters
y [int or label, optional] Label or position of the column to plot.
subplots=True argument must be passed.

If not provided,

**kwargs Keyword arguments to pass on to DataFrame.plot().

1412

Chapter 3. API reference


Returns

`matplotlib.axes.Axes` or `np.ndarray` of them

A NumPy array is returned when `subplots` is True.

See also:

* `Series.plot.pie` Generate a pie plot for a Series.
* `DataFrame.plot` Make plots of a DataFrame.

Examples

In the example below we have a DataFrame with the information about planet’s mass and radius. We pass the ‘mass’ column to the pie function to get a pie plot.

```
>>> df = pd.DataFrame({'mass': [0.330, 4.87, 5.97],
...    'radius': [2439.7, 6051.8, 6378.1]},
...    index=['Mercury', 'Venus', 'Earth'])
>>> plot = df.plot.pie(y='mass', figsize=(5, 5))
```

```
>>> plot = df.plot.pie(subplots=True, figsize=(11, 6))
```
```python
Series.hist(by, ax, grid, xlabelsize, ...) Draw histogram of the input series using matplotlib.
```

### 3.3.15 Serialization / IO / conversion

```python
Series.to_pickle(path[, compression, protocol]) Pickle (serialize) object to file.
Series.to_csv(path_or_buf, sep, na_rep, ...) Write object to a comma-separated values (csv) file.
Series.to_dict(into) Convert Series to {label -> value} dict or dict-like object.
Series.to_excel(excel_writer[, sheet_name, ...]) Write object to an Excel sheet.
Series.to_frame(name) Convert Series to DataFrame.
Series.to_xarray() Return an xarray object from the pandas object.
Series.to_hdf(path_or_buf, key[, mode, ...]) Write the contained data to an HDF5 file using HDFStore.
Series.to_sql(name, con[, schema, ...]) Write records stored in a DataFrame to a SQL database.
Series.to_json(path_or_buf, orient, ...) Convert the object to a JSON string.
Series.to_string([buf, na_rep, orient, ...]) Render a string representation of the Series.
Series.to_clipboard([excel, sep]) Copy object to the system clipboard.
Series.to_latex(buf, columns, col_space, ...) Render object to a LaTeX tabular, longtable, or nested table/tabular.
Series.to_markdown([buf, mode, index]) Print Series in Markdown-friendly format.
```

### 3.4 DataFrame

#### 3.4.1 Constructor

```python
DataFrame([data, index, columns, dtype, copy]) Two-dimensional, size-mutable, potentially heterogeneous tabular data.
```
columns [Index or array-like] Column labels to use for resulting frame. Will default to
RangelIndex (0, 1, 2, ..., n) if no column labels are provided.
dtype [dtype, default None] Data type to force. Only a single dtype is allowed. If None,
infer.
copy [bool, default False] Copy data from inputs. Only affects DataFrame / 2d ndarray input.

See also:
DataFrame.from_records Constructor from tuples, also record arrays.
DataFrame.from_dict From dicts of Series, arrays, or dicts.
read_csv Read a comma-separated values (csv) file into DataFrame.
read_table Read general delimited file into DataFrame.
read_clipboard Read text from clipboard into DataFrame.

Examples

Constructing DataFrame from a dictionary.

```python
>>> d = {'col1': [1, 2], 'col2': [3, 4]}
>>> df = pd.DataFrame(data=d)
>>> df
   col1  col2
0     1     3
1     2     4
```
Notice that the inferred dtype is int64.

```python
>>> df.dtypes
col1    int64
col2    int64
dtype: object
```
To enforce a single dtype:

```python
>>> df = pd.DataFrame(data=d, dtype=np.int8)
>>> df.dtypes
   col1   int8
   col2   int8
dtype: object
```

Constructing DataFrame from numpy ndarray:

```python
>>> df2 = pd.DataFrame(np.array([[1, 2, 3], [4, 5, 6], [7, 8, 9]]),
   columns=['a', 'b', 'c'])
```
```python
   a b c
0 1 2 3
1 4 5 6
2 7 8 9
```
Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>at</code></td>
<td>Access a single value for a row/column label pair.</td>
</tr>
<tr>
<td><code>attrs</code></td>
<td>Dictionary of global attributes on this object.</td>
</tr>
<tr>
<td><code>axes</code></td>
<td>Return a list representing the axes of the DataFrame.</td>
</tr>
<tr>
<td><code>columns</code></td>
<td>The column labels of the DataFrame.</td>
</tr>
<tr>
<td><code>dtypes</code></td>
<td>Return the dtypes in the DataFrame.</td>
</tr>
<tr>
<td><code>empty</code></td>
<td>Indicator whether DataFrame is empty.</td>
</tr>
<tr>
<td><code>iat</code></td>
<td>Access a single value for a row/column pair by integer position.</td>
</tr>
<tr>
<td><code>iloc</code></td>
<td>Purely integer-location based indexing for selection by position.</td>
</tr>
<tr>
<td><code>index</code></td>
<td>The index (row labels) of the DataFrame.</td>
</tr>
<tr>
<td><code>loc</code></td>
<td>Access a group of rows and columns by label(s) or a boolean array.</td>
</tr>
<tr>
<td><code>ndim</code></td>
<td>Return an int representing the number of axes / array dimensions.</td>
</tr>
<tr>
<td><code>shape</code></td>
<td>Return a tuple representing the dimensionality of the DataFrame.</td>
</tr>
<tr>
<td><code>size</code></td>
<td>Return an int representing the number of elements in this object.</td>
</tr>
<tr>
<td><code>style</code></td>
<td>Returns a Styler object.</td>
</tr>
<tr>
<td><code>values</code></td>
<td>Return a Numpy representation of the DataFrame.</td>
</tr>
</tbody>
</table>

pandas.DataFrame.at

**property** DataFrame.at
Access a single value for a row/column label pair.

Similar to `loc`, in that both provide label-based lookups. Use `at` if you only need to get or set a single value in a DataFrame or Series.

**Raises**

`KeyError` If ‘label’ does not exist in DataFrame.

**See also:**

- `DataFrame.iat` Access a single value for a row/column pair by integer position.
- `DataFrame.loc` Access a group of rows and columns by label(s).
- `Series.at` Access a single value using a label.
Examples

```python
>>> df = pd.DataFrame([[0, 2, 3], [0, 4, 1], [10, 20, 30]],
                   index=[4, 5, 6], columns=['A', 'B', 'C'])
>>> df
   A  B  C
4  0  2  3
5  0  4  1
6 10 20 30

Get value at specified row/column pair

```python
>>> df.at[4, 'B']
2
```n

Set value at specified row/column pair

```python
>>> df.at[4, 'B'] = 10
>>> df.at[4, 'B']
10
```n

Get value within a Series

```python
>>> df.loc[5].at['B']
4
```n

**pandas.DataFrame.attrs**

**property** pandas.DataFrame.attrs

Dictionary of global attributes on this object.

**Warning:** attrs is experimental and may change without warning.

**pandas.DataFrame.axes**

**property** pandas.DataFrame.axes

Return a list representing the axes of the DataFrame.

It has the row axis labels and column axis labels as the only members. They are returned in that order.

**Examples**

```python
>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [3, 4]})
>>> df.axes
[RangeIndex(start=0, stop=2, step=1), Index(['col1', 'col2'],
     dtype='object')]
```
pandas.DataFrame.columns

DataFrame.columns: Index
The column labels of the DataFrame.

pandas.DataFrame.dtypes

property DataFrame.dtypes
Return the dtypes in the DataFrame.

This returns a Series with the data type of each column. The result’s index is the original DataFrame’s columns. Columns with mixed types are stored with the object dtype. See the User Guide for more.

Returns
pandas.Series The data type of each column.

Examples

```python
def = pd.DataFrame({'float': [1.0],
...    'int': [1],
...    'datetime': [pd.Timestamp('20180310')],
...    'string': ['foo'])
def.dtypes
float       float64
int         int64
datetime    datetime64[ns]
string      object
dtype: object
```

pandas.DataFrame.empty

property DataFrame.empty
Indicator whether DataFrame is empty.

True if DataFrame is entirely empty (no items), meaning any of the axes are of length 0.

Returns
bool If DataFrame is empty, return True, if not return False.

See also:

Series.dropna Return series without null values.
DataFrame.dropna Return DataFrame with labels on given axis omitted where (all or any) data are missing.
Notes

If DataFrame contains only NaNs, it is still not considered empty. See the example below.

Examples

An example of an actual empty DataFrame. Notice the index is empty:

```python
>>> df_empty = pd.DataFrame({'A': []})
>>> df_empty
Empty DataFrame
Columns: [A]
Index: []
>>> df_empty.empty
True
```

If we only have NaNs in our DataFrame, it is not considered empty! We will need to drop the NaNs to make the DataFrame empty:

```python
>>> df = pd.DataFrame({'A': [np.nan]})
>>> df
   A
0  NaN
>>> df.empty
False
>>> df.dropna().empty
True
```

**pandas.DataFrame.iat**

**property** `DataFrame.iat`

Access a single value for a row/column pair by integer position.

Similar to `iloc`, in that both provide integer-based lookups. Use `iat` if you only need to get or set a single value in a DataFrame or Series.

**Raises**

- `IndexError` When integer position is out of bounds.

**See also:**

- `DataFrame.at` Access a single value for a row/column label pair.
- `DataFrame.loc` Access a group of rows and columns by label(s).
- `DataFrame.iloc` Access a group of rows and columns by integer position(s).
Examples

```python
>>> df = pd.DataFrame([[0, 2, 3], [0, 4, 1], [10, 20, 30]],
                      columns=['A', 'B', 'C'])
>>> df
   A  B  C
0  0  2  3
1  0  4  1
2 10 20 30
```

Get value at specified row/column pair

```python
>>> df.iat[1, 2]
1
```

Set value at specified row/column pair

```python
>>> df.iat[1, 2] = 10
>>> df.iat[1, 2]
10
```

Get value within a series

```python
>>> df.loc[0].iat[1]
2
```

**pandas.DataFrame.iloc**

**property** `DataFrame.iloc`

Purely integer-location based indexing for selection by position.

`.iloc[]` is primarily integer position based (from 0 to length-1 of the axis), but may also be used with a boolean array.

Allowed inputs are:

- An integer, e.g. 5.
- A list or array of integers, e.g. [4, 3, 0].
- A slice object with ints, e.g. 1:7.
- A boolean array.
- A callable function with one argument (the calling Series or DataFrame) and that returns valid output for indexing (one of the above). This is useful in method chains, when you don’t have a reference to the calling object, but would like to base your selection on some value.

`.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except `slice` indexers which allow out-of-bounds indexing (this conforms with python/numpy `slice` semantics).

See more at `Selection by Position`.

See also:

- `DataFrame.iat` Fast integer location scalar accessor.
- `DataFrame.loc` Purely label-location based indexer for selection by label.
- `Series.iloc` Purely integer-location based indexing for selection by position.
### Examples

```python
>>> mydict = [{'a': 1, 'b': 2, 'c': 3, 'd': 4},
            {'a': 100, 'b': 200, 'c': 300, 'd': 400},
            {'a': 1000, 'b': 2000, 'c': 3000, 'd': 4000}]

>>> df = pd.DataFrame(mydict)

>>> df
     a  b  c  d
0   1  2  3  4
1 100 200 300 400
2 1000 2000 3000 4000

### Indexing just the rows

With a scalar integer.

```python
>>> type(df.iloc[0])
<class 'pandas.core.series.Series'>

>>> df.iloc[0]
a 1
b 2
c 3
d 4
Name: 0, dtype: int64
```

With a list of integers.

```python
>>> df.iloc[[0]]
     a  b  c  d
0   1  2  3  4

>>> type(df.iloc[[0]])
<class 'pandas.core.frame.DataFrame'>
```

```python
>>> df.iloc[[0, 1]]
     a  b  c  d
0   1  2  3  4
1 100 200 300 400
```

With a slice object.

```python
>>> df.iloc[:3]
     a  b  c  d
0   1  2  3  4
1 100 200 300 400
2 1000 2000 3000 4000
```

With a boolean mask the same length as the index.

```python
>>> df.iloc[[True, False, True]]
     a  b  c  d
0   1  2  3  4
2 1000 2000 3000 4000
```

With a callable, useful in method chains. The x passed to the lambda is the DataFrame being sliced.

This selects the rows whose index label even.

```python
```
```python
>>> df.iloc[lambda x: x.index % 2 == 0]
a  b  c  d
0  1  2  3  4
2 1000 2000 3000 4000
```

### Indexing both axes

You can mix the indexer types for the index and columns. Use : to select the entire axis.

With scalar integers.

```python
>>> df.iloc[0, 1]
2
```

With lists of integers.

```python
>>> df.iloc[[0, 2], [1, 3]]
   b  d
0  2  4
2 2000 4000
```

With `slice` objects.

```python
>>> df.iloc[1:3, 0:3]
a  b  c
1 100 200 300
2 1000 2000 3000
```

With a boolean array whose length matches the columns.

```python
>>> df.iloc[:, [True, False, True, False]]
a  c
0 1 3
1 100 300
2 1000 3000
```

With a callable function that expects the Series or DataFrame.

```python
>>> df.iloc[:, lambda df: [0, 2]]
a  c
0 1 3
1 100 300
2 1000 3000
```

---

**pandas.DataFrame.index**

Dataframe.index: Index

The index (row labels) of the DataFrame.
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.DataFrame.loc

**property** DataFrame.loc

Access a group of rows and columns by label(s) or a boolean array.

`.loc[]` is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

- A single label, e.g. 5 or 'a', (note that 5 is interpreted as a *label* of the index, and **never** as an integer position along the index).
- A list or array of labels, e.g. ['a', 'b', 'c'].
- A slice object with labels, e.g. 'a':'f'.

**Warning:** Note that contrary to usual python slices, **both** the start and the stop are included.

- A boolean array of the same length as the axis being sliced, e.g. [True, False, True].
- A callable function with one argument (the calling Series or DataFrame) and that returns valid output for indexing (one of the above).

See more at *Selection by Label*

**Raises**

**KeyError**  If any items are not found.

See also:

**DataFrame.at**  Access a single value for a row/column label pair.

**DataFrame.iloc**  Access group of rows and columns by integer position(s).

**DataFrame.xs**  Returns a cross-section (row(s) or column(s)) from the Series/DataFrame.

**Series.loc**  Access group of values using labels.

**Examples**

**Getting values**

```
>>> df = pd.DataFrame([[1, 2], [4, 5], [7, 8]],
                    index=['cobra', 'viper', 'sidewinder'],
                    columns=['max_speed', 'shield'])
>>> df
      max_speed  shield
    cobra       1       2
    viper       4       5
    sidewinder  7       8
```

Single label. Note this returns the row as a Series.

```
>>> df.loc['viper']
max_speed    4
shield       5
Name: viper, dtype: int64
```
List of labels. Note using `[]` returns a DataFrame.

```
>>> df.loc[['viper', 'sidewinder']]
   max_speed  shield
viper       4       5
sidewinder  7       8
```

Single label for row and column

```
>>> df.loc['cobra', 'shield']
2
```

Slice with labels for row and single label for column. As mentioned above, note that both the start and stop of the slice are included.

```
>>> df.loc['cobra':'viper', 'max_speed']
cobra   1
viper   4
Name: max_speed, dtype: int64
```

Boolean list with the same length as the row axis

```
>>> df.loc[[False, False, True]]
   max_speed  shield
sidewinder  7       8
```

Conditional that returns a boolean Series

```
>>> df.loc[df['shield'] > 6]
   max_speed  shield
sidewinder  7       8
```

Conditional that returns a boolean Series with column labels specified

```
>>> df.loc[df['shield'] > 6, ['max_speed']]
   max_speed
sidewinder  7
```

Callable that returns a boolean Series

```
>>> df.loc[lambda df: df['shield'] == 8]
   max_speed  shield
sidewinder  7       8
```

Setting values

Set value for all items matching the list of labels

```
>>> df.loc[['viper', 'sidewinder'], ['shield']] = 50
>>> df
   max_speed  shield
  cobra      1       2
  viper      4       50
  sidewinder 7       50
```

Set value for an entire row
```python
>>> df.loc['cobra'] = 10
>>> df
  max_speed  shield
cobra    10      10
viper     4      50
sidewinder  7      50

Set value for an entire column

>>> df.loc[:, 'max_speed'] = 30
>>> df
  max_speed  shield
cobra    30      10
viper    30      50
sidewinder    30     50

Set value for rows matching callable condition

>>> df.loc[df['shield'] > 35] = 0
>>> df
  max_speed  shield
cobra    30      10
viper     0      0
sidewinder    0      0

Getting values on a DataFrame with an index that has integer labels

Another example using integers for the index

>>> df = pd.DataFrame([[1, 2], [4, 5], [7, 8]],
                   index=[7, 8, 9], columns=['max_speed', 'shield'])
>>> df
  max_speed  shield
7          1      2
8          4      5
9          7      8

Slice with integer labels for rows. As mentioned above, note that both the start and stop of the slice are included.

>>> df.loc[7:9]
  max_speed  shield
7          1      2
8          4      5
9          7      8

Getting values with a MultiIndex

A number of examples using a DataFrame with a MultiIndex

>>> tuples = [
...     ('cobra', 'mark i'), ('cobra', 'mark ii'),
...     ('sidewinder', 'mark i'), ('sidewinder', 'mark ii'),
...     ('viper', 'mark ii'), ('viper', 'mark iii')
... ]
>>> index = pd.MultiIndex.from_tuples(tuples)
>>> values = [[12, 2], [0, 4], [10, 20],
...           [1, 4], [7, 1], [16, 36]]
(continues on next page)
>>>
>>> df = pd.DataFrame(values, columns=['max_speed', 'shield'], index=index)
>>> df

<table>
<thead>
<tr>
<th></th>
<th>max_speed</th>
<th>shield</th>
</tr>
</thead>
<tbody>
<tr>
<td>cobra</td>
<td>mark i</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>mark ii</td>
<td>0</td>
</tr>
<tr>
<td>sidewinder</td>
<td>mark i</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>mark ii</td>
<td>1</td>
</tr>
<tr>
<td>viper</td>
<td>mark ii</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>mark iii</td>
<td>16</td>
</tr>
</tbody>
</table>

Single label. Note this returns a DataFrame with a single index.

```python
>>> df.loc['cobra']

<table>
<thead>
<tr>
<th></th>
<th>max_speed</th>
<th>shield</th>
</tr>
</thead>
<tbody>
<tr>
<td>mark i</td>
<td>12</td>
<td>2</td>
</tr>
<tr>
<td>mark ii</td>
<td>0</td>
<td>4</td>
</tr>
</tbody>
</table>
```

Single index tuple. Note this returns a Series.

```python
>>> df.loc[('cobra', 'mark ii')]

max_speed 0
shield 4
Name: (cobra, mark ii), dtype: int64
```

Single label for row and column. Similar to passing in a tuple, this returns a Series.

```python
>>> df.loc['cobra', 'mark i']

max_speed 12
shield 2
Name: (cobra, mark i), dtype: int64
```

Single tuple. Note using [[]] returns a DataFrame.

```python
>>> df.loc[['cobra', 'mark ii']]

<table>
<thead>
<tr>
<th></th>
<th>max_speed</th>
<th>shield</th>
</tr>
</thead>
<tbody>
<tr>
<td>cobra</td>
<td>mark ii</td>
<td>0</td>
</tr>
</tbody>
</table>
```

Single tuple for the index with a single label for the column

```python
>>> df.loc[['cobra', 'mark i'], 'shield']

2
```

Slice from index tuple to single label

```python
>>> df.loc[['cobra', 'mark i']:'viper']

<table>
<thead>
<tr>
<th></th>
<th>max_speed</th>
<th>shield</th>
</tr>
</thead>
<tbody>
<tr>
<td>cobra</td>
<td>mark i</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>mark ii</td>
<td>0</td>
</tr>
<tr>
<td>sidewinder</td>
<td>mark i</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>mark ii</td>
<td>1</td>
</tr>
<tr>
<td>viper</td>
<td>mark ii</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>mark iii</td>
<td>16</td>
</tr>
</tbody>
</table>
```

Slice from index tuple to index tuple
pandas: powerful Python data analysis toolkit, Release 1.1.1

```python
>>> df.loc[('cobra', 'mark i'):('viper', 'mark ii')]
   max_speed  shield
  cobra     mark i   12   2
        mark ii    0   4
sidewinder mark i  10  20
        mark ii   1   4
  viper     mark ii  7   1
```

**pandas.DataFrame.ndim**

**property DataFrame.ndim**

Return an int representing the number of axes / array dimensions.

Return 1 if Series. Otherwise return 2 if DataFrame.

See also:

*ndarray.ndim* Number of array dimensions.

**Examples**

```python
>>> s = pd.Series({'a': 1, 'b': 2, 'c': 3})
>>> s.ndim
1

>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [3, 4]})
>>> df.ndim
2
```

**pandas.DataFrame.shape**

**property DataFrame.shape**

Return a tuple representing the dimensionality of the DataFrame.

See also:

*ndarray.shape*

**Examples**

```python
>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [3, 4]})
>>> df.shape
(2, 2)

>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [3, 4],
... 'col3': [5, 6]})
>>> df.shape
(2, 3)
```
pandas.DataFrame.size

**property** DataFrame.size

Return an int representing the number of elements in this object.

Return the number of rows if Series. Otherwise return the number of rows times number of columns if DataFrame.

See also:

ndarray.size Number of elements in the array.

**Examples**

```python
>>> s = pd.Series({'a': 1, 'b': 2, 'c': 3})
>>> s.size
3

>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [3, 4]})
>>> df.size
4
```

pandas.DataFrame.style

**property** DataFrame.style

Returns a Styler object.

Contains methods for building a styled HTML representation of the DataFrame.

See also:

io.formats.style.Styler Helps style a DataFrame or Series according to the data with HTML and CSS.

pandas.DataFrame.values

**property** DataFrame.values

Return a Numpy representation of the DataFrame.

**Warning:** We recommend using DataFrame.to_numpy() instead.

Only the values in the DataFrame will be returned, the axes labels will be removed.

**Returns**

- **numpy.ndarray** The values of the DataFrame.

See also:

DataFrame.to_numpy Recommended alternative to this method.

DataFrame.index Retrieve the index labels.

DataFrame.columns Retrieving the column names.
Notes

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcast to int32. By numpy.find_common_type() convention, mixing int64 and uint64 will result in a float64 dtype.

Examples

A DataFrame where all columns are the same type (e.g., int64) results in an array of the same type.

```python
>>> df = pd.DataFrame({'age': [3, 29],
...                    'height': [94, 170],
...                    'weight': [31, 115]})

>>> df
   age  height  weight
0    3      94      31
1   29     170     115

>>> df.dtypes
age     int64
height   int64
weight   int64
dtype: object

>>> df.values
array([[ 3, 94, 31],
       [29, 170, 115]])
```

A DataFrame with mixed type columns (e.g., str/object, int64, float32) results in an ndarray of the broadest type that accommodates these mixed types (e.g., object).

```python
>>> df2 = pd.DataFrame([('parrot', 24.0, 'second'),
...                      ('lion', 80.5, 1),
...                      ('monkey', np.nan, None)],
...                     columns=('name', 'max_speed', 'rank'))

>>> df2.dtypes
name    object
max_speed     float64
rank      object
dtype: object

>>> df2.values
array([[parrot', 24.0, 'second'],
       ['lion', 80.5, 1],
       ['monkey', nan, None]], dtype=object)
```
<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>abs()</td>
<td>Return a Series/DataFrame with absolute numeric value of each element.</td>
</tr>
<tr>
<td>add(other[, axis, level, fill_value])</td>
<td>Get Addition of dataframe and other, element-wise (binary operator add).</td>
</tr>
<tr>
<td>add_prefix(prefix)</td>
<td>Prefix labels with string prefix.</td>
</tr>
<tr>
<td>add_suffix(suffix)</td>
<td>Suffix labels with string suffix.</td>
</tr>
<tr>
<td>agg([func, axis])</td>
<td>Aggregate using one or more operations over the specified axis.</td>
</tr>
<tr>
<td>aggregate([func, axis])</td>
<td>Aggregate using one or more operations over the specified axis.</td>
</tr>
<tr>
<td>align(other[, join, axis, level, copy, …])</td>
<td>Align two objects on their axes with the specified join method.</td>
</tr>
<tr>
<td>all([axis, bool_only, skipna, level])</td>
<td>Return whether all elements are True, potentially over an axis.</td>
</tr>
<tr>
<td>any([axis, bool_only, skipna, level])</td>
<td>Return whether any element is True, potentially over an axis.</td>
</tr>
<tr>
<td>append(other[, ignore_index, …])</td>
<td>Append rows of other to the end of caller, returning a new object.</td>
</tr>
<tr>
<td>apply(func[, axis, raw, result_type, args])</td>
<td>Apply a function along an axis of the DataFrame.</td>
</tr>
<tr>
<td>applymap(func)</td>
<td>Apply a function to a Dataframe elementwise.</td>
</tr>
<tr>
<td>asfreq(freq[, method, how, normalize, …])</td>
<td>Convert TimeSeries to specified frequency.</td>
</tr>
<tr>
<td>asof(where[, subset])</td>
<td>Return the last row(s) without any NaNs before where.</td>
</tr>
<tr>
<td>assign(**kwargs)</td>
<td>Assign new columns to a DataFrame.</td>
</tr>
<tr>
<td>astype(dtype[, copy, errors])</td>
<td>Cast a pandas object to a specified dtype dtype.</td>
</tr>
<tr>
<td>at_time(time[, asof, axis])</td>
<td>Select values at particular time of day (e.g., 9:30AM).</td>
</tr>
<tr>
<td>backfill([axis, inplace, limit, downcast])</td>
<td>Synonym for DataFrame.fillna() with method='bfill'.</td>
</tr>
<tr>
<td>between_time(start_time, end_time[, …])</td>
<td>Select values between particular times of the day (e.g., 9:00-9:30 AM).</td>
</tr>
<tr>
<td>bfill([axis, inplace, limit, downcast])</td>
<td>Synonym for DataFrame.fillna() with method='bfill'.</td>
</tr>
<tr>
<td>bool()</td>
<td>Return the bool of a single element Series or DataFrame.</td>
</tr>
<tr>
<td>boxplot([column, by, ax, fontsize, rot, …])</td>
<td>Make a box plot from DataFrame columns.</td>
</tr>
<tr>
<td>clip([lower, upper, axis, inplace])</td>
<td>Trim values at input threshold(s).</td>
</tr>
<tr>
<td>combine(other, func[, fill_value, overwrite])</td>
<td>Perform column-wise combine with another DataFrame.</td>
</tr>
<tr>
<td>combine_first(other)</td>
<td>Update null elements with value in the same location in other.</td>
</tr>
<tr>
<td>compare(other[, align_axis, keep_shape, …])</td>
<td>Compare to another DataFrame and show the differences.</td>
</tr>
<tr>
<td>convert_dtypes([infer_objects, …])</td>
<td>Convert columns to best possible dtypes using dtypes supporting pd.NA.</td>
</tr>
<tr>
<td>copy([deep])</td>
<td>Make a copy of this object’s indices and data.</td>
</tr>
<tr>
<td>corr([method, min_periods])</td>
<td>Compute pairwise correlation of columns, excluding NA/null values.</td>
</tr>
<tr>
<td>corrwith(other[, axis, drop, method])</td>
<td>Compute pairwise correlation.</td>
</tr>
</tbody>
</table>

continues on next page
Table 59 – continued from previous page

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>count([axis, level, numeric_only])</code></td>
<td>Count non-NA cells for each column or row.</td>
</tr>
<tr>
<td><code>cov([min_periods, ddof])</code></td>
<td>Compute pairwise covariance of columns, excluding NA/null values.</td>
</tr>
<tr>
<td><code>cummax([axis, skipna])</code></td>
<td>Return cumulative maximum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td><code>cummin([axis, skipna])</code></td>
<td>Return cumulative minimum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td><code>cumprod([axis, skipna])</code></td>
<td>Return cumulative product over a DataFrame or Series axis.</td>
</tr>
<tr>
<td><code>cumsum([axis, skipna])</code></td>
<td>Return cumulative sum over a DataFrame or Series axis.</td>
</tr>
<tr>
<td><code>describe([percentiles, include, exclude, ...])</code></td>
<td>Generate descriptive statistics.</td>
</tr>
<tr>
<td><code>diff([periods, axis])</code></td>
<td>First discrete difference of element.</td>
</tr>
<tr>
<td><code>div(other[, axis, level, fill_value])</code></td>
<td>Get Floating division of dataframe and other, element-wise (binary operator truediv).</td>
</tr>
<tr>
<td><code>divide(other[, axis, level, fill_value])</code></td>
<td>Get Floating division of dataframe and other, element-wise (binary operator truediv).</td>
</tr>
<tr>
<td><code>dot(other)</code></td>
<td>Compute the matrix multiplication between the DataFrame and other.</td>
</tr>
<tr>
<td><code>drop([labels, axis, index, columns, level, ...])</code></td>
<td>Drop specified labels from rows or columns.</td>
</tr>
<tr>
<td><code>drop_duplicates([subset, keep, inplace, ...])</code></td>
<td>Return DataFrame with duplicate rows removed.</td>
</tr>
<tr>
<td><code>droplevel([level[, axis]])</code></td>
<td>Return DataFrame with requested index / column level(s) removed.</td>
</tr>
<tr>
<td><code>dropna([axis, how, thresh, subset, inplace])</code></td>
<td>Remove missing values.</td>
</tr>
<tr>
<td><code>duplicated([subset, keep])</code></td>
<td>Return boolean Series denoting duplicate rows.</td>
</tr>
<tr>
<td><code>eq(other[, axis, level])</code></td>
<td>Get Equal to of dataframe and other, element-wise (binary operator eq).</td>
</tr>
<tr>
<td><code>equals(other)</code></td>
<td>Test whether two objects contain the same elements.</td>
</tr>
<tr>
<td><code>eval(expr[, inplace])</code></td>
<td>Evaluate a string describing operations on DataFrame columns.</td>
</tr>
<tr>
<td><code>ewm([com, span, halflife, alpha, ...])</code></td>
<td>Provide exponential weighted (EW) functions.</td>
</tr>
<tr>
<td><code>expanding([min_periods, center, axis])</code></td>
<td>Provide expanding transformations.</td>
</tr>
<tr>
<td><code>explode(column[, ignore_index])</code></td>
<td>Transform each element of a list-like to a row, replicating index values.</td>
</tr>
<tr>
<td><code>ffill([axis, inplace, limit, downcast])</code></td>
<td>Synonym for DataFrame.fillna() with method='ffill'.</td>
</tr>
<tr>
<td><code>fillna([value, method, axis, inplace, ...])</code></td>
<td>Fill NA/NaN values using the specified method.</td>
</tr>
<tr>
<td><code>filter([items, like, regex, axis])</code></td>
<td>Subset the dataframe rows or columns according to the specified index labels.</td>
</tr>
<tr>
<td><code>first(offset)</code></td>
<td>Select initial periods of time series data based on a date offset.</td>
</tr>
<tr>
<td><code>first_valid_index()</code></td>
<td>Return index for first non-NA/null value.</td>
</tr>
<tr>
<td><code>floordiv(other[, axis, level, fill_value])</code></td>
<td>Get Integer division of dataframe and other, element-wise (binary operator floordiv).</td>
</tr>
<tr>
<td><code>from_dict([data[, orient, dtype, columns]])</code></td>
<td>Construct DataFrame from dict of array-like or dicts.</td>
</tr>
<tr>
<td><code>from_records(data[, index, exclude, ...])</code></td>
<td>Convert structured or record ndarray to DataFrame.</td>
</tr>
<tr>
<td><code>ge(other[, axis, level])</code></td>
<td>Get Greater than or equal to of dataframe and other, element-wise (binary operator ge).</td>
</tr>
<tr>
<td><code>get(key[, default])</code></td>
<td>Get item from object for given key (ex: DataFrame column).</td>
</tr>
</tbody>
</table>

continues on next page
Table 59 – continued from previous page

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>groupby(by, axis, level, as_index, sort, ...)</code></td>
<td>Group DataFrame using a mapper or by a Series of columns.</td>
</tr>
<tr>
<td><code>gt(other[, axis, level])</code></td>
<td>Get Greater than of dataframe and other, element-wise (binary operator gt).</td>
</tr>
<tr>
<td><code>head([n])</code></td>
<td>Return the first n rows.</td>
</tr>
<tr>
<td><code>hist([column, by, grid, xlabelsize, xrot, ...])</code></td>
<td>Make a histogram of the DataFrame’s.</td>
</tr>
<tr>
<td><code>idxmax([axis, skipna])</code></td>
<td>Return index of first occurrence of maximum over requested axis.</td>
</tr>
<tr>
<td><code>idxmin([axis, skipna])</code></td>
<td>Return index of first occurrence of minimum over requested axis.</td>
</tr>
<tr>
<td><code>infer_objects()</code></td>
<td>Attempt to infer better dtypes for object columns.</td>
</tr>
<tr>
<td><code>info([verbose, buf, max_cols, memory_usage, ...])</code></td>
<td>Print a concise summary of a DataFrame.</td>
</tr>
<tr>
<td><code>insert(loc, column, value[, allow_duplicates])</code></td>
<td>Insert column into DataFrame at specified location.</td>
</tr>
<tr>
<td><code>interpolate([method, axis, limit, inplace, ...])</code></td>
<td>Please note that only method='linear' is supported for DataFrame/Series with a MultiIndex.</td>
</tr>
<tr>
<td><code>isin(values)</code></td>
<td>Whether each element in the DataFrame is contained in values.</td>
</tr>
<tr>
<td><code>isna()</code></td>
<td>Detect missing values.</td>
</tr>
<tr>
<td><code>isnull()</code></td>
<td>Detect missing values.</td>
</tr>
<tr>
<td><code>items()</code></td>
<td>Iterate over (column name, Series) pairs.</td>
</tr>
<tr>
<td><code>iteritems()</code></td>
<td>Iterate over (column name, Series) pairs.</td>
</tr>
<tr>
<td><code>iterrows()</code></td>
<td>Iterate over DataFrame rows as (index, Series) pairs.</td>
</tr>
<tr>
<td><code>itertuples([index, name])</code></td>
<td>Iterate over DataFrame rows as namedtuples.</td>
</tr>
<tr>
<td><code>join(right[, how, on, left_on, right_on, ...])</code></td>
<td>Join columns of another DataFrame.</td>
</tr>
<tr>
<td><code>keys()</code></td>
<td>Get the ‘info axis’ (see Indexing for more).</td>
</tr>
<tr>
<td><code>kurt([axis, skipna, level, numeric_only])</code></td>
<td>Return unbiased kurtosis over requested axis.</td>
</tr>
<tr>
<td><code>kurtosis([axis, skipna, level, numeric_only])</code></td>
<td>Return unbiased kurtosis over requested axis.</td>
</tr>
<tr>
<td><code>last(offset)</code></td>
<td>Select final periods of time series data based on a date offset.</td>
</tr>
<tr>
<td><code>last_valid_index()</code></td>
<td>Return index for last non-NA/null value.</td>
</tr>
<tr>
<td><code>le(other[, axis, level])</code></td>
<td>Get Less than or equal to of dataframe and other, element-wise (binary operator le).</td>
</tr>
<tr>
<td><code>lookup(row_labels, col_labels)</code></td>
<td>Label-based “fancy indexing” function for DataFrame.</td>
</tr>
<tr>
<td><code>lt(other[, axis, level])</code></td>
<td>Get Less than of dataframe and other, element-wise (binary operator lt).</td>
</tr>
<tr>
<td><code>mad([axis, skipna, level])</code></td>
<td>Return the mean absolute deviation of the values for the requested axis.</td>
</tr>
<tr>
<td><code>mask(cond[, other, inplace, axis, level, ...])</code></td>
<td>Replace values where the condition is True.</td>
</tr>
<tr>
<td><code>max([axis, skipna, level, numeric_only])</code></td>
<td>Return the maximum of the values for the requested axis.</td>
</tr>
<tr>
<td><code>mean([axis, skipna, level, numeric_only])</code></td>
<td>Return the mean of the values for the requested axis.</td>
</tr>
<tr>
<td><code>median([axis, skipna, level, numeric_only])</code></td>
<td>Return the median of the values for the requested axis.</td>
</tr>
<tr>
<td><code>melt([id_vars, value_vars, var_name, ...])</code></td>
<td>Unpivot a DataFrame from wide to long format, optionally leaving identifiers set.</td>
</tr>
<tr>
<td><code>memory_usage([index, deep])</code></td>
<td>Return the memory usage of each column in bytes.</td>
</tr>
<tr>
<td><code>merge(right[, how, on, left_on, right_on, ...])</code></td>
<td>Merge DataFrame or named Series objects with a database-style join.</td>
</tr>
</tbody>
</table>

continues on next page
Table 59 – continued from previous page

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>min()</code></td>
<td>Return the minimum of the values for the requested axis.</td>
</tr>
<tr>
<td><code>mod()</code></td>
<td>Get Modulo of dataframe and other, element-wise (binary operator <code>mod</code>).</td>
</tr>
<tr>
<td><code>mode()</code></td>
<td>Get the mode(s) of each element along the selected axis.</td>
</tr>
<tr>
<td><code>mul()</code></td>
<td>Get Multiplication of dataframe and other, element-wise (binary operator <code>mul</code>).</td>
</tr>
<tr>
<td><code>ne()</code></td>
<td>Get Not equal to of dataframe and other, element-wise (binary operator <code>ne</code>).</td>
</tr>
<tr>
<td><code>nlargest()</code></td>
<td>Return the first n rows ordered by columns in descending order.</td>
</tr>
<tr>
<td><code>notna()</code></td>
<td>Detect existing (non-missing) values.</td>
</tr>
<tr>
<td><code>notnull()</code></td>
<td>Detect existing (non-missing) values.</td>
</tr>
<tr>
<td><code>nsmallest()</code></td>
<td>Return the first n rows ordered by columns in ascending order.</td>
</tr>
<tr>
<td><code>nunique()</code></td>
<td>Count distinct observations over requested axis.</td>
</tr>
<tr>
<td><code>pad()</code></td>
<td>Synonym for <code>DataFrame.fillna()</code> with method='ffill'.</td>
</tr>
<tr>
<td><code>pct_change()</code></td>
<td>Percentage change between the current and a prior element.</td>
</tr>
<tr>
<td><code>pipe()</code></td>
<td>Apply func(self, *args, **kwargs).</td>
</tr>
<tr>
<td><code>pivot()</code></td>
<td>Return reshaped DataFrame organized by given index / column values.</td>
</tr>
<tr>
<td><code>pivot_table()</code></td>
<td>Create a spreadsheet-style pivot table as a DataFrame.</td>
</tr>
<tr>
<td><code>plot</code></td>
<td>Alias of pandas.plotting._core.PlotAccessor.</td>
</tr>
<tr>
<td><code>pop()</code></td>
<td>Return item and drop from frame.</td>
</tr>
<tr>
<td><code>pow()</code></td>
<td>Get Exponential power of dataframe and other, element-wise (binary operator <code>pow</code>).</td>
</tr>
<tr>
<td><code>prod()</code></td>
<td>Return the product of the values for the requested axis.</td>
</tr>
<tr>
<td><code>product()</code></td>
<td>Return the product of the values for the requested axis.</td>
</tr>
<tr>
<td><code>quantile()</code></td>
<td>Return values at the given quantile over requested axis.</td>
</tr>
<tr>
<td><code>query()</code></td>
<td>Query the columns of a DataFrame with a boolean expression.</td>
</tr>
<tr>
<td><code>radd()</code></td>
<td>Get Addition of dataframe and other, element-wise (binary operator <code>radd</code>).</td>
</tr>
<tr>
<td><code>rank()</code></td>
<td>Compute numerical data ranks (1 through n) along axis.</td>
</tr>
<tr>
<td><code>rdiv()</code></td>
<td>Get Floating division of dataframe and other, element-wise (binary operator <code>rtruediv</code>).</td>
</tr>
<tr>
<td><code>reindex(**kwargs)</code></td>
<td>Conform Series/DataFrame to new index with optional filling logic.</td>
</tr>
<tr>
<td><code>reindex_like()</code></td>
<td>Return an object with matching indices as other object.</td>
</tr>
</tbody>
</table>

continues on next page
Table 59 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>rename(**kwargs)</td>
<td>Alter axes labels.</td>
</tr>
<tr>
<td>rename_axis(**kwargs)</td>
<td>Set the name of the axis for the index or columns.</td>
</tr>
<tr>
<td>reorder_levels(order[, axis])</td>
<td>Rearrange index levels using input order.</td>
</tr>
<tr>
<td>replace([to_replace, value, inplace, limit,...])</td>
<td>Replace values given in to_replace with value.</td>
</tr>
<tr>
<td>resample(rule[, axis, closed, label,...])</td>
<td>Resample time-series data.</td>
</tr>
<tr>
<td>reset_index([level, drop, inplace,...])</td>
<td>Reset the index, or a level of it.</td>
</tr>
<tr>
<td>rfloordiv(other[, axis, level, fill_value])</td>
<td>Get Integer division of dataframe and other, element-wise (binary operator rfloordiv).</td>
</tr>
<tr>
<td>rmod(other[, axis, level, fill_value])</td>
<td>Get Modulo of dataframe and other, element-wise (binary operator rmod).</td>
</tr>
<tr>
<td>rmul(other[, axis, level, fill_value])</td>
<td>Get Multiplication of dataframe and other, element-wise (binary operator rmul).</td>
</tr>
<tr>
<td>rolling([window[, min_periods, center,...]])</td>
<td>Provide rolling window calculations.</td>
</tr>
<tr>
<td>round([decimals])</td>
<td>Round a DataFrame to a variable number of decimal places.</td>
</tr>
<tr>
<td>rpow(other[, axis, level, fill_value])</td>
<td>Get Exponential power of dataframe and other, element-wise (binary operator rpow).</td>
</tr>
<tr>
<td>rsub(other[, axis, level, fill_value])</td>
<td>Get Subtraction of dataframe and other, element-wise (binary operator rsub).</td>
</tr>
<tr>
<td>rtruediv(other[, axis, level, fill_value])</td>
<td>Get Floating division of dataframe and other, element-wise (binary operator rtruediv).</td>
</tr>
<tr>
<td>sample([n, frac, replace, weights,...])</td>
<td>Return a random sample of items from an axis of object.</td>
</tr>
<tr>
<td>select_dtypes([include, exclude])</td>
<td>Return a subset of the DataFrame’s columns based on the column dtypes.</td>
</tr>
<tr>
<td>sem([axis, skipna, level, ddof, numeric_only])</td>
<td>Return unbiased standard error of the mean over requested axis.</td>
</tr>
<tr>
<td>set_axis(labels[, axis, inplace])</td>
<td>Assign desired index to given axis.</td>
</tr>
<tr>
<td>set_index([keys[, drop, append, inplace,...]])</td>
<td>Set the DataFrame index using existing columns.</td>
</tr>
<tr>
<td>shift([periods, freq, axis, fill_value])</td>
<td>Shift index by desired number of periods with an optional time freq.</td>
</tr>
<tr>
<td>skew([axis, skipna, level, axis, fill_value])</td>
<td>Return unbiased skew over requested axis.</td>
</tr>
<tr>
<td>slice_shift([periods, axis])</td>
<td>Equivalent to shift without copying data.</td>
</tr>
<tr>
<td>sort_index([axis, level, ascending,...])</td>
<td>Sort object by labels (along an axis).</td>
</tr>
<tr>
<td>sort_values(by[, axis, ascending, inplace,...])</td>
<td>Sort by the values along either axis.</td>
</tr>
<tr>
<td>sparse</td>
<td>alias of pandas.core.arrays.sparse.accessor.SparseFrameAccessor</td>
</tr>
<tr>
<td>squeeze([axis])</td>
<td>Squeeze 1 dimensional axis objects into scalars.</td>
</tr>
<tr>
<td>stack([level, dropna])</td>
<td>Stack the prescribed level(s) from columns to index.</td>
</tr>
<tr>
<td>std([axis, skipna, level, ddof, numeric_only])</td>
<td>Return sample standard deviation over requested axis.</td>
</tr>
<tr>
<td>sub(other[, axis, level, fill_value])</td>
<td>Get Subtraction of dataframe and other, element-wise (binary operator sub).</td>
</tr>
<tr>
<td>subtract(other[, axis, level, fill_value])</td>
<td>Get Subtraction of dataframe and other, element-wise (binary operator sub).</td>
</tr>
<tr>
<td>sum([axis, skipna, level, numeric_only,...])</td>
<td>Return the sum of the values for the requested axis.</td>
</tr>
<tr>
<td>swapaxes([axis1, axis2[, copy]])</td>
<td>Interchange axes and swap values axes appropriately.</td>
</tr>
<tr>
<td>swaplevel((i[, j, axis])</td>
<td>Swap levels i and j in a MultiIndex on a particular axis.</td>
</tr>
<tr>
<td>tail([n])</td>
<td>Return the last n rows.</td>
</tr>
</tbody>
</table>

continues on next page
<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>take(indices[, axis, is_copy])</code></td>
<td>Return the elements in the given positional indices along an axis.</td>
</tr>
<tr>
<td><code>to_clipboard([excel, sep])</code></td>
<td>Copy object to the system clipboard.</td>
</tr>
<tr>
<td><code>to_csv([path_or_buf, sep, na_rep, ...])</code></td>
<td>Write object to a comma-separated values (csv) file.</td>
</tr>
<tr>
<td><code>to_dict([orient, into])</code></td>
<td>Convert the DataFrame to a dictionary.</td>
</tr>
<tr>
<td><code>to_excel(excel_writer[, sheet_name, na_rep, ...])</code></td>
<td>Write object to an Excel sheet.</td>
</tr>
<tr>
<td><code>to_feather(**kwargs)</code></td>
<td>Write a DataFrame to the binary Feather format.</td>
</tr>
<tr>
<td><code>to_gbq(destination_table[, project_id, ...])</code></td>
<td>Write a DataFrame to a Google BigQuery table.</td>
</tr>
<tr>
<td><code>to_hdf(path_or_buf, key[, mode, complevel, ...])</code></td>
<td>Write the contained data to an HDF5 file using HDFStore.</td>
</tr>
<tr>
<td><code>to_html([buf, columns, col_space, header, ...])</code></td>
<td>Render a DataFrame as an HTML table.</td>
</tr>
<tr>
<td><code>to_json([path_or_buf, orient, date_format, ...])</code></td>
<td>Convert the object to a JSON string.</td>
</tr>
<tr>
<td><code>to_latex([buf, columns, col_space, header, ...])</code></td>
<td>Render object to a LaTeX tabular, longtable, or nested table/tabular.</td>
</tr>
<tr>
<td><code>to_markdown([buf, columns, col_space, header, ...])</code></td>
<td>Render a DataFrame to a console-friendly tabular output.</td>
</tr>
<tr>
<td><code>to_period([freq, axis, copy])</code></td>
<td>Convert DataFrame from DatetimeIndex to PeriodIndex.</td>
</tr>
<tr>
<td><code>to_pickle(path[, compression, protocol])</code></td>
<td>Pickle (serialize) object to file.</td>
</tr>
<tr>
<td><code>to_records([index, column_dtypes, index_dtypes])</code></td>
<td>Convert DataFrame to a NumPy record array.</td>
</tr>
<tr>
<td><code>to_sql(name, con[, schema, if_exists, ...])</code></td>
<td>Write records stored in a DataFrame to a SQL database.</td>
</tr>
<tr>
<td><code>to_stata(**kwargs)</code></td>
<td>Export DataFrame object to Stata dta format.</td>
</tr>
<tr>
<td><code>to_string([buf, columns, col_space, header, ...])</code></td>
<td>Render a DataFrame to a console-friendly tabular output.</td>
</tr>
<tr>
<td><code>to_timestamp([freq, how, axis, copy])</code></td>
<td>Cast to DatetimeIndex of timestamps, at beginning of period.</td>
</tr>
<tr>
<td><code>to_xarray()</code></td>
<td>Return an xarray object from the pandas object.</td>
</tr>
<tr>
<td><code>transform(func[, axis])</code></td>
<td>Call func on self producing a DataFrame with transformed values.</td>
</tr>
<tr>
<td><code>transpose(*args[, copy])</code></td>
<td>Transpose index and columns.</td>
</tr>
<tr>
<td><code>truediv(other[, axis, level, fill_value])</code></td>
<td>Get Floating division of dataframe and other, element-wise (binary operator truediv).</td>
</tr>
<tr>
<td><code>truncate([before, after, axis, copy])</code></td>
<td>Truncate a Series or DataFrame before and after some index value.</td>
</tr>
<tr>
<td><code>tz_convert(tz[, axis, level, copy])</code></td>
<td>Convert tz-aware axis to target time zone.</td>
</tr>
<tr>
<td><code>tz_localize(tz[, axis, level, copy, ...])</code></td>
<td>Localize tz-naive index of a Series or DataFrame to target time zone.</td>
</tr>
<tr>
<td><code>unstack([level, fill_value])</code></td>
<td>Pivot a level of the (necessarily hierarchical) index labels.</td>
</tr>
<tr>
<td><code>update(other[, join, overwrite, ...])</code></td>
<td>Modify in place using non-NA values from another DataFrame.</td>
</tr>
<tr>
<td><code>value_counts([subset, normalize, sort, ...])</code></td>
<td>Return a Series containing counts of unique rows in the DataFrame.</td>
</tr>
<tr>
<td><code>var([axis, skipna, level, ddof, numeric_only])</code></td>
<td>Return unbiased variance over requested axis.</td>
</tr>
<tr>
<td><code>where(cond[, other, inplace, axis, level, ...])</code></td>
<td>Replace values where the condition is False.</td>
</tr>
</tbody>
</table>

Continues on next page
Table 59 – continued from previous page

| `xs(key[, axis, level, drop_level])` | Return cross-section from the Series/DataFrame. |

**pandas.DataFrame.abs**

**DataFrame.abs()**

Return a Series/DataFrame with absolute numeric value of each element.

This function only applies to elements that are all numeric.

**Returns**

- **abs** Series/DataFrame containing the absolute value of each element.

**See also:**

- **numpy.absolute** Calculate the absolute value element-wise.

**Notes**

For complex inputs, \(1.2 + 1j\), the absolute value is \(\sqrt{a^2 + b^2}\).

**Examples**

Absolute numeric values in a Series.

```python
>>> s = pd.Series([-1.10, 2, -3.33, 4])
>>> s.abs()
0   1.10
1   2.00
2   3.33
3   4.00
dtype: float64
```

Absolute numeric values in a Series with complex numbers.

```python
>>> s = pd.Series([1.2 + 1j])
>>> s.abs()
0  1.56205
dtype: float64
```

Absolute numeric values in a Series with a Timedelta element.

```python
>>> s = pd.Series([pd.Timedelta('1 days')])
>>> s.abs()
0  1 days
dtype: timedelta64[ns]
```

Select rows with data closest to certain value using argsort (from StackOverflow).

```python
>>> df = pd.DataFrame(
...     {'a': [4, 5, 6, 7],
...      'b': [10, 20, 30, 40],
...      'c': [100, 50, -30, -50]
...     }
... )
```

(continues on next page)
>>> df
   a  b  c
0  4 10 100
1  5  20  50
2  6  30 -30
3  7  40 -50

>>> df.loc[(df.c - 43).abs().argsort()]
   a  b  c
1  5  20  50
0  4  10 100
2  6  30 -30
3  7  40 -50

**pandas.DataFrame.add**

`DataFrame.add(other, axis='columns', level=None, fill_value=None)`

Get Addition of dataframe and other, element-wise (binary operator `add`).

Equivalent to `dataframe + other`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `radd`.

Among flexible wrappers (`add, sub, mul, div, mod, pow`) to arithmetic operators: `+`, `-`, `*`, `/`, `//`, `%`, `**`.

**Parameters**

- `other` [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.
- `axis` [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.
- `level` [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.
- `fill_value` [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

**Returns**

- `DataFrame` Result of the arithmetic operation.

**See also:**

- `DataFrame.add` Add DataFrames.
- `DataFrame.sub` Subtract DataFrames.
- `DataFrame.mul` Multiply DataFrames.
- `DataFrame.div` Divide DataFrames (float division).
- `DataFrame.truediv` Divide DataFrames (float division).
- `DataFrame.floordiv` Divide DataFrames (integer division).
- `DataFrame.mod` Calculate modulo (remainder after division).
- `DataFrame.pow` Calculate exponential power.
### Notes

Mismatched indices will be unioned together.

### Examples

```python
>>> df = pd.DataFrame({'angles': [0, 3, 4],
                      'degrees': [360, 180, 360],
                      'index': ['circle', 'triangle', 'rectangle']})
>>> df
  angles  degrees
circle     0      360
triangle    3      180
rectangle   4      360
```

Add a scalar with operator version which return the same results.

```python
>>> df + 1
  angles  degrees
circle    1      361
triangle   4      181
rectangle  5      361
```

```python
>>> df.add(1)
  angles  degrees
circle    1      361
triangle   4      181
rectangle  5      361
```

Divide by constant with reverse version.

```python
>>> df.div(10)
  angles  degrees
circle   0.0     36.0
triangle 0.3     18.0
rectangle 0.4    36.0
```

```python
>>> df.rdiv(10)
  angles  degrees
circle  inf     0.027778
triangle 3.33333 0.055556
rectangle 2.50000 0.027778
```

Subtract a list and Series by axis with operator version.

```python
>>> df - [1, 2]
  angles  degrees
circle   -1      358
triangle    2      178
rectangle   3      358
```

```python
>>> df.sub([1, 2], axis='columns')
  angles  degrees
circle   -1      358
triangle    2      178
rectangle   3      358
```
Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
                    index=['circle', 'triangle', 'rectangle'])
```

```
>>> df + other
angles  degrees
circle  0.0    NaN
triangle 9.0    NaN
rectangle 16.0   NaN
```

```
>>> df.mul(other, fill_value=0)
angles  degrees
circle  0.0
triangle 9.0
rectangle 16.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
                               'degrees': [360, 180, 360, 360, 540, 720]},
                               index=['A', 'A', 'A', 'B', 'B', 'B'],
                               ['circle', 'triangle', 'rectangle',
                               'square', 'pentagon', 'hexagon'])
```

```
>>> df_multindex
angles  degrees
A circle 0.0 360
triangle 3.0 180
rectangle 4.0 360
B square 4.0 360
pentagon 5.0 540
hexagon 6.0 720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
angles  degrees
A circle NaN 1.0
triangle 1.0 1.0
rectangle 1.0 1.0
B square 0.0 0.0
pentagon 0.0 0.0
hexagon 0.0 0.0
```
pandas.DataFrame.add_prefix

DataFrame.add_prefix(prefix)
Prefix labels with string prefix.

For Series, the row labels are prefixed. For DataFrame, the column labels are prefixed.

Parameters

prefix [str] The string to add before each label.

Returns

Series or DataFrame New Series or DataFrame with updated labels.

See also:

Series.add_suffix Suffix row labels with string suffix.
DataFrame.add_suffix Suffix column labels with string suffix.

Examples

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s
0    1
1    2
2    3
3    4
dtype: int64

>>> s.add_prefix('item_')
item_0 1
item_1 2
item_2 3
item_3 4
dtype: int64

>>> df = pd.DataFrame({'A': [1, 2, 3, 4], 'B': [3, 4, 5, 6]})
>>> df
   A  B
0  1  3
1  2  4
2  3  5
3  4  6

>>> df.add_prefix('col_')
   col_A  col_B
0      1      3
1      2      4
2      3      5
3      4      6
```
**pandas.DataFrame.add_suffix**

```python
dataframe.add_suffix(suffix)
```

Suffix labels with string `suffix`.

For Series, the row labels are suffixed. For DataFrame, the column labels are suffixed.

**Parameters**

- `suffix` [str] The string to add after each label.

**Returns**

- `Series` or `DataFrame` New Series or DataFrame with updated labels.

**See also:**

- `Series.add_prefix` Prefix row labels with string `prefix`.
- `DataFrame.add_prefix` Prefix column labels with string `prefix`.

**Examples**

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s
0    1
1    2
2    3
3    4
dtype: int64
```

```python
>>> s.add_suffix('_item')
0_item    1
1_item    2
2_item    3
3_item    4
dtype: int64
```

```python
>>> df = pd.DataFrame({'A': [1, 2, 3, 4], 'B': [3, 4, 5, 6]})
>>> df
   A  B
0  1  3
1  2  4
2  3  5
3  4  6
```

```python
>>> df.add_suffix('_col')
   A_col  B_col
0      1      3
1      2      4
2      3      5
3      4      6
```
DataFrame.agg (func=None, axis=0, *args, **kwargs)
Aggregate using one or more operations over the specified axis.
New in version 0.20.0.

Parameters

- **func** [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a DataFrame or when passed to DataFrame.apply. Accepted combinations are:
  - function
  - string function name
  - list of functions and/or function names, e.g. [np.sum, 'mean']
  - dict of axis labels -> functions, function names or list of such.
- **axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] If 0 or ‘index’: apply function to each column. If 1 or ‘columns’: apply function to each row.
- **args** Positional arguments to pass to **func**.
- **kwargs** Keyword arguments to pass to **func**.

Returns

scalar, Series or DataFrame  The return can be:
  - scalar : when Series.agg is called with single function
  - Series : when DataFrame.agg is called with a single function
  - DataFrame : when DataFrame.agg is called with several functions

The aggregation operations are always performed over an axis, either the index (default) or the column axis. This behavior is different from 
numpy aggregation functions (mean, median, prod, sum, std, var), where the default is to compute the aggregation of the flattened 
array, e.g., numpy.mean(arr_2d) as opposed to 
numpy.mean(arr_2d, axis=0).

agg is an alias for aggregate. Use the alias.

See also:

- **DataFrame.apply** Perform any type of operations.
- **DataFrame.transform** Perform transformation type operations.
- core.groupby.GroupBy Perform operations over groups.
- core.resample.Resampler Perform operations over resampled bins.
- core.window.Rolling Perform operations over rolling window.
- core.window.Expanding Perform operations over expanding window.
**Notes**

`agg` is an alias for `aggregate`. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

**Examples**

```python
df = pd.DataFrame([[1, 2, 3],
                   [4, 5, 6],
                   [7, 8, 9],
                   [np.nan, np.nan, np.nan]],
                  columns=['A', 'B', 'C'])
```

Aggregate these functions over the rows.

```python
df.agg(['sum', 'min'])
```

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>sum</td>
<td>12.0</td>
<td>15.0</td>
<td>18.0</td>
</tr>
<tr>
<td>min</td>
<td>1.0</td>
<td>2.0</td>
<td>3.0</td>
</tr>
</tbody>
</table>

Different aggregations per column.

```python
df.agg({'A' : ['sum', 'min'], 'B' : ['min', 'max']})
```

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>max</td>
<td>NaN 8.0</td>
</tr>
<tr>
<td>min</td>
<td>1.0 2.0</td>
</tr>
<tr>
<td>sum</td>
<td>12.0 NaN</td>
</tr>
</tbody>
</table>

Aggregate over the columns.

```python
df.agg("mean", axis="columns")
```

| 0  | 2.0 |
| 1  | 5.0 |
| 2  | 8.0 |
| 3  | NaN |

dtype: float64

**pandas.DataFrame.aggregate**

`DataFrame.aggregate` *(func=None, axis=0, *args, **kwargs)*

Aggregate using one or more operations over the specified axis.

New in version 0.20.0.

**Parameters**

- **func** [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a DataFrame or when passed to DataFrame.apply.

  Accepted combinations are:
  - function
• string function name
• list of functions and/or function names, e.g. [np.sum, 'mean']
• dict of axis labels -> functions, function names or list of such.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] If 0 or ‘index’: apply function to each column. If 1 or ‘columns’: apply function to each row.

*args Positional arguments to pass to **func**.

**kwargs Keyword arguments to pass to **func**.

Returns

**scalar, Series or DataFrame** The return can be:
  • scalar : when Series.agg is called with single function
  • Series : when DataFrame.agg is called with a single function
  • DataFrame : when DataFrame.agg is called with several functions

Return scalar, Series or DataFrame.

The aggregation operations are always performed over an axis, either the index (default) or the column axis. This behavior is different from

**numpy aggregation functions** (**mean**, **median**, **prod**, **sum**, **std**, **var**), where the default is to compute the aggregation of the flattened array, e.g., **numpy.mean(arr_2d)** as opposed to **numpy.mean(arr_2d, axis=0)**.

**agg** is an alias for **aggregate**. Use the alias.

See also:

**DataFrame.agg** Perform any type of operations.

**DataFrame.transform** Perform transformation type operations.

**core.groupby.GroupBy** Perform operations over groups.

**core.resample.Resampler** Perform operations over resampled bins.

**core.window.Rolling** Perform operations over rolling window.

**core.window.Expanding** Perform operations over expanding window.

**core.window.ExponentialMovingWindow** Perform operation over exponential weighted window.
Notes

`agg` is an alias for `aggregate`. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

Examples

```python
>>> df = pd.DataFrame([[1, 2, 3],
...                     [4, 5, 6],
...                     [7, 8, 9],
...                     [np.nan, np.nan, np.nan]],
...                     columns=['A', 'B', 'C'])

Aggregate these functions over the rows.

```python
>>> df.agg(['sum', 'min'])
```

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>sum</td>
<td>12.0</td>
<td>15.0</td>
<td>18.0</td>
</tr>
<tr>
<td>min</td>
<td>1.0</td>
<td>2.0</td>
<td>3.0</td>
</tr>
</tbody>
</table>

Different aggregations per column.

```python
>>> df.agg({'A' : ['sum', 'min'], 'B' : ['min', 'max']})
```

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>max</td>
<td>NaN</td>
<td>8.0</td>
</tr>
<tr>
<td>min</td>
<td>1.0</td>
<td>2.0</td>
</tr>
<tr>
<td>sum</td>
<td>12.0</td>
<td>NaN</td>
</tr>
</tbody>
</table>

Aggregate over the columns.

```python
>>> df.agg("mean", axis="columns")
```

<table>
<thead>
<tr>
<th></th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>2.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>5.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>8.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>NaN</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

dtype: float64

`pandas.DataFrame.align`

DataFrame.align(other, join='outer', axis=None, level=None, copy=True, fill_value=None, method=None, limit=None, fill_axis=0, broadcast_axis=None)

Align two objects on their axes with the specified join method.

Join method is specified for each axis Index.

Parameters

- **other** [DataFrame or Series]
- **join** [{‘outer’, ‘inner’, ‘left’, ‘right’}, default ‘outer’]
- **axis** [allowed axis of the other object, default None] Align on index (0), columns (1), or both (None).
- **level** [int or level name, default None] Broadcast across a level, matching Index values on the passed MultiIndex level.
copy [bool, default True] Always returns new objects. If copy=False and no reindexing is required then original objects are returned.

fill_value [scalar, default np.NaN] Value to use for missing values. Defaults to NaN, but can be any “compatible” value.

  • pad / ffill: propagate last valid observation forward to next valid.
  • backfill / bfill: use NEXT valid observation to fill gap.

limit [int, default None] If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled. Must be greater than 0 if not None.

fill_axis [{0 or ‘index’, 1 or ‘columns’}, default 0] Filling axis, method and limit.

broadcast_axis [{0 or ‘index’, 1 or ‘columns’}, default None] Broadcast values along this axis, if aligning two objects of different dimensions.

Returns
(left, right) [(DataFrame, type of other)] Aligned objects.

pandas.DataFrame.all

DataFrame.all (axis=0, bool_only=None, skipna=True, level=None, **kwargs)
Return whether all elements are True, potentially over an axis.

Returns True unless there at least one element within a series or along a Dataframe axis that is False or equivalent (e.g. zero or empty).

Parameters

axis [{0 or ‘index’, 1 or ‘columns’, None}, default 0] Indicate which axis or axes should be reduced.
  • 0 / ‘index’ : reduce the index, return a Series whose index is the original column labels.
  • 1 / ‘columns’ : reduce the columns, return a Series whose index is the original index.
  • None : reduce all axes, return a scalar.

bool_only [bool, default None] Include only boolean columns. If None, will attempt to use everything, then use only boolean data. Not implemented for Series.

skipna [bool, default True] Exclude NA/null values. If the entire row/column is NA and skipna is True, then the result will be True, as for an empty row/column. If skipna is False, then NA are treated as True, because these are not equal to zero.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

**kwargs [any, default None] Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns
Series or DataFrame If level is specified, then, DataFrame is returned; otherwise, Series is returned.

See also:

Series.all Return True if all elements are True.

DataFrame.any Return True if one (or more) elements are True.

Examples

Series

```python
>>> pd.Series([True, True]).all()
True
>>> pd.Series([True, False]).all()
False
>>> pd.Series([]).all()
True
>>> pd.Series([np.nan]).all()
True
>>> pd.Series([np.nan]).all(skipna=False)
True
```

DataFrames

Create a dataframe from a dictionary.

```python
>>> df = pd.DataFrame({'col1': [True, True], 'col2': [True, False]})
>>> df
   col1  col2
0    True  True
1    True  False
```

Default behaviour checks if column-wise values all return True.

```python
>>> df.all()
   col1  col2
0   True  True
dtype: bool
```

Specify axis='columns' to check if row-wise values all return True.

```python
>>> df.all(axis='columns')
0  True
1  False
dtype: bool
```

Or axis=None for whether every value is True.

```python
>>> df.all(axis=None)
False
```
DataFrame.any (axis=0, bool_only=None, skipna=True, level=None, **kwargs)

Return whether any element is True, potentially over an axis.

Returns False unless there at least one element within a series or along a Dataframe axis that is True or equivalent (e.g. non-zero or non-empty).

Parameters

axis [[0 or ‘index’, 1 or ‘columns’, None], default 0] Indicate which axis or axes should be reduced.

• 0 / ‘index’ : reduce the index, return a Series whose index is the original column labels.
• 1 / ‘columns’ : reduce the columns, return a Series whose index is the original index.
• None : reduce all axes, return a scalar.

bool_only [bool, default None] Include only boolean columns. If None, will attempt to use everything, then use only boolean data. Not implemented for Series.

skipna [bool, default True] Exclude NA/null values. If the entire row/column is NA and skipna is True, then the result will be False, as for an empty row/column. If skipna is False, then NA are treated as True, because these are not equal to zero.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

**kwargs [any, default None] Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

Series or DataFrame If level is specified, then, DataFrame is returned; otherwise, Series is returned.

See also:

numpy.any Numpy version of this method.
Series.any Return whether any element is True.
Series.all Return whether all elements are True.
DataFrame.any Return whether any element is True over requested axis.
DataFrame.all Return whether all elements are True over requested axis.

Examples

Series

For Series input, the output is a scalar indicating whether any element is True.

```python
>>> pd.Series([False, False]).any()
False
>>> pd.Series([True, False]).any()
True
>>> pd.Series([]).any()
```

(continues on next page)
False
>>> pd.Series([np.nan]).any()
False
>>> pd.Series([np.nan]).any(skipna=False)
True

**DataFrame**

Whether each column contains at least one True element (the default).

```python
>>> df = pd.DataFrame({'A': [1, 2], 'B': [0, 2], 'C': [0, 0]})
>>> df
   A  B  C
0  1  0  0
1  2  2  0
```

```python
>>> df.any()
A   True
B  True
C  False
dtype: bool
```

Aggregating over the columns.

```python
>>> df = pd.DataFrame({'A': [True, False], 'B': [1, 2]})
>>> df
   A  B
0  True 1
1  False 2
```

```python
>>> df.any(axis='columns')
0   True
1   True
dtype: bool
```

```python
>>> df = pd.DataFrame({'A': [True, False], 'B': [1, 0]})
>>> df
   A  B
0  True 1
1  False 0
```

```python
>>> df.any(axis='columns')
0   True
1  False
dtype: bool
```

Aggregating over the entire DataFrame with `axis=None`.

```python
>>> df.any(axis=None)
True
```

`any` for an empty DataFrame is an empty Series.

```python
>>> pd.DataFrame([]).any()
Series([], dtype: bool)
```
pandas.DataFrame.append

DataFrame.append(other, ignore_index=False, verify_integrity=False, sort=False)

Append rows of other to the end of caller, returning a new object.

Columns in other that are not in the caller are added as new columns.

Parameters

other [DataFrame or Series/dict-like object, or list of these] The data to append.
ignore_index [bool, default False] If True, the resulting axis will be labeled 0, 1, ..., n-1.
verify_integrity [bool, default False] If True, raise ValueError on creating index with duplicates.
sort [bool, default False] Sort columns if the columns of self and other are not aligned.

New in version 0.23.0.
Changed in version 1.0.0: Changed to not sort by default.

Returns

DataFrame

See also:

concat General function to concatenate DataFrame or Series objects.

Notes

If a list of dict/series is passed and the keys are all contained in the DataFrame’s index, the order of the columns in the resulting DataFrame will be unchanged.

Iteratively appending rows to a DataFrame can be more computationally intensive than a single concatenate. A better solution is to append those rows to a list and then concatenate the list with the original DataFrame all at once.

Examples

```python
>>> df = pd.DataFrame([[1, 2], [3, 4]], columns=list('AB'))
```
```
  A  B
0 1 2
1 3 4
```
```python
>>> df2 = pd.DataFrame([[5, 6], [7, 8]], columns=list('AB'))
```
```python
>>> df.append(df2)
```
```
  A  B
0 1 2
1 3 4
0 5 6
1 7 8
```

With ignore_index set to True:
The following, while not recommended methods for generating DataFrames, show two ways to generate a DataFrame from multiple data sources.

Less efficient:

```python
>>> df = pd.DataFrame(columns=['A'])
>>> for i in range(5):
...   df = df.append({'A': i}, ignore_index=True)

>>> df
A
0 0
1 1
2 2
3 3
4 4
```

More efficient:

```python
>>> pd.concat([pd.DataFrame([i], columns=['A']) for i in range(5)], ignore_index=True)

   A
0 0
1 1
2 2
3 3
4 4
```

---

**pandas.DataFrame.apply**

DataFrame.apply(func, axis=0, raw=False, result_type=None, args=(), **kwds)

Apply a function along an axis of the DataFrame.

Objects passed to the function are Series objects whose index is either the DataFrame’s index (axis=0) or the DataFrame’s columns (axis=1). By default (result_type=None), the final return type is inferred from the return type of the applied function. Otherwise, it depends on the result_type argument.

**Parameters**

- **func** [function] Function to apply to each column or row.
- **axis** [[0 or ‘index’, 1 or ‘columns’], default 0] Axis along which the function is applied:
  - 0 or ‘index’: apply function to each column.
  - 1 or ‘columns’: apply function to each row.
- **raw** [bool, default False] Determines if row or column is passed as a Series or ndarray object:
  - False: passes each row or column as a Series to the function.
• True: the passed function will receive ndarray objects instead. If you are just applying a NumPy reduction function this will achieve much better performance.

result_type [[‘expand’, ‘reduce’, ‘broadcast’, None], default None] These only act when axis=1 (columns):
  • ‘expand’: list-like results will be turned into columns.
  • ‘reduce’: returns a Series if possible rather than expanding list-like results. This is the opposite of ‘expand’.
  • ‘broadcast’: results will be broadcast to the original shape of the DataFrame, the original index and columns will be retained.

The default behaviour (None) depends on the return value of the applied function: list-like results will be returned as a Series of those. However if the apply function returns a Series these are expanded to columns.

New in version 0.23.0.

args [tuple] Positional arguments to pass to func in addition to the array/series.

**kwds Additional keyword arguments to pass as keywords arguments to func.

Returns

Series or DataFrame Result of applying func along the given axis of the DataFrame.

See also:

DataFrame.applymap For elementwise operations.

DataFrame.aggregate Only perform aggregating type operations.

DataFrame.transform Only perform transforming type operations.

Examples

```python
>>> df = pd.DataFrame([[4, 9]] * 3, columns=['A', 'B'])
>>> df
   A  B
0  4  9
1  4  9
2  4  9

Using a numpy universal function (in this case the same as np.sqrt(df)):

```python
>>> df.apply(np.sqrt)
   A  B
0  2.0  3.0
1  2.0  3.0
2  2.0  3.0
```

Using a reducing function on either axis

```python
>>> df.apply(np.sum, axis=0)
   A   B
0  12  27
dtype: int64
```
>>> df.apply(np.sum, axis=1)
0  13
1  13
2  13
dtype: int64

Returning a list-like will result in a Series

>>> df.apply(lambda x: [1, 2], axis=1)
0  [1, 2]
1  [1, 2]
2  [1, 2]
dtype: object

Passing result_type='expand' will expand list-like results to columns of a Dataframe

>>> df.apply(lambda x: [1, 2], axis=1, result_type='expand')
       0  1
0   1  2
1   1  2
2   1  2

Returning a Series inside the function is similar to passing result_type='expand'. The resulting column names will be the Series index.

>>> df.apply(lambda x: pd.Series([1, 2], index=['foo', 'bar']), axis=1)
     foo  bar
0   1   2
1   1   2
2   1   2

Passing result_type='broadcast' will ensure the same shape result, whether list-like or scalar is returned by the function, and broadcast it along the axis. The resulting column names will be the originals.

>>> df.apply(lambda x: [1, 2], axis=1, result_type='broadcast')
       A  B
0   1   2
1   1   2
2   1   2

**pandas.DataFrame.applymap**

Dataframe.applymap(func)

Apply a function to a Dataframe elementwise.

This method applies a function that accepts and returns a scalar to every element of a Dataframe.

**Parameters**

- **func** [callable] Python function, returns a single value from a single value.

**Returns**

- **DataFrame** Transformed DataFrame.

**See also:**

- **DataFrame.apply** Apply a function along input axis of DataFrame.
Examples

```python
>>> df = pd.DataFrame([[1, 2.12], [3.356, 4.567]])
>>> df
  0 1
0 1.000 2.120
1 3.356 4.567
```

```python
>>> df.applymap(lambda x: len(str(x)))
  0 1
0 3 4
1 5 5
```

Note that a vectorized version of `func` often exists, which will be much faster. You could square each number elementwise.

```python
>>> df.applymap(lambda x: x**2)
  0 1
0 1.000000 4.494400
1 11.262736 20.857489
```

But it’s better to avoid applymap in that case.

```python
>>> df ** 2
  0 1
0 1.000000 4.494400
1 11.262736 20.857489
```

**pandas.DataFrame.asfreq**

`DataFrame.asfreq(freq, method=None, how=None, normalize=False, fill_value=None)`

Convert TimeSeries to specified frequency.

Optionally provide filling method to pad/backfill missing values.

Returns the original data conformed to a new index with the specified frequency. `resample` is more appropriate if an operation, such as summarization, is necessary to represent the data at the new frequency.

**Parameters**

- `freq` [DateOffset or str] Frequency DateOffset or string.
- `method` [{'backfill'/'bfill', 'pad'/'ffill'}, default None] Method to use for filling holes in reindexed Series (note this does not fill NaNs that already were present):
  - ‘pad’ / ‘ffill’: propagate last valid observation forward to next valid
  - ‘backfill’ / ‘bfill’: use NEXT valid observation to fill.
- `how` [{'start', 'end'}, default end] For PeriodIndex only (see `PeriodIndex.asfreq`).
- `normalize` [bool, default False] Whether to reset output index to midnight.
- `fill_value` [scalar, optional] Value to use for missing values, applied during upsampling (note this does not fill NaNs that already were present).

**Returns**

- `Same type as caller` Object converted to the specified frequency.
See also:

**reindex** Conform DataFrame to new index with optional filling logic.

Notes

To learn more about the frequency strings, please see this link.

Examples

Start by creating a series with 4 one minute timestamps.

```python
>>> index = pd.date_range('1/1/2000', periods=4, freq='T')
>>> series = pd.Series([0.0, None, 2.0, 3.0], index=index)
>>> df = pd.DataFrame({'s':series})
>>> df
   s
0 0.0
1 NaN
2 2.0
3 3.0
```

Upsample the series into 30 second bins.

```python
>>> df.asfreq(freq='30S')
   s
0 0.0
1 NaN
2 NaN
3 2.0
4 NaN
5 9.0
6 9.0
7 3.0
```

Upsample again, providing a fill value.

```python
>>> df.asfreq(freq='30S', fill_value=9.0)
   s
0 0.0
1 9.0
2 NaN
3 9.0
4 2.0
5 9.0
6 3.0
```

Upsample again, providing a method.

```python
>>> df.asfreq(freq='30S', method='bfill')
   s
0 0.0
1 NaN
2 NaN
3 2.0
4 2.0
```

(continues on next page)
pandas.DataFrame.asof

DataFrame.asof(where, subset=None)
Return the last row(s) without any NaNs before where.
The last row (for each element in where, if list) without any NaN is taken. In case of a DataFrame, the last row without NaN considering only the subset of columns (if not None)
If there is no good value, NaN is returned for a Series or a Series of NaN values for a DataFrame

Parameters
where [date or array-like of dates] Date(s) before which the last row(s) are returned.
subset [str or array-like of str, default None] For DataFrame, if not None, only use these columns to check for NaNs.

Returns
scalar, Series, or DataFrame The return can be:
• scalar : when self is a Series and where is a scalar
• Series: when self is a Series and where is an array-like, or when self is a DataFrame and where is a scalar
• DataFrame : when self is a DataFrame and where is an array-like

Return scalar, Series, or DataFrame.

See also:
merge_asof Perform an asof merge. Similar to left join.

Notes
Dates are assumed to be sorted. Raises if this is not the case.

Examples
A Series and a scalar where.
```python
>>> s = pd.Series([1, 2, np.nan, 4], index=[10, 20, 30, 40])
>>> s
10  1.0
20  2.0
30  NaN
40  4.0
dtype: float64

>>> s.asof(20)
2.0
```
For a sequence `where`, a Series is returned. The first value is NaN, because the first element of `where` is before the first index value.

```python
>>> s.asof([5, 20])
5   NaN
20  2.0
dtype: float64
```

Missing values are not considered. The following is 2.0, not NaN, even though NaN is at the index location for 30.

```python
>>> s.asof(30)
2.0
```

Take all columns into consideration

```python
>>> df = pd.DataFrame({'a': [10, 20, 30, 40, 50],
...                     'b': [None, None, None, None, 500],
...                     'c': [1.0, 1.5, 2.0, 2.5, 3.0]},
...                    index=pd.DatetimeIndex(['2018-02-27 09:01:00',
...                                              '2018-02-27 09:02:00',
...                                              '2018-02-27 09:03:00',
...                                              '2018-02-27 09:04:00',
...                                              '2018-02-27 09:05:00']))
```

```python
>>> df.asof(pd.DatetimeIndex(['2018-02-27 09:03:30',
...                             '2018-02-27 09:04:30'])),
...                    subset=['a'])
```

```python
a b
2018-02-27 09:03:30 30.0 NaN
2018-02-27 09:04:30 40.0 NaN
```

**pandas.DataFrame.assign**

**DataFrame.assign(**kwargs**)**

Assign new columns to a DataFrame.

Returns a new object with all original columns in addition to new ones. Existing columns that are reassigned will be overwritten.

**Parameters**

**kwargs** [dict of {str: callable or Series}] The column names are keywords. If the values are callable, they are computed on the DataFrame and assigned to the new columns. The callable must not change input DataFrame (though pandas doesn’t check it). If the values are not callable, (e.g. a Series, scalar, or array), they are simply assigned.

**Returns**

**DataFrame** A new DataFrame with the new columns in addition to all the existing columns.
Notes

Assigning multiple columns within the same assign is possible. Later items in `**kwargs` may refer to newly created or modified columns in `df`; items are computed and assigned into `df` in order.

Changed in version 0.23.0: Keyword argument order is maintained.

Examples

```python
>>> df = pd.DataFrame({'temp_c': [17.0, 25.0]},
                    index=['Portland', 'Berkeley'])
```

```text
temp_c
Portland 17.0
Berkeley 25.0
```

Where the value is a callable, evaluated on `df`:

```python
>>> df.assign(temp_f=lambda x: x.temp_c * 9 / 5 + 32)
```

```text
temp_c temp_f
Portland 17.0 62.6
Berkeley 25.0 77.0
```

Alternatively, the same behavior can be achieved by directly referencing an existing Series or sequence:

```python
>>> df.assign(temp_f=df['temp_c'] * 9 / 5 + 32)
```

```text
temp_c temp_f
Portland 17.0 62.6
Berkeley 25.0 77.0
```

You can create multiple columns within the same assign where one of the columns depends on another one defined within the same assign:

```python
>>> df.assign(temp_f=lambda x: x['temp_c'] * 9 / 5 + 32, 
               temp_k=lambda x: (x['temp_f'] + 459.67) * 5 / 9)
```

```text
temp_c temp_f temp_k
Portland 17.0 62.6 290.15
Berkeley 25.0 77.0 298.15
```

### pandas.DataFrame.astype

DataFrame `.astype(dtype, copy=True, errors='raise')`

Cast a pandas object to a specified `dtype` `dtype`.

**Parameters**

- `dtype` [data type, or dict of column name -> data type] Use a numpy.dtype or Python type to cast entire pandas object to the same type. Alternatively, use `{col: dtype, ...}`, where col is a column label and dtype is a numpy.dtype or Python type to cast one or more of the DataFrame's columns to column-specific types.

- `copy` [bool, default True] Return a copy when `copy=True` (be very careful setting `copy=False` as changes to values then may propagate to other pandas objects).

- `errors` [‘raise’, ‘ignore’], default ‘raise’] Control raising of exceptions on invalid data for provided `dtype`.  

3.4. DataFrame
• **raise**: allow exceptions to be raised
• **ignore**: suppress exceptions. On error return original object.

**Returns**

**casted** [same type as caller]

**See also:**

to\_datetime Convert argument to datetime.
to\_timedelta Convert argument to timedelta.
to\_numeric Convert argument to a numeric type.
numpy\_ndarray\_astype Cast a numpy array to a specified type.

**Examples**

Create a DataFrame:

```python
>>> d = {'col1': [1, 2], 'col2': [3, 4]}
>>> df = pd.DataFrame(data=d)
>>> df.dtypes
col1    int64
col2    int64
dtype: object
```

Cast all columns to int32:

```python
>>> df.astype('int32').dtypes
col1    int32
col2    int32
dtype: object
```

Cast col1 to int32 using a dictionary:

```python
>>> df.astype({'col1': 'int32'}).dtypes
col1    int32
col2    int64
dtype: object
```

Create a series:

```python
>>> ser = pd.Series([1, 2], dtype='int32')
>>> ser
0    1
1    2
dtype: int32
>>> ser.astype('int64')
0    1
1    2
dtype: int64
```

Convert to categorical type:
Convert to ordered categorical type with custom ordering:

```python
>>> cat_dtype = pd.api.types.CategoricalDtype(
...     categories=[2, 1], ordered=True)
```  
```python
>>> ser.astype(cat_dtype)
0 1
1 2
dtype: category
Categories (2, int64): [2 < 1]
```

Note that using `copy=False` and changing data on a new pandas object may propagate changes:

```python
>>> s1 = pd.Series([1, 2])
```  
```python
>>> s2 = s1.astype('int64', copy=False)
```  
```python
>>> s2[0] = 10
```  
```python
0 10
1 2
dtype: int64
```

Create a series of dates:

```python
>>> ser_date = pd.Series(pd.date_range('20200101', periods=3))
```  
```python
>>> ser_date
0 2020-01-01
1 2020-01-02
2 2020-01-03
dtype: datetime64[ns]
```

Datetimes are localized to UTC first before converting to the specified timezone:

```python
>>> ser_date.astype('datetime64[ns, US/Eastern]')
0 2019-12-31 19:00:00-05:00
1 2020-01-01 19:00:00-05:00
2 2020-01-02 19:00:00-05:00
dtype: datetime64[ns, US/Eastern]
```

### pandas.DataFrame.at_time

DataFrame.**at_time**(time, asof=False, axis=None)

Select values at particular time of day (e.g., 9:30AM).

**Parameters**

- **time** [datetime.time or str]
- **axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] New in version 0.24.0.

**Returns**

- Series or DataFrame
Raises

TypeError  If the index is not a `DatetimeIndex`

See also:

between_time  Select values between particular times of the day.
first  Select initial periods of time series based on a date offset.
last  Select final periods of time series based on a date offset.

`DatetimeIndex.indexer_at_time`  Get just the index locations for values at particular time of the day.

Examples

```python
>>> i = pd.date_range('2018-04-09', periods=4, freq='12H')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
   A
2018-04-09 00:00:00 1
2018-04-09 12:00:00 2
2018-04-10 00:00:00 3
2018-04-10 12:00:00 4

>>> ts.at_time('12:00')
   A
2018-04-09 12:00:00 2
2018-04-10 12:00:00 4
```

`pandas.DataFrame.backfill`

`DataFrame.backfill`  Synonym for `DataFrame.fillna()` with method='bfill'.

Parameters

[klass] or None  Object with missing values filled or None if inplace=True.

`pandas.DataFrame.between_time`

`DataFrame.between_time`  Select values between particular times of the day (e.g., 9:00-9:30 AM).

Parameters

start_time  [datetime.time or str] Initial time as a time filter limit.
end_time  [datetime.time or str] End time as a time filter limit.
include_start  [bool, default True] Whether the start time needs to be included in the result.
include_end [bool, default True] Whether the end time needs to be included in the result.

axis [[0 or ‘index’, 1 or ‘columns’], default 0] Determine range time on index or columns value.

New in version 0.24.0.

Returns

Series or DataFrame Data from the original object filtered to the specified dates range.

Raises

TypeError If the index is not a DatetimeIndex

See also:

at_time Select values at a particular time of the day.

first Select initial periods of time series based on a date offset.

last Select final periods of time series based on a date offset.

DatetimeIndex.indexer_between_time Get just the index locations for values between particular times of the day.

Examples

```python
>>> i = pd.date_range('2018-04-09', periods=4, freq='1D20min')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
          A
2018-04-09 00:00:00  1
2018-04-10 00:20:00  2
2018-04-11 00:40:00  3
2018-04-12 01:00:00  4

>>> ts.between_time('0:15', '0:45')
          A
2018-04-10 00:20:00  2
2018-04-11 00:40:00  3

You get the times that are not between two times by setting start_time later than end_time:

```
pandas.DataFrame.bfill

DataFrame.bfill (axis=None, inplace=False, limit=None, downcast=None)
Synonym for DataFrame.fillna() with method='bfill'.

Returns

{klass} or None  Object with missing values filled or None if inplace=True.

pandas.DataFrame.bool

DataFrame.bool()

Return the bool of a single element Series or DataFrame.

This must be a boolean scalar value, either True or False. It will raise a ValueError if the Series or DataFrame does not have exactly 1 element, or that element is not boolean (integer values 0 and 1 will also raise an exception).

Returns

bool  The value in the Series or DataFrame.

See also:

Series.astype Change the data type of a Series, including to boolean.
DataFrame.astype Change the data type of a DataFrame, including to boolean.
numpy.bool_ NumPy boolean data type, used by pandas for boolean values.

Examples

The method will only work for single element objects with a boolean value:

```python
>>> pd.Series([True]).bool()
True

>>> pd.Series([False]).bool()
False
```

```python
>>> pd.DataFrame({'col': [True]}).bool()
True

>>> pd.DataFrame({'col': [False]}).bool()
False
```

pandas.DataFrame.boxplot

DataFrame.boxplot (column=None, by=None, ax=None, fontsize=None, rot=0, grid=True, figsize=None, layout=None, return_type=None, backend=None, **kwargs)

Make a box plot from DataFrame columns.

Make a box-and-whisker plot from DataFrame columns, optionally grouped by some other columns. A box plot is a method for graphically depicting groups of numerical data through their quartiles. The box extends from the Q1 to Q3 quartile values of the data, with a line at the median (Q2). The whiskers extend from the edges of box to show the range of the data. By default, they extend no more than 1.5 * IQR (IQR = Q3 - Q1) from the edges of the box, ending at the farthest data point within that interval. Outliers are plotted as separate dots.
For further details see Wikipedia’s entry for `boxplot`.

**Parameters**

- **column** [str or list of str, optional] Column name or list of names, or vector. Can be any valid input to `pandas.DataFrame.groupby()`.
- **by** [str or array-like, optional] Column in the DataFrame to `pandas.DataFrame.groupby()`. One box-plot will be done per value of columns in `by`.
- **ax** [object of class matplotlib.axes.Axes, optional] The matplotlib axes to be used by `boxplot`.
- **fontsize** [float or str] Tick label font size in points or as a string (e.g., `large`).
- **rot** [int or float, default 0] The rotation angle of labels (in degrees) with respect to the screen coordinate system.
- **grid** [bool, default True] Setting this to True will show the grid.
- **figsize** [A tuple (width, height) in inches] The size of the figure to create in matplotlib.
- **layout** [tuple (rows, columns), optional] For example, (3, 5) will display the subplots using 3 columns and 5 rows, starting from the top-left.
- **return_type** [{'axes', 'dict', 'both'} or None, default 'axes'] The kind of object to return. The default is `axes`.
  - 'axes' returns the matplotlib axes the boxplot is drawn on.
  - 'dict' returns a dictionary whose values are the matplotlib Lines of the boxplot.
  - 'both' returns a namedtuple with the axes and dict.
  - when grouping with `by`, a Series mapping columns to `return_type` is returned.
    
    If `return_type` is `None`, a NumPy array of axes with the same shape as `layout` is returned.

- **backend** [str, default None] Backend to use instead of the backend specified in the option `plotting.backend`. For instance, `matplotlib`. Alternatively, to specify the `plotting.backend` for the whole session, set `pd.options.plotting.backend`.
  
  New in version 1.0.0.

- ****kwargs All other plotting keyword arguments to be passed to `matplotlib.pyplot.boxplot()`.

**Returns**

- **result** See Notes.

**See also:**

- `Series.plot.hist` Make a histogram.
- `matplotlib.pyplot.boxplot` Matplotlib equivalent plot.
Notes

The return type depends on the return_type parameter:

- 'axes': object of class matplotlib.axes.Axes
- 'dict': dict of matplotlib.lines.Line2D objects
- 'both': a namedtuple with structure (ax, lines)

For data grouped with by, return a Series of the above or a numpy array:

- Series
- array (for return_type = None)

Use return_type='dict' when you want to tweak the appearance of the lines after plotting. In this case a dict containing the Lines making up the boxes, caps, fliers, medians, and whiskers is returned.

Examples

Boxplots can be created for every column in the dataframe by df.boxplot() or indicating the columns to be used:

```python
>>> np.random.seed(1234)
>>> df = pd.DataFrame(np.random.randn(10, 4),
...                   columns=['Col1', 'Col2', 'Col3', 'Col4'])
>>> boxplot = df.boxplot(column=['Col1', 'Col2', 'Col3'])
```

Boxplots of variables distributions grouped by the values of a third variable can be created using the option by. For instance:

```python
>>> df = pd.DataFrame(np.random.randn(10, 2),
...                   columns=['Col1', 'Col2'])
...                      'B', 'B', 'B', 'B', 'B'])
>>> boxplot = df.boxplot(by='X')
```

A list of strings (i.e. ['X', 'Y']) can be passed to boxplot in order to group the data by combination of the variables in the x-axis:

```python
>>> df = pd.DataFrame(np.random.randn(10, 3),
...                   columns=['Col1', 'Col2', 'Col3'])
...                      'B', 'B', 'B', 'B', 'B'])
>>> df['Y'] = pd.Series(['A', 'B', 'A', 'B', 'A',
...                      'B', 'A', 'B', 'A', 'B'])
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by=['X', 'Y'])
```

The layout of boxplot can be adjusted giving a tuple to layout:

```python
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by='X',
...                       layout=(2, 1))
```

Additional formatting can be done to the boxplot, like suppressing the grid (grid=False), rotating the labels in the x-axis (i.e. rot=45) or changing the fontsize (i.e. fontsize=15):

```python
>>> boxplot = df.boxplot(grid=False, rot=45, fontsize=15)
```
3.4. DataFrame
The parameter `return_type` can be used to select the type of element returned by `boxplot`. When `return_type='axes'` is selected, the matplotlib axes on which the boxplot is drawn are returned:

```python
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], return_type='axes')
>>> type(boxplot)
<class 'matplotlib.axes._subplots.AxesSubplot'>
```

When grouping with `by`, a Series mapping columns to `return_type` is returned:

```python
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by='X',
...                       return_type='axes')
>>> type(boxplot)
<class 'pandas.core.series.Series'>
```

If `return_type` is `None`, a NumPy array of axes with the same shape as `layout` is returned:

```python
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by='X',
...                       return_type=None)
>>> type(boxplot)
<class 'numpy.ndarray'>
```

### pandas.DataFrame.clip

DataFrame.clip(lower=None, upper=None, axis=None, inplace=False, *args, **kwargs)

Trim values at input threshold(s).

Assigns values outside boundary to boundary values. Thresholds can be singular values or array like, and in the latter case the clipping is performed element-wise in the specified axis.

**Parameters**

- `lower` [float or array_like, default None] Minimum threshold value. All values below this threshold will be set to it.
- `upper` [float or array_like, default None] Maximum threshold value. All values above this threshold will be set to it.
- `axis` [int or str axis name, optional] Align object with lower and upper along the given axis.
- `inplace` [bool, default False] Whether to perform the operation in place on the data.
- `*args, **kwargs` Additional keywords have no effect but might be accepted for compatibility with numpy.

**Returns**

Series or DataFrame Same type as calling object with the values outside the clip boundaries replaced.

**See also:**

- `Series.clip` Trim values at input threshold in series.
- `DataFrame.clip` Trim values at input threshold in dataframe.
- `numpy.clip` Clip (limit) the values in an array.
Examples

```python
>>> data = {'col_0': [9, -3, 0, -1, 5], 'col_1': [-2, -7, 6, 8, -5]}
>>> df = pd.DataFrame(data)
>>> df
   col_0 col_1
0     9   -2
1    -3   -7
2     0    6
3    -1    8
4     5   -5
Clips per column using lower and upper thresholds:

```  
```python
>>> df.clip(-4, 6)
   col_0 col_1
0     6   -2
1    -3   -4
2     0    6
3    -1    6
4     5   -4
```

Clips using specific lower and upper thresholds per column element:

```python
>>> t = pd.Series([2, -4, -1, 6, 3])
>>> t
0    2
1   -4
2   -1
3    6
4    3
dtype: int64
```  
```python
>>> df.clip(t, t + 4, axis=0)
   col_0 col_1
0     6    2
1    -3   -4
2     0    3
3     6    8
4     5    3
```

pandas.DataFrame.combine

DataFrame.combine(other, func, fill_value=None, overwrite=True)
Perform column-wise combine with another DataFrame.

Combines a DataFrame with other DataFrame using func to element-wise combine columns. The row and column indexes of the resulting DataFrame will be the union of the two.

Parameters

other [DataFrame] The DataFrame to merge column-wise.

func [function] Function that takes two series as inputs and return a Series or a scalar.
Used to merge the two dataframes column by columns.

fill_value [scalar value, default None] The value to fill NaNs with prior to passing any column to the merge func.
overwrite [bool, default True] If True, columns in self that do not exist in other will be overwritten with NaNs.

Returns

DataFrame Combination of the provided DataFrames.

See also:

DataFrame.combine_first Combine two DataFrame objects and default to non-null values in frame calling the method.

Examples

Combine using a simple function that chooses the smaller column.

```python
def take_smaller(s1, s2):
    return s1 if s1.sum() < s2.sum() else s2

>>> df1 = pd.DataFrame({'A': [0, 0], 'B': [4, 4]})
>>> df2 = pd.DataFrame({'A': [1, 1], 'B': [3, 3]})
>>> df1.combine(df2, take_smaller)
A  B
0  3
1  3
```

Example using a true element-wise combine function.

```python
>>> df1 = pd.DataFrame({'A': [5, 0], 'B': [2, 4]})
>>> df2 = pd.DataFrame({'A': [1, 1], 'B': [3, 3]})
>>> df1.combine(df2, np.minimum)
A  B
0  1  2
1  0  3
```

Using fill_value fills Nones prior to passing the column to the merge function.

```python
>>> df1 = pd.DataFrame({'A': [0, 0], 'B': [None, 4]})
>>> df2 = pd.DataFrame({'A': [1, 1], 'B': [3, 3]})
>>> df1.combine(df2, take_smaller, fill_value=-5)
A  B
0  0  -5.0
1  0  4.0
```

However, if the same element in both dataframes is None, that None is preserved

```python
>>> df1 = pd.DataFrame({'A': [0, 0], 'B': [None, 4]})
>>> df2 = pd.DataFrame({'A': [1, 1], 'B': [None, 3]})
>>> df1.combine(df2, take_smaller, fill_value=-5)
A  B
0  0  -5.0
1  0  3.0
```

Example that demonstrates the use of overwrite and behavior when the axis differ between the dataframes.

```python
>>> df1 = pd.DataFrame({'A': [0, 0], 'B': [4, 4]})
>>> df2 = pd.DataFrame({'B': [3, 3], 'C': [-10, 1], }, index=[1, 2])
>>> df1.combine(df2, take_smaller)
A  B  C
0  4  3
1  4  1
```

(continues on next page)
```python
>>> df1 = pd.DataFrame({'A': [0, 1, 2], 'B': [3, 3, 3], 'C': [1, 1, 1]}, index=[0, 1, 2])

0  NaN NaN NaN
1  NaN 3.0 -10.0
2  NaN 3.0  1.0
```

```python
>>> df1.combine(df2, take_smaller, overwrite=False)
    A     B     C
0  0.0   NaN  NaN
1  0.0   3.0  -10.0
2  NaN   3.0   1.0
```

Demonstrating the preference of the passed in dataframe.

```python
>>> df2 = pd.DataFrame({'B': [3, 3], 'C': [1, 1]}, index=[1, 2])
>>> df2.combine(df1, take_smaller)
    A     B     C
0  0.0   NaN  NaN
1  0.0   3.0  NaN
2  NaN   3.0  NaN
```

```python
>>> df2.combine(df1, take_smaller, overwrite=False)
    A     B     C
0  0.0   NaN  NaN
1  0.0   3.0  1.0
2  NaN   3.0  1.0
```

**pandas.DataFrame.combine_first**

`DataFrame.combine_first(other)`

Update null elements with value in the same location in `other`.

Combine two DataFrame objects by filling null values in one DataFrame with non-null values from other DataFrame. The row and column indexes of the resulting DataFrame will be the union of the two.

**Parameters**

- `other` [DataFrame] Provided DataFrame to use to fill null values.

**Returns**

- `DataFrame`

**See also:**

- `DataFrame.combine` Perform series-wise operation on two DataFrames using a given function.
Examples

```python
>>> df1 = pd.DataFrame({'A': [None, 0], 'B': [None, 4]})
>>> df2 = pd.DataFrame({'A': [1, 1], 'B': [3, 3]})
>>> df1.combine_first(df2)
          A   B
0       1.0  3.0
1       0.0  4.0
```

Null values still persist if the location of that null value does not exist in `other`

```python
>>> df1 = pd.DataFrame({'A': [None, 0], 'B': [4, None]})
>>> df2 = pd.DataFrame({'B': [3, 3], 'C': [1, 1]}, index=[1, 2])
>>> df1.combine_first(df2)
          A  B  C
0   NaN  4.0  NaN
1  0.0  3.0  1.0
2   NaN  3.0  1.0
```

**pandas.DataFrame.compare**

DataFrame.compare(other, align_axis=1, keep_shape=False, keep_equal=False)

Compare to another DataFrame and show the differences.

New in version 1.1.0.

**Parameters**

- `other` [DataFrame] Object to compare with.
- `align_axis` [{0 or ‘index’, 1 or ‘columns’}, default 1] Determine which axis to align the comparison on.
  - 0, or ‘index’ [Resulting differences are stacked vertically] with rows drawn alternately from self and other.
  - 1, or ‘columns’ [Resulting differences are aligned horizontally] with columns drawn alternately from self and other.
- `keep_shape` [bool, default False] If true, all rows and columns are kept. Otherwise, only the ones with different values are kept.
- `keep_equal` [bool, default False] If true, the result keeps values that are equal. Otherwise, equal values are shown as NaNs.

**Returns**

DataFrame DataFrame that shows the differences stacked side by side.

The resulting index will be a MultiIndex with ‘self’ and ‘other’ stacked alternately at the inner level.

**See also:**

Series.compare Compare with another Series and show differences.
Notes

Matching NaNs will not appear as a difference.

Examples

```python
>>> df = pd.DataFrame(
...     {
...         "col1": ["a", "a", "b", "b", "a"],
...         "col2": [1.0, 2.0, 3.0, np.nan, 5.0],
...         "col3": [1.0, 2.0, 3.0, 4.0, 5.0]
...     },
...     columns=["col1", "col2", "col3"],
... )
>>> df
    col1 col2  col3
0     a   1.0  1.0
1     a   2.0  2.0
2     b   3.0  3.0
3     b NaN  4.0
4     a   5.0  5.0

>>> df2 = df.copy()
>>> df2.loc[0, 'col1'] = 'c'
>>> df2.loc[2, 'col3'] = 4.0
>>> df2
    col1  col2  col3
0     c   1.0  1.0
1     a   2.0  2.0
2     b   3.0  4.0
3     b  NaN  4.0
4     a   5.0  5.0

Align the differences on columns

```python
```python
>>> df.compare(df2)
    col1   col3
self other self other
0     a   c  NaN  NaN
2   NaN  NaN  3.0  4.0
```  

Stack the differences on rows

```python
>>> df.compare(df2, align_axis=0)
    col1   col3
  self other self other
0    a  NaN  NaN  NaN
2   NaN  NaN  3.0  4.0
```  

Keep the equal values

```python
>>> df.compare(df2, keep_equal=True)
    col1   col3
self other self other
0    a  NaN  NaN  NaN
2   NaN  NaN  3.0  4.0
```
Keep all original rows and columns

```python
>>> df.compare(df2, keep_shape=True)
col1    col2    col3
self other self other self other
0   a    c   NaN   NaN   NaN   NaN
1   NaN   NaN   NaN   NaN   NaN   NaN
2   NaN   NaN   NaN   NaN   3.0   4.0
3   NaN   NaN   NaN   NaN   NaN   NaN
4   NaN   NaN   NaN   NaN   NaN   NaN
```

Keep all original rows and columns and also all original values

```python
>>> df.compare(df2, keep_shape=True, keep_equal=True)
col1    col2    col3
self other self other self other
0   a    c   1.0   1.0   1.0   1.0
1   a    a   2.0   2.0   2.0   2.0
2   b    b   3.0   3.0   3.0   4.0
3   b    b   NaN   NaN   4.0   4.0
4   a    a   5.0   5.0   5.0   5.0
```

#### pandas.DataFrame.convert_dtypes


Convert columns to best possible dtypes using dtypes supporting `pd.NA`.

New in version 1.0.0.

**Parameters**

- **infer_objects** [bool, default True] Whether object dtypes should be converted to the best possible types.
- **convert_string** [bool, default True] Whether object dtypes should be converted to `StringDtype()`.
- **convert_integer** [bool, default True] Whether, if possible, conversion can be done to integer extension types.
- **convert_boolean** [bool, default True] Whether object dtypes should be converted to `BooleanDtypes()`.

**Returns**

- **Series** or **DataFrame** Copy of input object with new dtype.

See also:

- **infer_objects** Infer dtypes of objects.
- **to_datetime** Convert argument to datetime.
- **to_timedelta** Convert argument to timedelta.
to_numeric Convert argument to a numeric type.

Notes

By default, convert_dtypes will attempt to convert a Series (or each Series in a DataFrame) to dtypes that support pd.NA. By using the options convert_string, convert_integer, and convert_boolean, it is possible to turn off individual conversions to StringDtype, the integer extension types or BooleanDtype, respectively.

For object-dtyped columns, if infer_objects is True, use the inference rules as during normal Series/DataFrame construction. Then, if possible, convert to StringDtype, BooleanDtype or an appropriate integer extension type, otherwise leave as object.

If the dtype is integer, convert to an appropriate integer extension type.

If the dtype is numeric, and consists of all integers, convert to an appropriate integer extension type.

In the future, as new dtypes are added that support pd.NA, the results of this method will change to support those new dtypes.

Examples

```python
>>> df = pd.DataFrame(
...     {
...         "a": pd.Series([1, 2, 3], dtype=np.dtype("int32")),
...         "b": pd.Series(["x", "y", "z"], dtype=np.dtype("O")),
...         "c": pd.Series([True, False, np.nan], dtype=np.dtype("O")),
...         "d": pd.Series(["h", "i", np.nan], dtype=np.dtype("O")),
...         "e": pd.Series([10, np.nan, 20], dtype=np.dtype("float")),
...         "f": pd.Series([np.nan, 100.5, 200], dtype=np.dtype("float")),
...     }
... )

Start with a DataFrame with default dtypes.

```python
def
```

```python
>> df
   a  b  c  d  e  f
0  1  x  True  h  10.0  NaN
1  2  y  False  i  NaN  100.5
2  3  z  NaN  NaN  20.0  200.0
```

```python
>>> df.dtypes
a    int32
b    object
c    object
d    object
e    float64
f    float64
dtype: object
```

Convert the DataFrame to use best possible dtypes.

```python
>>> dfn = df.convert_dtypes()
```

```python
>>> dfn
   a  b  c  d  e  f
0  1  x  True  h   10  NaN
```

(continues on next page)
Start with a Series of strings and missing data represented by np.nan.

```python
>>> s = pd.Series(['a', 'b', np.nan])
>>> s
0    a
1    b
2  NaN
dtype: object
```

Obtain a Series with dtype StringDtype.

```python
>>> s.convert_dtypes()
0    a
1    b
2  <NA>
dtype: string
```

**pandas.DataFrame.copy**

DataFrame.copy (**deep=True**)  
Make a copy of this object’s indices and data.  

*When deep=True (default), a new object will be created with a copy of the calling object’s data and indices. Modifications to the data or indices of the copy will not be reflected in the original object (see notes below). When deep=False, a new object will be created without copying the calling object’s data or index (only references to the data and index are copied). Any changes to the data of the original will be reflected in the shallow copy (and vice versa).*

**Parameters**

- **deep** [bool, default True] Make a deep copy, including a copy of the data and the indices. With deep=False neither the indices nor the data are copied.

**Returns**

- **copy** [Series or DataFrame] Object type matches caller.
Notes

When `deep=True`, data is copied but actual Python objects will not be copied recursively, only the reference to the object. This is in contrast to `copy.deepcopy` in the Standard Library, which recursively copies object data (see examples below).

While `Index` objects are copied when `deep=True`, the underlying numpy array is not copied for performance reasons. Since `Index` is immutable, the underlying data can be safely shared and a copy is not needed.

Examples

```python
default_copy = s.copy()
default_copy
```

Shallow copy versus default (deep) copy:

```python
shallow_copy = s.copy()
shallow_copy
```

Shallow copy shares data and index with original.

```python
shallow.values is shallow.values and shallow.index is shallow.index
```

Deep copy has own copy of data and index.

```python
shallow.values is deep.values or shallow.index is deep.index
```

Updates to the data shared by shallow copy and original is reflected in both; deep copy remains unchanged.

```python
shallow[1] = 4
shallow
```

(continues on next page)
Note that when copying an object containing Python objects, a deep copy will copy the data, but will not do so recursively. Updating a nested data object will be reflected in the deep copy.

```python
>>> s = pd.Series([[1, 2], [3, 4]])
>>> deep = s.copy()
>>> s[0][0] = 10
>>> s
0  [10, 2]  
1  [3, 4]  
dtype: object
>>> deep
0  [10, 2]  
1  [3, 4]  
dtype: object
```

**pandas.DataFrame.corr**

Dataframe.
corr**(method='pearson', min_periods=1)**

Compute pairwise correlation of columns, excluding NA/null values.

**Parameters**

- **method** ['pearson', 'kendall', 'spearman'] or callable] Method of correlation:
  - pearson : standard correlation coefficient
  - kendall : Kendall Tau correlation coefficient
  - spearman : Spearman rank correlation
  - callable: callable with input two 1d ndarrays and returning a float. Note that the returned matrix from corr will have 1 along the diagonals and will be symmetric regardless of the callable's behavior.

- **min_periods** [int, optional] Minimum number of observations required per pair of columns to have a valid result. Currently only available for Pearson and Spearman correlation.

**Returns**

- **DataFrame** Correlation matrix.

**See also:**

- **DataFrame.corrwith** Compute pairwise correlation with another DataFrame or Series.
- **Series.corr** Compute the correlation between two Series.
Examples

```python
>>> def histogram_intersection(a, b):
    ...
    v = np.minimum(a, b).sum().round(decimals=1)
    ...
    return v

>>> df = pd.DataFrame([(.2, .3), (.0, .6), (.6, .0), (.2, .1)],
    ...
    columns=['dogs', 'cats'])

>>> df.corr(method=histogram_intersection)
     dogs  cats
dogs  1.0  0.3
cats  0.3  1.0
```

**pandas.DataFrame.corrwith**

DataFrame.corrwith(other, axis=0, drop=False, method='pearson')

Compute pairwise correlation.

Pairwise correlation is computed between rows or columns of DataFrame with rows or columns of Series or DataFrame. DataFrames are first aligned along both axes before computing the correlations.

**Parameters**

- **other**  [DataFrame, Series] Object with which to compute correlations.
- **axis**  [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis to use. 0 or ‘index’ to compute column-wise, 1 or ‘columns’ for row-wise.
- **drop**  [bool, default False] Drop missing indices from result.
- **method**  [{‘pearson’, ‘kendall’, ‘spearman’} or callable] Method of correlation:
  - pearson : standard correlation coefficient
  - kendall : Kendall Tau correlation coefficient
  - spearman : Spearman rank correlation
  - callable: callable with input two 1d ndarrays and returning a float.

New in version 0.24.0.

**Returns**

- **Series**  Pairwise correlations.

**See also:**

- DataFrame.corr  Compute pairwise correlation of columns.

**pandas.DataFrame.count**

DataFrame.count(axis=0, level=None, numeric_only=False)

Count non-NA cells for each column or row.

The values None, NaN, NaT, and optionally numpy.inf (depending on pandas.options.mode.use_inf_as_na) are considered NA.

**Parameters**
axis [{0 or 'index', 1 or 'columns'}, default 0] If 0 or 'index' counts are generated for each column. If 1 or 'columns' counts are generated for each row.

level [int or str, optional] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame. A str specifies the level name.

numeric_only [bool, default False] Include only float, int or boolean data.

Returns

Series or DataFrame For each column/row the number of non-NA/null entries. If level is specified returns a DataFrame.

See also:

Series.count Number of non-NA elements in a Series.

DataFrame.shape Number of DataFrame rows and columns (including NA elements).

DataFrame.isna Boolean same-sized DataFrame showing places of NA elements.

Examples

Constructing DataFrame from a dictionary:

```python
>>> df = pd.DataFrame({'Person': ['John', 'Myla', 'Lewis', 'John', 'Myla'],
...                    'Age': [24., np.nan, 21., 33., 26.],
...                    'Single': [False, True, True, True, False]})
```

Notice the uncounted NA values:

```python
>>> df.count()
Person    5
Age       4
Single    5
dtype: int64
```

Counts for each row:

```python
>>> df.count(axis='columns')
0   3
1   2
2   3
3   3
4   3
dtype: int64
```

Counts for one level of a MultiIndex:
```python
>>> df.set_index(["Person", "Single"]).count(level="Person")
  Age
Person  
  John   2
  Lewis  1
  Myla   1
```

**pandas.DataFrame.cov**

`DataFrame.cov(min_periods=None, ddof=1)`

Compute pairwise covariance of columns, excluding NA/null values.

Compute the pairwise covariance among the series of a DataFrame. The returned data frame is the covariance matrix of the columns of the DataFrame.

Both NA and null values are automatically excluded from the calculation. (See the note below about bias from missing values.) A threshold can be set for the minimum number of observations for each value created. Comparisons with observations below this threshold will be returned as NaN.

This method is generally used for the analysis of time series data to understand the relationship between different measures across time.

**Parameters**

- `min_periods` [int, optional] Minimum number of observations required per pair of columns to have a valid result.
- `ddof` [int, default 1] Delta degrees of freedom. The divisor used in calculations is \(N - ddof\), where \(N\) represents the number of elements.

**Returns**

- `DataFrame` The covariance matrix of the series of the DataFrame.

**See also:**

- `Series.cov` Compute covariance with another Series.
- `core.window.ExponentialMovingWindow.cov` Exponential weighted sample covariance.
- `core.window.Expanding.cov` Expanding sample covariance.
- `core.window.Rolling.cov` Rolling sample covariance.

**Notes**

Returns the covariance matrix of the DataFrame’s time series. The covariance is normalized by N-ddof.

For DataFrames that have Series that are missing data (assuming that data is missing at random) the returned covariance matrix will be an unbiased estimate of the variance and covariance between the member Series.

However, for many applications this estimate may not be acceptable because the estimate covariance matrix is not guaranteed to be positive semi-definite. This could lead to estimate correlations having absolute values which are greater than one, and/or a non-invertible covariance matrix. See Estimation of covariance matrices for more details.
Examples

```python
>>> df = pd.DataFrame([(1, 2), (0, 3), (2, 0), (1, 1)],
...    columns=['dogs', 'cats'])
>>> df.cov()
dogs  cats
dogs  0.666667 -1.000000
cats -1.000000  1.666667

>>> np.random.seed(42)
>>> df = pd.DataFrame(np.random.randn(1000, 5),
...    columns=['a', 'b', 'c', 'd', 'e'])
>>> df.cov()
a   b   c   d   e
a  0.998438 -0.020161 0.059277 -0.008943 0.014144
b -0.020161 1.059352 -0.008543 -0.024738 0.009826
c  0.059277 -0.008543 1.010670 -0.001486 -0.000271
d -0.008943 -0.024738 -0.001486 0.921297 -0.013692
e  0.014144 0.009826 -0.000271 -0.013692 0.977795
```

Minimum number of periods

This method also supports an optional `min_periods` keyword that specifies the required minimum number of non-NA observations for each column pair in order to have a valid result:

```python
>>> np.random.seed(42)
>>> df = pd.DataFrame(np.random.randn(20, 3),
...    columns=['a', 'b', 'c'])
>>> df.loc[df.index[:5], 'a'] = np.nan
>>> df.loc[df.index[5:10], 'b'] = np.nan
>>> df.cov(min_periods=12)
a   b   c
a  0.316741 NaN -0.150812
b  NaN 1.248003 0.191417
c -0.150812 0.191417 0.895202
```

**pandas.DataFrame.cummax**

DataFrame.cummax(\(\text{axis}=None, \text{skipna}=\text{True}, \text{args}, \text{kwargs}\))

Return cumulative maximum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative maximum.

**Parameters**

- **axis** \([0 \text{ or ‘index’}, 1 \text{ or ‘columns’}], \text{default 0} \) The index or the name of the axis. 0 is equivalent to None or ‘index’.

- **skipna** \([\text{bool, default True}] \) Exclude NA/null values. If an entire row/column is NA, the result will be NA.

- **args, **kwargs** Additional keywords have no effect but might be accepted for compatibility with NumPy.

**Returns**

Series or DataFrame Return cumulative maximum of Series or DataFrame.

See also:
core.window.Expanding.max  Similar functionality but ignores NaN values.

DataFrame.max  Return the maximum over DataFrame axis.

DataFrame.cummax  Return cumulative maximum over DataFrame axis.

DataFrame.cummin  Return cumulative minimum over DataFrame axis.

DataFrame.cumsum  Return cumulative sum over DataFrame axis.

DataFrame.cumprod  Return cumulative product over DataFrame axis.

Examples

Series

```python
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1    NaN
2    5.0
3   -1.0
4     0.0
dtype: float64
```

By default, NA values are ignored.

```python
>>> s.cummax()
0    2.0
1    NaN
2    5.0
3    5.0
4    5.0
dtype: float64
```

To include NA values in the operation, use skipna=False

```python
>>> s.cummax(skipna=False)
0    2.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64
```

DataFrame

```python
>>> df = pd.DataFrame([[2.0, 1.0],
...                     [3.0, np.nan],
...                     [1.0, 0.0]],
...                    columns=list('AB'))
>>> df
   A  B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the maximum in each column. This is equivalent to axis=None or axis='index'.

3.4. DataFrame
pandas: powerful Python data analysis toolkit, Release 1.1.1

```python
>>> df.cummax()
   A   B
0  2.0  1.0
1  3.0  NaN
2  3.0  1.0

To iterate over columns and find the maximum in each row, use `axis=1`

```python
>>> df.cummax(axis=1)
   A   B
0  2.0  2.0
1  3.0  NaN
2  1.0  1.0
```

pandas.DataFrame.cummin

DataFrame.cummin(axis=None, skipna=True, *args, **kwargs)
Return cumulative minimum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative minimum.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] The index or the name of the axis. 0 is equivalent to None or 'index'.

skipna [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

*args, **kwargs Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

Series or DataFrame Return cumulative minimum of Series or DataFrame.

See also:

core.window.Expanding.min Similar functionality but ignores NaN values.
DataFrame.min Return the minimum over DataFrame axis.
DataFrame.cummax Return cumulative maximum over DataFrame axis.
DataFrame.cummin Return cumulative minimum over DataFrame axis.
DataFrame.cumsum Return cumulative sum over DataFrame axis.
DataFrame.cumprod Return cumulative product over DataFrame axis.
Examples

Series

```python
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1   NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.

```python
>>> s.cummin()
0    2.0
1   NaN
2    2.0
3   -1.0
4   -1.0
dtype: float64
```

To include NA values in the operation, use `skipna=False`

```python
>>> s.cummin(skipna=False)
0    2.0
1   NaN
2   NaN
3   NaN
4   NaN
dtype: float64
```

DataFrame

```python
>>> df = pd.DataFrame([[2.0, 1.0], ...
...                      [3.0, np.nan], ...
...                      [1.0, 0.0]], ...
...                     columns=list('AB'))
>>> df
   A  B
0  2.0  1.0
1  3.0   NaN
2  1.0   0.0
```

By default, iterates over rows and finds the minimum in each column. This is equivalent to `axis=None` or `axis='index'`.

```python
>>> df.cummin()
   A  B
0  2.0  1.0
1  2.0   NaN
2  1.0   0.0
```

To iterate over columns and find the minimum in each row, use `axis=1`

```python
>>> df.cummin(axis=1)
```

(continues on next page)
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.DataFrame.cumprod

DataFrame.cumprod(axis=None, skipna=True, args, kwargs)

Return cumulative product over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative product.

Parameters

- **axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] The index or the name of the axis. 0 is equivalent to None or ‘index’.
- **skipna** [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.
- **args, **kwargs** Additional keywords have no effect but might be accepted for compatibility with NumPy.

Returns

Series or DataFrame Return cumulative product of Series or DataFrame.

See also:

core.window.Expanding.prod Similar functionality but ignores NaN values.

DataFrame.prod Return the product over DataFrame axis.

DataFrame.cummax Return cumulative maximum over DataFrame axis.

DataFrame.cummin Return cumulative minimum over DataFrame axis.

DataFrame.cumsum Return cumulative sum over DataFrame axis.

DataFrame.cumprod Return cumulative product over DataFrame axis.

Examples

Series

```py
>>> s = pd.Series([2, np.nan, 5, -1, 0])
```

By default, NA values are ignored.
```python
>>> s.cumprod()
0   2.0
1   NaN
2  10.0
3 -10.0
4   0.0
dtype: float64

To include NA values in the operation, use `skipna=False`

```python
>>> s.cumprod(skipna=False)
0   2.0
1   NaN
2   NaN
3   NaN
4   NaN
dtype: float64
```

### DataFrame

```python
>>> df = pd.DataFrame([[2.0, 1.0],
                      [3.0, np.nan],
                      [1.0, 0.0]],
                    columns=list('AB'))
```

```python
>>> df
df
A   B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the product in each column. This is equivalent to `axis=None` or `axis='index'`.

```python
>>> df.cumprod()
df
A   B
0  2.0  1.0
1  6.0  NaN
2  6.0  0.0
```

To iterate over columns and find the product in each row, use `axis=1`

```python
>>> df.cumprod(axis=1)
df
A   B
0  2.0  2.0
1  3.0  NaN
2  1.0  0.0
```
**pandas.DataFrame.cumsum**

DataFrame.cumsum(axis=None, skipna=True, *args, **kwargs)

Return cumulative sum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative sum.

**Parameters**

- **axis** [[0 or 'index', 1 or 'columns'], default 0] The index or the name of the axis. 0 is equivalent to None or 'index'.
- **skipna** [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.
- **args, **kwargs Additional keywords have no effect but might be accepted for compatibility with NumPy.

**Returns**

Series or DataFrame Return cumulative sum of Series or DataFrame.

See also:

core.window.Expanding.sum Similar functionality but ignores NaN values.

DataFrame.sum Return the sum over DataFrame axis.

DataFrame.cummax Return cumulative maximum over DataFrame axis.

DataFrame.cummin Return cumulative minimum over DataFrame axis.

DataFrame.cumsum Return cumulative sum over DataFrame axis.

DataFrame.cumprod Return cumulative product over DataFrame axis.

**Examples**

**Series**

```python
>>> s = pd.Series([2, np.nan, 5, -1, 0])
```

```python
>>> s
0    2.0
1    NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.

```python
>>> s.cumsum()
0   2.0
1   NaN
2    7.0
3    6.0
4    6.0
dtype: float64
```

To include NA values in the operation, use skipna=False
```python
>>> s.cumsum(skipna=False)
0  2.0
1  NaN
2  NaN
3  NaN
4  NaN
dtype: float64
```

**DataFrame**

```python
>>> df = pd.DataFrame([[2.0, 1.0],
...                    [3.0, np.nan],
...                    [1.0, 0.0]],
...                    columns=list('AB'))
>>> df
   A  B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the sum in each column. This is equivalent to `axis=None` or `axis='index'`.

```python
>>> df.cumsum()
   A  B
0  2.0  3.0
1  5.0  NaN
2  6.0  1.0
```

To iterate over columns and find the sum in each row, use `axis=1`

```python
>>> df.cumsum(axis=1)
   A  B
0  2.0  3.0
1  3.0  NaN
2  1.0  1.0
```

**pandas.DataFrame.describe**

`DataFrame.describe(percentiles=None, include=None, exclude=None, date-time_is_numeric=False)`

Generate descriptive statistics.

Descriptive statistics include those that summarize the central tendency, dispersion and shape of a dataset’s distribution, excluding NaN values.

Analyzes both numeric and object series, as well as DataFrame column sets of mixed data types. The output will vary depending on what is provided. Refer to the notes below for more detail.

**Parameters**

- `percentiles` [list-like of numbers, optional] The percentiles to include in the output. All should fall between 0 and 1. The default is `[.25, .5, .75]`, which returns the 25th, 50th, and 75th percentiles.

- `include` ['all', list-like of dtypes or None (default), optional] A white list of data types to include in the result. Ignored for `Series`. Here are the options:
• ‘all’ : All columns of the input will be included in the output.
• A list-like of dtypes : Limits the results to the provided data types. To limit the result to numeric types submit `numpy.number`. To limit it instead to object columns submit the `numpy.object` data type. Strings can also be used in the style of `select_dtypes` (e.g. `df.describe(include=['O'])`). To select pandas categorical columns, use 'category'
• None (default) : The result will include all numeric columns.

`exclude` [list-like of dtypes or None (default), optional] A black list of data types to omit from the result. Ignored for `Series`. Here are the options:

• A list-like of dtypes : Excludes the provided data types from the result. To exclude numeric types submit `numpy.number`. To exclude object columns submit the data type `numpy.object`. Strings can also be used in the style of `select_dtypes` (e.g. `df.describe(include=['O'])`). To exclude pandas categorical columns, use 'category'
• None (default) : The result will exclude nothing.

`datetime_is_numeric` [bool, default False] Whether to treat datetime dtypes as numeric. This affects statistics calculated for the column. For DataFrame input, this also controls whether datetime columns are included by default.

New in version 1.1.0.

Returns

`Series` or `DataFrame` Summary statistics of the Series or Dataframe provided.

See also:

`DataFrame.count` Count number of non-NA/null observations.
`DataFrame.max` Maximum of the values in the object.
`DataFrame.min` Minimum of the values in the object.
`DataFrame.mean` Mean of the values.
`DataFrame.std` Standard deviation of the observations.
`DataFrame.select_dtypes` Subset of a DataFrame including/excluding columns based on their dtype.

Notes

For numeric data, the result’s index will include `count`, `mean`, `std`, `min`, `max` as well as lower, 50 and upper percentiles. By default the lower percentile is 25 and the upper percentile is 75. The 50 percentile is the same as the median.

For object data (e.g. strings or timestamps), the result’s index will include `count`, `unique`, `top`, and `freq`. The `top` is the most common value. The `freq` is the most common value’s frequency. Timestamps also include the `first` and `last` items.

If multiple object values have the highest count, then the `count` and `top` results will be arbitrarily chosen from among those with the highest count.

For mixed data types provided via a `DataFrame`, the default is to return only an analysis of numeric columns. If the dataframe consists only of object and categorical data without any numeric columns,
the default is to return an analysis of both the object and categorical columns. If include='all' is provided as an option, the result will include a union of attributes of each type.

The include and exclude parameters can be used to limit which columns in a DataFrame are analyzed for the output. The parameters are ignored when analyzing a Series.

Examples

Describing a numeric Series.

```python
g = pd.Series([1, 2, 3])
g.describe()
```

Describing a categorical Series.

```python
g = pd.Series(['a', 'a', 'b', 'c'])
g.describe()
```

Describing a timestamp Series.

```python
g = pd.Series([np.datetime64("2000-01-01"),
               np.datetime64("2010-01-01"),
               np.datetime64("2010-01-01")])
g.describe(datetime_is_numeric=True)
```

Describing a DataFrame. By default only numeric fields are returned.

```python
df = pd.DataFrame({'categorical': pd.Categorical(['d', 'e', 'f']),
                   'numeric': [1, 2, 3],
                   'object': ['a', 'b', 'c']})
df.describe()
```
count  3.0
mean  2.0
std   1.0
min   1.0
25%   1.5
50%   2.0
75%   2.5
max   3.0

Describing all columns of a DataFrame regardless of data type.

```python
>>> df.describe(include='all')
```

```
categorical          numeric          object
count                  3             3.0             3
unique                 3             NaN             3
top                    f             NaN             a
freq                   1             NaN             1
mean                   NaN           2.0             NaN
std                    NaN           1.0             NaN
min                    NaN           1.0             NaN
25%                    NaN           1.5             NaN
50%                    NaN           2.0             NaN
75%                    NaN           2.5             NaN
max                    NaN           3.0             NaN
```

Describing a column from a DataFrame by accessing it as an attribute.

```python
>>> df.numeric.describe()
```

```
count  3.0
mean   2.0
std    1.0
min    1.0
25%    1.5
50%    2.0
75%    2.5
max    3.0
Name: numeric, dtype: float64
```

Including only numeric columns in a DataFrame description.

```python
>>> df.describe(include=[np.number])
```

```
numeric
count  3.0
mean   2.0
std    1.0
min    1.0
25%    1.5
50%    2.0
75%    2.5
max    3.0
```

Including only string columns in a DataFrame description.

```python
>>> df.describe(include=[object])
```

```
object
count  3
```
Including only categorical columns from a DataFrame description.

```python
>>> df.describe(include=['category'])
categorical
    count  3
    unique 3
top   f
freq  1
```

Excluding numeric columns from a DataFrame description.

```python
>>> df.describe(exclude=[np.number])
categorical  object
    count  3  3
    unique 3  3
top   f  a
freq  1  1
```

Excluding object columns from a DataFrame description.

```python
>>> df.describe(exclude=[object])
categorical  numeric
    count  3  3.0
    unique 3  NaN
top   f  NaN
freq  1  NaN
mean  NaN  2.0
std   NaN  1.0
min  NaN  1.0
25%  NaN  1.5
50%  NaN  2.0
75%  NaN  2.5
max  NaN  3.0
```

**pandas.DataFrame.diff**

`DataFrame.diff(periods=1, axis=0)`

First discrete difference of element.

Calculates the difference of a Dataframe element compared with another element in the Dataframe (default is element in previous row).

**Parameters**

- **periods** [int, default 1] Periods to shift for calculating difference, accepts negative values.
- **axis** [[0 or ‘index’, 1 or ‘columns’], default 0] Take difference over rows (0) or columns (1).

**Returns**

- **Dataframe** First differences of the Series.
See also:

**Dataframe.pct_change** Percent change over given number of periods.

**Dataframe.shift** Shift index by desired number of periods with an optional time freq.

**Series.diff** First discrete difference of object.

Notes

For boolean dtypes, this uses `operator.xor()` rather than `operator.sub()`. The result is calculated according to current dtype in Dataframe, however dtype of the result is always float64.

Examples

Difference with previous row

```python
>>> df = pd.DataFrame({'a': [1, 2, 3, 4, 5, 6],
                  'b': [1, 1, 2, 3, 5, 8],
                  'c': [1, 4, 9, 16, 25, 36]})
>>> df
   a  b  c
0  1  1  1
1  2  1  4
2  3  2  9
3  4  3 16
4  5  5 25
5  6  8 36
>>> df.diff()
    a    b    c
0 NaN  NaN  NaN
1  1.0  0.0  3.0
2  1.0  1.0  5.0
3  1.0  1.0  7.0
4  1.0  2.0  9.0
5  1.0  3.0 11.0
```

Difference with previous column

```python
>>> df.diff(axis=1)
    a    b    c
0  NaN  0.0  0.0
1  NaN -1.0  3.0
2  NaN -1.0  7.0
3  NaN -1.0 13.0
4  NaN  0.0 20.0
5  NaN  2.0 28.0
```

Difference with 3rd previous row

```python
>>> df.diff(periods=3)
    a    b    c
0  NaN  NaN  NaN
1  NaN  NaN  NaN
2  NaN  NaN  NaN
(continues on next page)
```
Difference with following row

```python
>>> df.diff(periods=-1)
    a     b     c
0  3.0  2.0  15.0
1  3.0  4.0  21.0
2  3.0  6.0  27.0
3  3.0  8.0  33.0
4  3.0 10.0  39.0
```

Overflow in input dtype

```python
>>> df = pd.DataFrame({'a': [1, 0]}, dtype=np.uint8)
>>> df.diff()
    a
0  NaN
1  255.0
```

### pandas.DataFrame.div

DataFrame.div(other, axis='columns', level=None, fill_value=None)

Get Floating division of dataframe and other, element-wise (binary operator `truediv`).

Equivalent to `dataframe / other`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `rtruediv`.

Among flexible wrappers (add, sub, mul, div, mod, pow) to arithmetic operators: `+`, `-`, `*`, `/`, `//`, `%`, `**`.

**Parameters**

- **other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.
- **axis** [(0 or ‘index’, 1 or ‘columns’)] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.
- **level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.
- **fill_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

**Returns**

- **DataFrame** Result of the arithmetic operation.

**See also:**

- `DataFrame.add` Add DataFrames.
- `DataFrame.sub` Subtract DataFrames.
DataFrame.mul Multiply DataFrames.

DataFrame.div Divide DataFrames (float division).

DataFrame.truediv Divide DataFrames (float division).

DataFrame.floordiv Divide DataFrames (integer division).

DataFrame.mod Calculate modulo (remainder after division).

DataFrame.pow Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```python
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                     'degrees': [360, 180, 360]},
...                     index=['circle', 'triangle', 'rectangle'])
>>> df
    angles  degrees
circle     0       360
triangle   3       180
rectangle  4       360
```

Add a scalar with operator version which return the same results.

```python
>>> df + 1
    angles  degrees
circle     1       361
triangle   4       181
rectangle  5       361
```

```python
>>> df.add(1)
    angles  degrees
circle     1       361
triangle   4       181
rectangle  5       361
```

Divide by constant with reverse version.

```python
>>> df.div(10)
    angles  degrees
circle     0.0      36.0
triangle   0.3      18.0
rectangle  0.4      36.0
```

```python
>>> df.rdiv(10)
    angles  degrees
circle     inf      0.027778
triangle  3.333333  0.055556
rectangle 2.500000  0.027778
```

Subtract a list and Series by axis with operator version.
>>> df = [1, 2]
angles  degrees
circle  -1     358
triangle 2      178
rectangle 3      358

>>> df.sub([1, 2], axis='columns')
angles  degrees
circle  -1     358
triangle 2      178
rectangle 3      358

>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
         axis='index')
angles  degrees
circle  -1     359
triangle 2      179
rectangle 3      359

Multiply a DataFrame of different shape with operator version.

>>> other = pd.DataFrame({'angles': [0, 3, 4]},
                        index=['circle', 'triangle', 'rectangle'])

>>> df * other
angles  degrees
circle  0      NaN
triangle 9      NaN
rectangle 16     NaN

>>> df.mul(other, fill_value=0)
angles  degrees
circle  0      0.0
triangle 9      0.0
rectangle 16     0.0

Divide by a MultiIndex by level.

>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
                              'degrees': [360, 180, 360, 360, 540, 720],
                              index=[['A', 'A', 'A', 'B', 'B', 'B'],
                                     ['circle', 'triangle', 'rectangle',
                                      'square', 'pentagon', 'hexagon']])

>>> df_multindex
A angles  degrees
circle  0      360
triangle 3      180
rectangle 4      360
B square 4      360
pentagon 5      540
hexagon 6      720

3.4. DataFrame
```python
>>> df.div(df_multindex, level=1, fill_value=0)
```

<table>
<thead>
<tr>
<th>angles</th>
<th>degrees</th>
</tr>
</thead>
<tbody>
<tr>
<td>A circle</td>
<td>NaN</td>
</tr>
<tr>
<td>triangle</td>
<td>1.0</td>
</tr>
<tr>
<td>rectangle</td>
<td>1.0</td>
</tr>
<tr>
<td>B square</td>
<td>0.0</td>
</tr>
<tr>
<td>pentagon</td>
<td>0.0</td>
</tr>
<tr>
<td>hexagon</td>
<td>0.0</td>
</tr>
</tbody>
</table>

**pandas.DataFrame.divide**

DataFrame.divide(other, axis='columns', level=None, fill_value=None)

Get Floating division of dataframe and other, element-wise (binary operator truediv).

Equivalent to dataframe / other, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, rtruediv.

Among flexible wrappers (add, sub, mul, div, mod, pow) to arithmetic operators: +, -, *, /, //, %, **.

**Parameters**

- **other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.
- **axis** [[0 or 'index', 1 or 'columns']] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.
- **level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.
- **fill_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

**Returns**

DataFrame Result of the arithmetic operation.

**See also:**

DataFrame.add Add DataFrames.
DataFrame.sub Subtract DataFrames.
DataFrame.mul Multiply DataFrames.
DataFrame.div Divide DataFrames (float division).
DataFrame.truediv Divide DataFrames (float division).
DataFrame.floordiv Divide DataFrames (integer division).
DataFrame.mod Calculate modulo (remainder after division).
DataFrame.pow Calculate exponential power.
Notes

Mismatched indices will be unioned together.

Examples

```python
>>> df = pd.DataFrame({'angles': [0, 3, 4],
... 'degrees': [360, 180, 360]},
... index=['circle', 'triangle', 'rectangle'])
>>> df
           angles  degrees
    circle        0      360
    triangle      3      180
    rectangle     4      360

Add a scalar with operator version which return the same results.

```python
>>> df + 1
           angles  degrees
    circle       1      361
    triangle      4      181
    rectangle     5      361
```

```python
>>> df.add(1)
           angles  degrees
    circle       1      361
    triangle      4      181
    rectangle     5      361
```

Divide by constant with reverse version.

```python
>>> df.div(10)
           angles  degrees
    circle    0.0     36.0
    triangle  0.3     18.0
    rectangle 0.4     36.0
```

```python
>>> df.rdiv(10)
           angles  degrees
    circle    inf   0.027778
    triangle  3.333333  0.055556
    rectangle 2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```python
>>> df - [1, 2]
           angles  degrees
    circle     -1      358
    triangle     2      178
    rectangle     3      358
```

```python
>>> df.sub([1, 2], axis='columns')
           angles  degrees
    circle     -1      358
    triangle     2      178
    rectangle     3      358
```
Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> df * other
```

```
angles  degrees
circle  0   NaN
triangle 9   NaN
rectangle 16  NaN
```

```
>>> df.mul(other, fill_value=0)
```

```
angles  degrees
circle  0   0.0
triangle 9   0.0
rectangle 16  0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                               'degrees': [360, 180, 360, 360, 540, 720]},
...                               index=['A', 'A', 'A', 'B', 'B', 'B'],
...                               ['circle', 'triangle', 'rectangle',
...                            'square', 'pentagon', 'hexagon'])
>>> df_multindex
```

```
   angles  degrees
   A circle  0  360
  triangle  3  180
     rectangle 4  360
   B square  4  360
    pentagon 5  540
  hexagon  6  720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
```

```
   angles  degrees
   A circle  NaN  1.0
  triangle  1.0  1.0
     rectangle 1.0  1.0
   B square  0.0  0.0
    pentagon 0.0  0.0
  hexagon  0.0  0.0
```
pandas.DataFrame.dot

**DataFrame.dot**(other)
Compute the matrix multiplication between the DataFrame and other.

This method computes the matrix product between the DataFrame and the values of an other Series, DataFrame or a numpy array.

It can also be called using self @ other in Python >= 3.5.

**Parameters**

other [Series, DataFrame or array-like] The other object to compute the matrix product with.

**Returns**

Series or DataFrame If other is a Series, return the matrix product between self and other as a Series. If other is a DataFrame or a numpy.array, return the matrix product of self and other in a DataFrame of a np.array.

**See also:**

*Series.dot* Similar method for Series.

**Notes**

The dimensions of DataFrame and other must be compatible in order to compute the matrix multiplication. In addition, the column names of DataFrame and the index of other must contain the same values, as they will be aligned prior to the multiplication.

The dot method for Series computes the inner product, instead of the matrix product here.

**Examples**

Here we multiply a DataFrame with a Series.

```python
>>> df = pd.DataFrame([[0, 1, -2, -1], [1, 1, 1, 1]])
>>> s = pd.Series([1, 1, 2, 1])
>>> df.dot(s)
0   -4
1    5
dtype: int64
```

Here we multiply a DataFrame with another DataFrame.

```python
>>> other = pd.DataFrame([[0, 1], [1, 2], [-1, -1], [2, 0]])
>>> df.dot(other)
   0  1
0  1  4
1  2  2
```

Note that the dot method give the same result as @

```python
>>> df @ other
   0  1
0  1  4
1  2  2
```
The dot method works also if other is an np.array.

```python
>>> arr = np.array([[0, 1], [1, 2], [-1, -1], [2, 0]])
>>> df.dot(arr)
 0  1
 0  1  4
 1  2  2
```

Note how shuffling of the objects does not change the result.

```python
>>> s2 = s.reindex([1, 0, 2, 3])
>>> df.dot(s2)
 0  -4
 1   5
dtype: int64
```

### pandas.DataFrame.drop

DataFrame's `.drop` method can be used to remove rows or columns by specifying label names and corresponding axis, or by specifying directly index or column names. When using a multi-index, labels on different levels can be removed by specifying the level.

**Parameters**

- **labels** [single label or list-like] Index or column labels to drop.
- **axis** [{0 or 'index', 1 or 'columns'}, default 0] Whether to drop labels from the index (0 or ‘index’) or columns (1 or ‘columns’).
- **index** [single label or list-like] Alternative to specifying axis (labels, axis=0 is equivalent to index=labels).
- **columns** [single label or list-like] Alternative to specifying axis (labels, axis=1 is equivalent to columns=labels).
- **level** [int or level name, optional] For MultiIndex, level from which the labels will be removed.
- **inplace** [bool, default False] If False, return a copy. Otherwise, do operation inplace and return None.
- **errors** [{‘ignore’, ‘raise’}, default ‘raise’] If ‘ignore’, suppress error and only existing labels are dropped.

**Returns**

DataFrame DataFrame without the removed index or column labels.

**Raises**

- **KeyError** If any of the labels is not found in the selected axis.

See also:

- `DataFrame.loc` Label-location based indexer for selection by label.
**DataFrame.dropna** Return DataFrame with labels on given axis omitted where (all or any) data are missing.

**DataFrame.drop_duplicates** Return DataFrame with duplicate rows removed, optionally only considering certain columns.

**Series.drop** Return Series with specified index labels removed.

### Examples

```python
def = pd.DataFrame(np.arange(12).reshape(3, 4),
                   columns=['A', 'B', 'C', 'D'])
def
```

```
A  B  C  D
0  0  1  2  3
1  4  5  6  7
2  8  9 10 11
```

Drop columns

```python
def.drop(['B', 'C'], axis=1)
def.drop(columns=['B', 'C'])
```

```
A  D
0  0  3
1  4  7
2  8 11
```

Drop a row by index

```python
def.drop([0, 1])
```

```
A  B  C  D
2  8  9 10 11
```

Drop columns and/or rows of MultiIndex DataFrame

```python
midx = pd.MultiIndex(levels=[['lama', 'cow', 'falcon'],
                            ['speed', 'weight', 'length']],
                     codes=[[0, 0, 0, 1, 1, 1, 2, 2, 2],
                            [0, 1, 2, 0, 1, 2, 0, 1, 2]])
def = pd.DataFrame(index=midx, columns=['big', 'small'],
                   data=[[45, 30], [200, 100], [1.5, 1], [30, 20],
                         [250, 150], [1.5, 0.8], [320, 250],
                         [1, 0.8], [0.3, 0.2]])
def
```

```
<table>
<thead>
<tr>
<th></th>
<th>big</th>
<th>small</th>
</tr>
</thead>
<tbody>
<tr>
<td>lama</td>
<td>speed</td>
<td>45.0</td>
</tr>
<tr>
<td></td>
<td>weight</td>
<td>200.0</td>
</tr>
<tr>
<td></td>
<td>length</td>
<td>1.5</td>
</tr>
<tr>
<td>cow</td>
<td>speed</td>
<td>30.0</td>
</tr>
<tr>
<td></td>
<td>weight</td>
<td>250.0</td>
</tr>
<tr>
<td></td>
<td>length</td>
<td>1.5</td>
</tr>
<tr>
<td>falcon</td>
<td>speed</td>
<td>320.0</td>
</tr>
</tbody>
</table>
```

(continues on next page)
pandas: powerful Python data analysis toolkit, Release 1.1.1

(pandas: powerful Python data analysis toolkit, Release 1.1.1)

weight 1.0 0.8
length 0.3 0.2

```python
>>> df.drop(index='cow', columns='small')
big
lama speed 45.0
weight 200.0
length 1.5
falcon speed 320.0
weight 1.0
length 0.3
```

```python
>>> df.drop(index='length', level=1)
big small
lama speed 45.0 30.0
weight 200.0 100.0
cow speed 30.0 20.0
weight 250.0 150.0
falcon speed 320.0 250.0
weight 1.0 0.8
```

**pandas.DataFrame.drop_duplicates**

**Dataframe**.drop_duplicates(subset=None, keep='first', inplace=False, ignore_index=False)

Return DataFrame with duplicate rows removed.

Considering certain columns is optional. Indexes, including time indexes are ignored.

**Parameters**

- **subset** [column label or sequence of labels, optional] Only consider certain columns for identifying duplicates, by default use all of the columns.
- **keep** [{‘first’, ‘last’, False}, default ‘first’] Determines which duplicates (if any) to keep. - first : Drop duplicates except for the first occurrence. - last : Drop duplicates except for the last occurrence. - False : Drop all duplicates.
- **inplace** [bool, default False] Whether to drop duplicates in place or to return a copy.
- **ignore_index** [bool, default False] If True, the resulting axis will be labeled 0, 1, ..., n - 1.

**Returns**

- **DataFrame** DataFrame with duplicates removed or None if inplace=True.

**See also:**

- **DataFrame.value_counts** Count unique combinations of columns.
Examples

Consider dataset containing ramen rating.

```python
>>> df = pd.DataFrame({
...     'brand': ['Yum Yum', 'Yum Yum', 'Indomie', 'Indomie', 'Indomie'],
...     'style': ['cup', 'cup', 'cup', 'pack', 'pack'],
...     'rating': [4, 4, 3.5, 15, 5]
... })
>>> df
   brand style rating
0   Yum Yum   cup   4.0
1   Yum Yum   cup   4.0
2   Indomie   cup   3.5
3   Indomie   pack  15.0
4   Indomie   pack   5.0
```

By default, it removes duplicate rows based on all columns.

```python
>>> df.drop_duplicates()
   brand style rating
0   Yum Yum   cup   4.0
2   Indomie   cup   3.5
3   Indomie   pack  15.0
4   Indomie   pack   5.0
```

To remove duplicates on specific column(s), use `subset`.

```python
>>> df.drop_duplicates(subset=['brand'])
   brand style rating
0   Yum Yum   cup   4.0
2   Indomie   cup   3.5
```

To remove duplicates and keep last occurrences, use `keep`.

```python
>>> df.drop_duplicates(subset=['brand', 'style'], keep='last')
   brand style rating
1   Yum Yum   cup   4.0
2   Indomie   cup   3.5
4   Indomie   pack   5.0
```

`pandas.DataFrame.droplevel`  
`DataFrame.droplevel(level, axis=0)`  
Return DataFrame with requested index / column level(s) removed.

New in version 0.24.0.

Parameters

- `level` [int, str, or list-like] If a string is given, must be the name of a level. If list-like, elements must be names or positional indexes of levels.
- `axis` [{0 or ‘index’, 1 or ‘columns’}, default 0] Axis along which the level(s) is removed:
  - 0 or ‘index’: remove level(s) in column.
  - 1 or ‘columns’: remove level(s) in row.
Returns

DataFrame DataFrame with requested index / column level(s) removed.

Examples

```python
>>> df = pd.DataFrame([... [1, 2, 3, 4], ... [5, 6, 7, 8], ... [9, 10, 11, 12] ... ]).set_index([0, 1]).rename_axis(["a", "b"])
```

```python
>>> df.columns = pd.MultiIndex.from_tuples([... ("c", "e"), ("d", "f") ... ], names=["level_1", "level_2"])
```

```python
>>> df
level_1   c   d
level_2   e   f
  a   b
1  2   3   4
5  6   7   8
9 10  11  12
```

```python
>>> df.droplevel('a')
level_1   c   d
level_2   e   f
  b
2   3   4
6   7   8
10  11  12
```

```python
>>> df.droplevel('level_2', axis=1)
level_1   c   d
level_2   e   f
  a   b
1  2   3   4
5  6   7   8
9 10  11  12
```

pandas.DataFrame.dropna

DataFrame.dropna(axis=0, how='any', thresh=None, subset=None, inplace=False)
Remove missing values.

See the User Guide for more on which values are considered missing, and how to work with missing data.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] Determine if rows or columns which contain missing values are removed.

- 0, or ‘index’ : Drop rows which contain missing values.
- 1, or ‘columns’ : Drop columns which contain missing value.
Changed in version 1.0.0: Pass tuple or list to drop on multiple axes. Only a single axis is allowed.

- **how** [{‘any’, ‘all’}, default ‘any’] Determine if row or column is removed from DataFrame, when we have at least one NA or all NA.
  - ‘any’: If any NA values are present, drop that row or column.
  - ‘all’: If all values are NA, drop that row or column.

- **thresh** [int, optional] Require that many non-NA values.

- **subset** [array-like, optional] Labels along other axis to consider, e.g. if you are dropping rows these would be a list of columns to include.

- **inplace** [bool, default False] If True, do operation in-place and return None.

**Returns**

- **DataFrame** DataFrame with NA entries dropped from it.

**See also:**

- **DataFrame.isna** Indicate missing values.
- **DataFrame.notna** Indicate existing (non-missing) values.
- **DataFrame.fillna** Replace missing values.
- **Series.dropna** Drop missing values.
- **Index.dropna** Drop missing indices.

**Examples**

```python
>>> df = pd.DataFrame({"name": ['Alfred', 'Batman', 'Catwoman'],
...                      "toy": [np.nan, 'Batmobile', 'Bullwhip'],
...                      "born": [pd.NaT, pd.Timestamp("1940-04-25"), pd.NaT]})
```

Drop the rows where at least one element is missing.

```bash
>>> df.dropna()
name     toy      born
1  Batman  Batmobile 1940-04-25
```

Drop the columns where at least one element is missing.

```bash
>>> df.dropna(axis='columns')
name
0  Alfred
1  Batman
2  Catwoman
```

Drop the rows where all elements are missing.

```bash
>>> df.dropna(axis='columns')
name
0  Alfred
1  Batman
2  Catwoman
```
```python
>>> df.dropna(how='all')
   name    toy    born
0  Alfred      NaN    NaT
1  Batman  Batmobile  1940-04-25
2  Catwoman     Bullwhip    NaT
Keep only the rows with at least 2 non-NA values.
```  
```python
>>> df.dropna(thresh=2)
   name    toy    born
1  Batman  Batmobile  1940-04-25
2  Catwoman     Bullwhip    NaT
Define in which columns to look for missing values.
```  
```python
>>> df.dropna(subset=['name', 'born'])
   name    toy    born
1  Batman  Batmobile  1940-04-25
Keep the DataFrame with valid entries in the same variable.
```  
```python
>>> df.dropna(inplace=True)
```

**pandas.DataFrame.duplicated**

DataFrame.duplicated(subset=None, keep='first')

Return boolean Series denoting duplicate rows.

Considering certain columns is optional.

**Parameters**

- **subset** [column label or sequence of labels, optional] Only consider certain columns for identifying duplicates, by default use all of the columns.
- **keep** [‘first’, ‘last’, False], default ‘first’ Determines which duplicates (if any) to mark.
  
  - first: Mark duplicates as True except for the first occurrence.
  - last: Mark duplicates as True except for the last occurrence.
  - False: Mark all duplicates as True.

**Returns**

Series Boolean series for each duplicated rows.

**See also:**

* Index.duplicated Equivalent method on index.
* Series.duplicated Equivalent method on Series.
* Series.drop_duplicates Remove duplicate values from Series.
* DataFrame.drop_duplicates Remove duplicate values from DataFrame.
Examples

Consider dataset containing ramen rating.

```python
>>> df = pd.DataFrame({
...     'brand': ['Yum Yum', 'Yum Yum', 'Indomie', 'Indomie', 'Indomie'],
...     'style': ['cup', 'cup', 'cup', 'pack', 'pack'],
...     'rating': [4, 4, 3.5, 15, 5]
... })
```

```python
>>> df
     brand  style rating
0     Yum     cup   4.0
1     Yum     cup   4.0
2   Indomie   cup   3.5
3   Indomie   pack  15.0
4   Indomie   pack   5.0
```

By default, for each set of duplicated values, the first occurrence is set on False and all others on True.

```python
>>> df.duplicated()
0    False
1     True
2    False
3     False
4     False
dtype: bool
```

By using `last`, the last occurrence of each set of duplicated values is set on False and all others on True.

```python
>>> df.duplicated(keep='last')
0   True
1  False
2  False
3  False
4  False
dtype: bool
```

By setting `keep` on False, all duplicates are True.

```python
>>> df.duplicated(keep=False)
0  True
1  True
2  False
3  False
4  False
dtype: bool
```

To find duplicates on specific column(s), use `subset`.

```python
>>> df.duplicated(subset=['brand'])
0  False
1   True
2  False
3   True
4   True
dtype: bool
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.DataFrame.eq

DataFrame.eq(other, axis='columns', level=None)
Get Equal to of dataframe and other, element-wise (binary operator eq).
Among flexible wrappers (eq, ne, le, lt, ge, gt) to comparison operators.
Equivalent to ==, =!, <=, <, >=, > with support to choose axis (rows or columns) and level for comparison.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.
axis [{0 or 'index', 1 or 'columns'}, default 'columns'] Whether to compare by the index (0 or 'index') or columns (1 or 'columns').
level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

DataFrame of bool Result of the comparison.

See also:

DataFrame.eq Compare DataFrames for equality elementwise.
DataFrame.ne Compare DataFrames for inequality elementwise.
DataFrame.le Compare DataFrames for less than inequality or equality elementwise.
DataFrame.lt Compare DataFrames for strictly less than inequality elementwise.
DataFrame.ge Compare DataFrames for greater than inequality or equality elementwise.
DataFrame.gt Compare DataFrames for strictly greater than inequality elementwise.

Notes
Mismatched indices will be unioned together. NaN values are considered different (i.e. NaN != NaN).

Examples

```python
>>> df = pd.DataFrame({'cost': [250, 150, 100],
...                   'revenue': [100, 250, 300]},
...                   index=['A', 'B', 'C'])
>>> df
   cost  revenue
A  250    100
B  150    250
C  100    300
```

Comparison with a scalar, using either the operator or method:

```python
>>> df == 100
   cost  revenue
A  False    True
B  False    False
C  True     False
```
When `other` is a `Series`, the columns of a DataFrame are aligned with the index of `other` and broadcast:

```python
>>> df != pd.Series([100, 250], index=['cost', 'revenue'])
    cost  revenue
  A   True    True
  B   True    False
  C   False    True
```

Use the method to control the broadcast axis:

```python
>>> df.ne(pd.Series([100, 300], index=['A', 'D']), axis='index')
    cost  revenue
  A   True    False
  B   True    True
  C   True    True
  D   True    True
```

When comparing to an arbitrary sequence, the number of columns must match the number elements in `other`:

```python
>>> df == [250, 100]
    cost  revenue
  A   True    True
  B   False    False
  C   False    False
```

Use the method to control the axis:

```python
>>> df.eq([250, 250, 100], axis='index')
    cost  revenue
  A   True    False
  B   False    True
  C   True    False
```

Compare to a DataFrame of different shape.

```python
>>> other = pd.DataFrame({'revenue': [300, 250, 100, 150]},
                        index=['A', 'B', 'C', 'D'])
>>> df.gt(other)
    cost  revenue
  A     True   False
  B     True    True
  C     True    True
  D     True    True
```

(continues on next page)
A False False
B False False
C False True
D False False

Compare to a MultiIndex by level.

```python
>>> df_multindex = pd.DataFrame({'cost': [250, 150, 100, 150, 300, 220],
                               'revenue': [100, 250, 300, 200, 175, 225],
                               'index': [['Q1', 'Q1', 'Q1', 'Q2', 'Q2', 'Q2'],
                                         ['A', 'B', 'C', 'A', 'B', 'C']])
>>> df_multindex
   cost  revenue
Q1 A    250     100
      B    150     250
      C     100     300
Q2 A    150     200
      B    300     175
      C    220     225
```

```python
>>> df.le(df_multindex, level=1)
   cost  revenue
Q1 A   True   True
      B   True   True
      C   True   True
Q2 A  False   True
      B   True   False
      C   True   False
```

### pandas.DataFrame.equals

**DataFrame.equals**(other)

Test whether two objects contain the same elements.

This function allows two Series or DataFrames to be compared against each other to see if they have the same shape and elements. NaNs in the same location are considered equal. The column headers do not need to have the same type, but the elements within the columns must be the same dtype.

**Parameters**

- **other** [Series or DataFrame] The other Series or DataFrame to be compared with the first.

**Returns**

- **bool** True if all elements are the same in both objects, False otherwise.

**See also:**

- **Series.eq** Compare two Series objects of the same length and return a Series where each element is True if the element in each Series is equal, False otherwise.

- **DataFrame.eq** Compare two DataFrame objects of the same shape and return a DataFrame where each element is True if the respective element in each DataFrame is equal, False otherwise.

- **testing.assert_series_equal** Raises an AssertionError if left and right are not equal. Provides an easy interface to ignore inequality in dtypes, indexes and precision among others.
**testing.assert_frame_equal**  Like assert_series_equal, but targets DataFrames.

**numpy.array_equal**  Return True if two arrays have the same shape and elements, False otherwise.

**Notes**

This function requires that the elements have the same dtype as their respective elements in the other Series or DataFrame. However, the column labels do not need to have the same type, as long as they are still considered equal.

**Examples**

```python
>>> df = pd.DataFrame({1: [10], 2: [20]})
>>> df
   1  2
0 10 20

DataFrames df and exactly_equal have the same types and values for their elements and column labels, which will return True.

```python
>>> exactly_equal = pd.DataFrame({1: [10], 2: [20]})
>>> exactly_equal
   1  2
0 10 20
>>> df.equals(exactly_equal)
True
```

DataFrames df and different_column_type have the same element types and values, but have different types for the column labels, which will still return True.

```python
>>> different_column_type = pd.DataFrame({1.0: [10], 2.0: [20]})
>>> different_column_type
   1.0  2.0
0  10  20
>>> df.equals(different_column_type)
True
```

DataFrames df and different_data_type have different types for the same values for their elements, and will return False even though their column labels are the same values and types.

```python
>>> different_data_type = pd.DataFrame({1: [10.0], 2: [20.0]})
>>> different_data_type
   1   2
0 10.0 20.0
>>> df.equals(different_data_type)
False
```
pandas.DataFrame.eval

pandas.DataFrame.eval(expr, inplace=False, **kwargs)
Evaluate a string describing operations on DataFrame columns.

Operates on columns only, not specific rows or elements. This allows eval to run arbitrary code, which can make you vulnerable to code injection if you pass user input to this function.

Parameters

expr [str] The expression string to evaluate.

inplace [bool, default False] If the expression contains an assignment, whether to perform the operation inplace and mutate the existing DataFrame. Otherwise, a new DataFrame is returned.

**kwargs See the documentation for eval() for complete details on the keyword arguments accepted by query().

Returns

ndarray, scalar, or pandas object The result of the evaluation.

See also:

DataFrame.query Evaluates a boolean expression to query the columns of a frame.

DataFrame.assign Can evaluate an expression or function to create new values for a column.

eval Evaluate a Python expression as a string using various backends.

Notes

For more details see the API documentation for eval(). For detailed examples see enhancing performance with eval.

Examples

```python
>>> df = pd.DataFrame({'A': range(1, 6), 'B': range(10, 0, -2)})
>>> df
   A  B
0  1 10
1  2  8
2  3  6
3  4  4
4  5  2
>>> df.eval('A + B')
   0  11
  1  10
  2  9
  3  8
  4  7
dtype: int64
```

Assignment is allowed though by default the original DataFrame is not modified.
>>> df.eval('C = A + B')
    A  B  C
0  1  10  11
1  2  8  10
2  3  6  9
3  4  4  8
4  5  2  7

Use `inplace=True` to modify the original DataFrame.

>>> df.eval('C = A + B', inplace=True)
>>> df
    A  B  C
0  1  10  11
1  2  8  10
2  3  6  9
3  4  4  8
4  5  2  7

Multiple columns can be assigned to using multi-line expressions:

>>> df.eval('''
... C = A + B
... D = A - B
... '''
... )
    A  B  C  D
0  1  10  11 -9
1  2  8  10 -6
2  3  6  9 -3
3  4  4  8  0
4  5  2  7  3

**pandas.DataFrame.ewm**

DataFrame.ewm (com=None, span=None, halflife=None, alpha=None, min_periods=0, adjust=True, ignore_na=False, axis=0, times=None)

Provide exponential weighted (EW) functions.

Available EW functions: mean(), var(), std(), corr(), cov().

Exactly one parameter: com, span, halflife, or alpha must be provided.

**Parameters**

- **com** [float, optional] Specify decay in terms of center of mass, $\alpha = 1/(1 + \text{com})$, for $\text{com} \geq 0$.
- **span** [float, optional] Specify decay in terms of span, $\alpha = 2/(\text{span}+1)$, for $\text{span} \geq 1$. 

---

3.4. DataFrame
halflife [float, str, timedelta, optional] Specify decay in terms of half-life, \( \alpha = 1 - \exp\left(-\ln(2)/\text{halflife}\right) \), for \( \text{halflife} > 0 \).

If times is specified, the time unit (str or timedelta) over which an observation decays to half its value. Only applicable to \textit{mean()} and halflife value will not apply to the other functions.

New in version 1.1.0.

alpha [float, optional] Specify smoothing factor \( \alpha \) directly, \( 0 < \alpha \leq 1 \).

min_periods [int, default 0] Minimum number of observations in window required to have a value (otherwise result is NA).

adjust [bool, default True] Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average).

- When adjust=True (default), the EW function is calculated using weights \( w_i = (1 - \alpha)^i \). For example, the EW moving average of the series \([x_0, x_1, ..., x_t]\) would be:

\[
y_t = \frac{x_t + (1 - \alpha)x_{t-1} + (1 - \alpha)^2x_{t-2} + ... + (1 - \alpha)^tx_0}{1 + (1 - \alpha) + (1 - \alpha)^2 + ... + (1 - \alpha)^t}
\]

- When adjust=False, the exponentially weighted function is calculated recursively:

\[
y_0 = x_0 \\
y_t = (1 - \alpha)y_{t-1} + \alpha x_t,
\]

ignore_na [bool, default False] Ignore missing values when calculating weights; specify True to reproduce pre-0.15.0 behavior.

- When ignore_na=False (default), weights are based on absolute positions. For example, the weights of \( x_0 \) and \( x_2 \) used in calculating the final weighted average of \([x_0, None, x_2]\) are \((1 - \alpha)^2\) and \(1\) if adjust=True, and \((1 - \alpha)^2\) and \(\alpha\) if adjust=False.

- When ignore_na=True (reproducing pre-0.15.0 behavior), weights are based on relative positions. For example, the weights of \( x_0 \) and \( x_2 \) used in calculating the final weighted average of \([x_0, None, x_2]\) are \(1 - \alpha\) and \(1\) if adjust=True, and \(1 - \alpha\) and \(\alpha\) if adjust=False.

axis [{0, 1}, default 0] The axis to use. The value 0 identifies the rows, and 1 identifies the columns.

times [str, np.ndarray, Series, default None] New in version 1.1.0.

Times corresponding to the observations. Must be monotonically increasing and datetime64[ns] dtype.

If str, the name of the column in the DataFrame representing the times.

If 1-D array like, a sequence with the same shape as the observations.

Only applicable to \textit{mean()}.

Returns

\textit{DataFrame} A Window sub-classed for the particular operation.

See also:

\begin{verbatim}
pandas: powerful Python data analysis toolkit, Release 1.1.1
\end{verbatim}
**rolling** Provides rolling window calculations.

**expanding** Provides expanding transformations.

**Notes**

More details can be found at: *Exponentially weighted windows*.

**Examples**

```python
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]})
>>> df
      B
0     0
1     1
2     2
3   NaN
4     4

>>> df.ewm(com=0.5).mean()
      B
0  0.000000
1  0.750000
2  1.615385
3  1.615385
4  3.670213

Specifying times with a timedelta halflife when computing mean.

```python
>>> times = ['2020-01-01', '2020-01-03', '2020-01-10', '2020-01-15', '2020-01-17']
>>> df.ewm(halflife='4 days', times=pd.DatetimeIndex(times)).mean()
      B
0  0.000000
1  0.585786
2  1.523889
3  1.523889
4  3.233686
```

**pandas.DataFrame.expanding**

Dataframe.**expanding** *min_periods=1, center=None, axis=0*

Provide expanding transformations.

**Parameters**

- `min_periods [int, default 1]` Minimum number of observations in window required to have a value (otherwise result is NA).
- `center [bool, default False]` Set the labels at the center of the window.
- `axis [int or str, default 0]`

**Returns**

- a Window sub-classed for the particular operation
See also:

- **rolling**  Provides rolling window calculations.
- **ewm**  Provides exponential weighted functions.

**Notes**

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

**Examples**

```python
gf = pd.DataFrame({"B": [0, 1, 2, np.nan, 4]})
gf

0    0.0
1    1.0
2    2.0
3   NaN
4    4.0

gf.expanding(2).sum()

0  NaN
1  1.0
2  3.0
3  3.0
4  7.0
```

**pandas.DataFrame.explode**

DataFrame.explode(column, ignore_index=False)

Transform each element of a list-like to a row, replicating index values.

New in version 0.25.0.

<table>
<thead>
<tr>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>column</strong></td>
</tr>
<tr>
<td><strong>ignore_index</strong></td>
</tr>
</tbody>
</table>

New in version 1.1.0.

<table>
<thead>
<tr>
<th>Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>DataFrame</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Raises</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ValueError</strong></td>
</tr>
</tbody>
</table>

See also:
**DataFrame.unstack** Pivot a level of the (necessarily hierarchical) index labels.

**DataFrame.melt** Unpivot a DataFrame from wide format to long format.

**Series.explode** Explode a DataFrame from list-like columns to long format.

**Notes**

This routine will explode list-likes including lists, tuples, Series, and np.ndarray. The result dtype of the subset rows will be object. Scalars will be returned unchanged. Empty list-likes will result in a np.nan for that row.

**Examples**

```python
>>> df = pd.DataFrame({'A': [[1, 2, 3], 'foo', [], [3, 4]], 'B': 1})
>>> df
   A    B
0 [1, 2, 3] 1
1   foo  1
2     []  1
3 [3, 4]  1
```

```python
>>> df.explode('A')
   A    B
0  1    1
0  2    1
0  3    1
1  foo  1
2   NaN  1
3  3    1
3  4    1
```

**pandas.DataFrame.ffill**

**DataFrame.ffill** *(axis=None, inplace=False, limit=None, downcast=None)*

Synonym for **DataFrame.fillna()** with method='ffill'.

**Returns**

{klass} or None Object with missing values filled or None if inplace=True.

**pandas.DataFrame.fillna**

**DataFrame.fillna** *(value=None, method=None, axis=None, inplace=False, limit=None, downcast=None)*

Fill NA/NaN values using the specified method.

**Parameters**

value [scalar, dict, Series, or DataFrame] Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). Values not in the dict/Series/DataFrame will not be filled. This value cannot be a list.

axis  [{0 or ‘index’, 1 or ‘columns’}] Axis along which to fill missing values.

inplace  [bool, default False] If True, fill in-place. Note: this will modify any other views on this object (e.g., a no-copy slice for a column in a DataFrame).

limit  [int, default None] If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled. Must be greater than 0 if not None.

downcast  [dict, default is None] A dict of item->dtype of what to downcast if possible, or the string ‘infer’ which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible).

Returns

DataFrame or None  Object with missing values filled or None if inplace=True.

See also:

interpolate  Fill NaN values using interpolation.

reindex  Conform object to new index.

asfreq  Convert TimeSeries to specified frequency.

Examples

```python
>>> df = pd.DataFrame([[np.nan, 2, np.nan, 0],
...                     [3, 4, np.nan, 1],
...                     [np.nan, np.nan, np.nan, 5],
...                     [np.nan, 3, np.nan, 4]],
...                    columns=list('ABCD'))
>>> df
     A  B   C  D
0   NaN 2.0  NaN 0
1   3.0 4.0  NaN 1
2   NaN  NaN  NaN 5
3   NaN  3.0  NaN 4
```

Replace all NaN elements with 0s.

```python
>>> df.fillna(0)
     A  B   C  D
0  0.0 2.0  0.0 0
1  3.0 4.0  0.0 1
2  0.0 0.0  0.0 5
3  0.0 3.0  0.0 4
```

We can also propagate non-null values forward or backward.

```python
>>> df.fillna(method='ffill')
     A  B   C  D
0   NaN 2.0  NaN 0
1   3.0 4.0  NaN 1
2   0.0 0.0  0.0 5
3   0.0 3.0  0.0 4
```
Replace all NaN elements in column ‘A’, ‘B’, ‘C’, and ‘D’, with 0, 1, 2, and 3 respectively.

```python
>>> values = {'A': 0, 'B': 1, 'C': 2, 'D': 3}
>>> df.fillna(value=values)
       A   B   C   D
0  0.0  2.0  2.0  0.0
1  3.0  4.0  2.0  1.0
2  0.0  1.0  2.0  5.0
3  0.0  3.0  2.0  4.0
```

Only replace the first NaN element.

```python
>>> df.fillna(value=values, limit=1)
       A   B   C   D
0  0.0  2.0  2.0  0.0
1  3.0  4.0  NaN  1.0
2  NaN  1.0  NaN  5.0
3  NaN  3.0  NaN  4.0
```

### pandas.DataFrame.filter

**DataFrame.filter**(items=None, like=None, regex=None, axis=None)  
Subset the dataframe rows or columns according to the specified index labels.

Note that this routine does not filter a dataframe on its contents. The filter is applied to the labels of the index.

**Parameters**

- **items** [list-like] Keep labels from axis which are in items.
- **like** [str] Keep labels from axis for which “like in label == True”.
- **regex** [str (regular expression)] Keep labels from axis for which re.search(regex, label) == True.
- **axis** [[0 or ‘index’, 1 or ‘columns’, None], default None] The axis to filter on, expressed either as an index (int) or axis name (str). By default this is the info axis, ‘index’ for Series, ‘columns’ for DataFrame.

**Returns**

same type as input object

**See also:**

- **DataFrame.loc** Access a group of rows and columns by label(s) or a boolean array.
Notes

The items, like, and regex parameters are enforced to be mutually exclusive.

axis defaults to the info axis that is used when indexing with [].

Examples

```python
>>> df = pd.DataFrame(np.array(((1, 2, 3), (4, 5, 6))),
...                    index=['mouse', 'rabbit'],
...                    columns=['one', 'two', 'three'])
>>> df
   one  two  three
mouse  1    2    3
rabbit 4    5    6

>>> # select columns by name
>>> df.filter(items=['one', 'three'])
   one  three
mouse   1    3
rabbit   4    6

>>> # select columns by regular expression
>>> df.filter(regex='e$', axis=1)
   one  three
mouse   1    3
rabbit   4    6

>>> # select rows containing 'bbi'
>>> df.filter(like='bbi', axis=0)
   one  two  three
rabbit 4    5    6
```

pandas.DataFrame.first

DataFrame.first(offset)

Select initial periods of time series data based on a date offset.

When having a DataFrame with dates as index, this function can select the first few rows based on a date offset.

Parameters

offset [str, DateOffset or dateutil.relativedelta] The offset length of the data that will be selected. For instance, ‘1M’ will display all the rows having their index within the first month.

Returns

Series or DataFrame A subset of the caller.

Raises

TypeError If the index is not a DatetimeIndex.
last Select final periods of time series based on a date offset.

at_time Select values at a particular time of the day.

between_time Select values between particular times of the day.

Examples

```python
>>> i = pd.date_range('2018-04-09', periods=4, freq='2D')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
      A
2018-04-09  1
2018-04-11  2
2018-04-13  3
2018-04-15  4

Get the rows for the first 3 days:

```python
>>> ts.first('3D')
      A
2018-04-09  1
2018-04-11  2
```

Notice the data for 3 first calendar days were returned, not the first 3 days observed in the dataset, and therefore data for 2018-04-13 was not returned.

pandas.DataFrame.first_valid_index

DataFrame.first_valid_index() Return index for first non-NA/null value.

Returns

scalar [type of index]

Notes

If all elements are non-NA/null, returns None. Also returns None for empty Series/DataFrame.

pandas.DataFrame.floordiv

DataFrame.floordiv(other, axis='columns', level=None, fill_value=None) Get Integer division of dataframe and other, element-wise (binary operator `floordiv`). Equivalent to `dataframe // other`, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, `rfloordiv`.

Among flexible wrappers (`add`, `sub`, `mul`, `div`, `mod`, `pow`) to arithmetic operators: `+`, `-`, `*`, `/`, `//`, `%`, `**`.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.
axis  [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.

level  [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value  [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

DataFrame  Result of the arithmetic operation.

See also:

DataFrame.add  Add DataFrames.
DataFrame.sub  Subtract DataFrames.
DataFrame.mul  Multiply DataFrames.
DataFrame.div  Divide DataFrames (float division).
DataFrame.truediv  Divide DataFrames (float division).
DataFrame.floordiv  Divide DataFrames (integer division).
DataFrame.mod  Calculate modulo (remainder after division).
DataFrame.pow  Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```python
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
>>> df
   angles  degrees
circle    0      360
triangle   3      180
rectangle  4      360
```

Add a scalar with operator version which return the same results.

```python
>>> df + 1
   angles  degrees
circle    1      361
triangle   4      181
rectangle  5      361
```
divide by constant with reverse version.

```python
>>> df.div(10)
angles degrees
circle 0.0 36.0
triangle 0.3 18.0
rectangle 0.4 36.0
```

subtract a list and series by axis with operator version.

```python
>>> df - [1, 2]
angles degrees
circle -1 358
triangle 2 178
rectangle 3 358
```

multiply a DataFrame of different shape with operator version.

```python
other = pd.DataFrame({'angles': [0, 3, 4]},
                     index=['circle', 'triangle', 'rectangle'])
>>> df * other
angles degrees
circle 0 NaN
triangle 9 NaN
rectangle 16 NaN
```
Divide by a MultiIndex by level.

```python
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                             'degrees': [360, 180, 360, 360, 540, 720],
...                             'index': ['A', 'A', 'A', 'B', 'B', 'B'],
...                             'circle', 'triangle', 'rectangle',
...                             'square', 'pentagon', 'hexagon']})
>>> df_multindex
  angles  degrees
   A  circle    0    360
     triangle   3    180
     rectangle  4    360
   B    square   4    360
     pentagon   5    540
     hexagon   6    720
```

```python
>>> df.div(df_multindex, level=1, fill_value=0)
  angles  degrees
   A  circle  NaN     1.0
     triangle  1.0     1.0
     rectangle  1.0     1.0
   B    square  0.0     0.0
     pentagon  0.0     0.0
     hexagon  0.0     0.0
```

`pandas.DataFrame.from_dict`

classmethod `DataFrame.from_dict`(data, orient='columns', dtype=None, columns=None)  
Construct DataFrame from dict of array-like or dicts.  
Creates DataFrame object from dictionary by columns or by index allowing dtype specification.

Parameters

data [dict] Of the form {field : array-like} or {field : dict}.
orient ['columns', 'index'], default 'columns' The “orientation” of the data. If the keys of the passed dict should be the columns of the resulting DataFrame, pass ‘columns’ (default). Otherwise if the keys should be rows, pass ‘index’.
dtype [dtype, default None] Data type to force, otherwise infer.
columns [list, default None] Column labels to use when orient='index'. Raises a ValueError if used with orient='columns'.

Returns

DataFrame

See also:
DataFrame.from_records DataFrame from structured ndarray, sequence of tuples or dicts, or DataFrame.

DataFrame DataFrame object creation using constructor.

Examples

By default the keys of the dict become the DataFrame columns:

```python
>>> data = {'col_1': [3, 2, 1, 0], 'col_2': ['a', 'b', 'c', 'd']}
>>> pd.DataFrame.from_dict(data)
       col_1 col_2
    0    3    a
    1    2    b
    2    1    c
    3    0    d
```

Specify orient='index' to create the DataFrame using dictionary keys as rows:

```python
>>> data = {'row_1': [3, 2, 1, 0], 'row_2': ['a', 'b', 'c', 'd']}
>>> pd.DataFrame.from_dict(data, orient='index')
      0  1  2  3
row_1 3  2  1  0
row_2 a  b  c  d
```

When using the ‘index’ orientation, the column names can be specified manually:

```python
>>> pd.DataFrame.from_dict(data, orient='index',
...                        columns=['A', 'B', 'C', 'D'])
   A  B  C  D
row_1 3  2  1  0
row_2 a  b  c  d
```

pandas.DataFrame.from_records

classmethod DataFrame.from_records(data, index=None, exclude=None, columns=None, coerce_float=False, nrows=None)

Convert structured or record ndarray to DataFrame.

Creates a DataFrame object from a structured ndarray, sequence of tuples or dicts, or DataFrame.

Parameters

- **data**: [structured ndarray, sequence of tuples or dicts, or DataFrame] Structured input data.
- **index**: [str, list of fields, array-like] Field of array to use as the index, alternately a specific set of input labels to use.
- **exclude**: [sequence, default None] Columns or fields to exclude.
- **columns**: [sequence, default None] Column names to use. If the passed data do not have names associated with them, this argument provides names for the columns. Otherwise this argument indicates the order of the columns in the result (any names not found in the data will become all-NA columns).
- **coerce_float**: [bool, default False] Attempt to convert values of non-string, non-numeric objects (like decimal.Decimal) to floating point, useful for SQL result sets.
nrows [int, default None] Number of rows to read if data is an iterator.

Returns

DataFrame

See also:

DataFrame.from_dict DataFrame from dict of array-like or dicts.

DataFrame DataFrame object creation using constructor.

Examples

Data can be provided as a structured ndarray:

```python
>>> data = np.array([(3, 'a'), (2, 'b'), (1, 'c'), (0, 'd')],
                   dtype=[('col_1', 'i4'), ('col_2', 'U1')])
```

```text
>> pd.DataFrame.from_records(data)
col_1   col_2
0   3   a
1   2   b
2   1   c
3   0   d
```

Data can be provided as a list of dicts:

```python
>>> data = [{'col_1': 3, 'col_2': 'a'},
          {'col_1': 2, 'col_2': 'b'},
          {'col_1': 1, 'col_2': 'c'},
          {'col_1': 0, 'col_2': 'd'}]
```

```text
>> pd.DataFrame.from_records(data)
col_1   col_2
0   3   a
1   2   b
2   1   c
3   0   d
```

Data can be provided as a list of tuples with corresponding columns:

```python
>>> data = [(3, 'a'), (2, 'b'), (1, 'c'), (0, 'd')]
```

```text
>> pd.DataFrame.from_records(data, columns=['col_1', 'col_2'])
col_1   col_2
0   3   a
1   2   b
2   1   c
3   0   d
```
DataFrame.ge

DataFrame.ge(other, axis='columns', level=None)
Get Greater than or equal to of dataframe and other, element-wise (binary operator ge).

Among flexible wrappers (eq, ne, le, lt, ge, gt) to comparison operators.
Equivalent to ==, !=, <=, <, >=, > with support to choose axis (rows or columns) and level for comparison.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.
axis [{0 or 'index', 1 or 'columns'}, default 'columns'] Whether to compare by the index (0 or 'index') or columns (1 or 'columns').
level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

DataFrame of bool Result of the comparison.

See also:

DataFrame.eq Compare DataFrames for equality elementwise.
DataFrame.ne Compare DataFrames for inequality elementwise.
DataFrame.le Compare DataFrames for less than inequality or equality elementwise.
DataFrame.lt Compare DataFrames for strictly less than inequality elementwise.
DataFrame.ge Compare DataFrames for greater than inequality or equality elementwise.
DataFrame.gt Compare DataFrames for strictly greater than inequality elementwise.

Notes

Mismatched indices will be unioned together. NaN values are considered different (i.e. NaN != NaN).

Examples

```
>>> df = pd.DataFrame({'cost': [250, 150, 100],
...                    'revenue': [100, 250, 300]},
...                    index=['A', 'B', 'C'])
>>> df
   cost  revenue
A   250     100
B   150     250
C   100     300

Comparison with a scalar, using either the operator or method:
```
```
>>> df == 100
   cost  revenue
A  False     True
```
(continues on next page)
When other is a Series, the columns of a DataFrame are aligned with the index of other and broadcast:

```python
>>> df != pd.Series([100, 250], index=['cost', 'revenue'])
   cost  revenue
A   True     True
B   True     False
C  False     True
```

Use the method to control the broadcast axis:

```python
>>> df.ne(pd.Series([100, 300], index=['A', 'D']), axis='index')
   cost  revenue
A   True     False
B   True     True
C  True     True
D  True     True
```

When comparing to an arbitrary sequence, the number of columns must match the number elements in other:

```python
>>> df == [250, 100]
   cost  revenue
A   True     True
B  False     False
C  False     False
```

Use the method to control the axis:

```python
>>> df.eq([250, 250, 100], axis='index')
   cost  revenue
A  False     False
B   True     True
C  True     False
```

Compare to a DataFrame of different shape.

```python
>>> other = pd.DataFrame({'revenue': [300, 250, 100, 150]},
                        index=['A', 'B', 'C', 'D'])
>>> other
revenue
A     300
B     250
C     100
D     150

>>> df.gt(other)
   cost  revenue
```

(continues on next page)
Compare to a MultiIndex by level.

```python
>>> df_multindex = pd.DataFrame({'cost': [250, 150, 100, 150, 300, 220],
... 'revenue': [100, 250, 300, 200, 175, 225],
... 'index': [ ['Q1', 'Q1', 'Q1', 'Q2', 'Q2', 'Q2'],
... [ 'A', 'B', 'C', 'A', 'B', 'C']])
>>> df_multindex
  cost  revenue
Q1  A    250       100
    B    150       250
    C    100       300
Q2  A    150       200
    B    300       175
    C    220       225

>>> df.le(df_multindex, level=1)
  cost  revenue
Q1  A    True      True
    B    True      True
    C    True      True
Q2  A    False     True
    B    True      False
    C    True      False
```

**pandas.DataFrame.get**

`DataFrame.get(key, default=None)`

Get item from object for given key (ex: DataFrame column).

Returns default value if not found.

**Parameters**

- `key` [object]

**Returns**

- `value` [same type as items contained in object]

**pandas.DataFrame.groupby**

`DataFrame.groupby(by=None, axis=0, level=None, as_index=True, sort=True, group_keys=True, squeeze=<object object>, observed=False, dropna=True)`

Group DataFrame using a mapper or by a Series of columns.

A groupby operation involves some combination of splitting the object, applying a function, and combining the results. This can be used to group large amounts of data and compute operations on these groups.

**Parameters**
by [mapping, function, label, or list of labels] Used to determine the groups for the
groupby. If by is a function, it’s called on each value of the object’s index. If a
dict or Series is passed, the Series or dict VALUES will be used to determine the
groups (the Series’ values are first aligned; see .align() method). If an ndarray
is passed, the values are used as-is to determine the groups. A label or list of labels
may be passed to group by the columns in self. Notice that a tuple is interpreted
as a (single) key.

axis [[0 or ‘index’, 1 or ‘columns’], default 0] Split along rows (0) or columns (1).

level [int, level name, or sequence of such, default None] If the axis is a MultiIndex
(hierarchical), group by a particular level or levels.

as_index [bool, default True] For aggregated output, return object with group labels
as the index. Only relevant for DataFrame input. as_index=False is effectively
“SQL-style” grouped output.

sort [bool, default True] Sort group keys. Get better performance by turning this off.
Note this does not influence the order of observations within each group. Groupby
preserves the order of rows within each group.

group_keys [bool, default True] When calling apply, add group keys to index to iden-
tify pieces.

squeeze [bool, default False] Reduce the dimensionality of the return type if possible,
otherwise return a consistent type.
Deprecation since version 1.1.0.

observed [bool, default False] This only applies if any of the groupers are Categoricals.
If True: only show observed values for categorical groupers. If False: show all
values for categorical groupers.
New in version 0.23.0.

dropna [bool, default True] If True, and if group keys contain NA values, NA values
together with row/column will be dropped. If False, NA values will also be treated
as the key in groups
New in version 1.1.0.

Returns

DataFrameGroupBy Returns a groupby object that contains information about the
groups.

See also:

resample Convenience method for frequency conversion and resampling of time series.

Notes

See the user guide for more.
Examples

```python
groupby (["Animal"]).mean()
Animal
Falcon 375.0
Parrot 25.0
```

Hierarchical Indexes

We can groupby different levels of a hierarchical index using the `level` parameter:

```python
groupby (level=0).mean()
Animal
Falcon 370.0
Parrot 25.0
```

We can also choose to include NA in group keys or not by setting `dropna` parameter, the default setting is `True`:

```python
groupby (by="b").sum()
a c b
1.0 2 3
2.0 2 5
```
```python
>>> df.groupby(by=["b"], dropna=False).sum()
    a  c
  b  1.0  2  3
   2.0  2  5
    NaN  1  4
```

```python
>>> l = ["a", 12, 12], [None, 12.3, 33.], ["b", 12.3, 123], ["a", 1, 1]
>>> df = pd.DataFrame(l, columns=["a", "b", "c"])
```

```python
>>> df.groupby(by="a").sum()
    b  c
  a  13.0  13.0
  b  12.3  123.0
```

```python
>>> df.groupby(by="a", dropna=False).sum()
    b  c
  a  13.0  13.0
  b  12.3  123.0
    NaN  12.3  33.0
```

### pandas.DataFrame.gt

DataFrame.gt( other, axis='columns', level=None)

Get Greater than of dataframe and other, element-wise (binary operator gt).

Among flexible wrappers (eq, ne, le, lt, ge, gt) to comparison operators.

Equivalent to ==, !=, <=, <, >=, > with support to choose axis (rows or columns) and level for comparison.

**Parameters**

- **other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.
- **axis** [{0 or ‘index’, 1 or ‘columns’}, default ‘columns’] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’).
- **level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

**Returns**

DataFrame of bool Result of the comparison.

**See also:**

- **DataFrame.eq** Compare DataFrames for equality elementwise.
- **DataFrame.ne** Compare DataFrames for inequality elementwise.
- **DataFrame.le** Compare DataFrames for less than inequality or equality elementwise.
- **DataFrame.lt** Compare DataFrames for strictly less than inequality elementwise.
- **DataFrame.ge** Compare DataFrames for greater than inequality or equality elementwise.
**DataFrame.gt** Compare DataFrames for strictly greater than inequality elementwise.

**Notes**

Mismatched indices will be unioned together. *NaN* values are considered different (i.e. *NaN* != *NaN*).

**Examples**

```python
>>> df = pd.DataFrame({'cost': [250, 150, 100],
...                    'revenue': [100, 250, 300]},
...                   index=['A', 'B', 'C'])
>>> df
       cost  revenue
    A      250     100
    B      150     250
    C      100     300

Comparison with a scalar, using either the operator or method:

```python
>>> df == 100
       cost  revenue
    A   False     True
    B   False    False
    C    True    False
```

```python
>>> df.eq(100)
       cost  revenue
    A   False     True
    B   False    False
    C    True    False
```

When `other` is a `Series`, the columns of a DataFrame are aligned with the index of `other` and broadcast:

```python
>>> df != pd.Series([100, 250], index=['cost', 'revenue'])
       cost  revenue
    A    True     True
    B    True    False
    C   False     True
```

Use the method to control the broadcast axis:

```python
>>> df.ne(pd.Series([100, 300], index=['A', 'D']), axis='index')
       cost  revenue
    A    True    False
    B    True     True
    C    True     True
    D    True     True
```

When comparing to an arbitrary sequence, the number of columns must match the number elements in `other`:

```python
>>> df == [250, 100]
       cost  revenue
    A    True     True
```

(continues on next page)
Use the method to control the axis:

```python
>>> df.eq([250, 250, 100], axis='index')
   cost  revenue
A  True   False
B  False  True
C  True   False
```

Compare to a DataFrame of different shape.

```python
>>> other = pd.DataFrame({'revenue': [300, 250, 100, 150]},
                       index=['A', 'B', 'C', 'D'])
>>> other
          revenue
A      300
B      250
C      100
D      150
```

```python
>>> df.gt(other)
   cost  revenue
A  False  False
B  False  False
C  False  True
D  False  False
```

Compare to a MultiIndex by level.

```python
>>> df_multindex = pd.DataFrame({'cost': [250, 150, 100, 150, 300, 220],
                               'revenue': [100, 250, 300, 200, 175, 225],
                               index=[['Q1', 'Q1', 'Q1', 'Q2', 'Q2', 'Q2'],
                                      ['A', 'B', 'C', 'A', 'B', 'C']])
>>> df_multindex
   cost  revenue
Q1 A  250    100
   B  150    250
   C  100    300
Q2 A  150    200
   B  300    175
   C  220    225
```

```python
>>> df.le(df_multindex, level=1)
   cost  revenue
Q1 A  True   True
   B  True   True
   C  True   True
Q2 A  False  True
   B  True   False
   C  True   False
```
**pandas.DataFrame.head**

DataFrame.head(n=5)

Return the first $n$ rows.

This function returns the first $n$ rows for the object based on position. It is useful for quickly testing if your object has the right type of data in it.

For negative values of $n$, this function returns all rows except the last $n$ rows, equivalent to $\text{df}[:-n]$.

**Parameters**

- **n** [int, default 5] Number of rows to select.

**Returns**

- **same type as caller** The first $n$ rows of the caller object.

**See also:**

*DataFrame.tail* Returns the last $n$ rows.

**Examples**

```python
>>> df = pd.DataFrame({'animal': ['alligator', 'bee', 'falcon', 'lion', ...
                     'monkey', 'parrot', 'shark', 'whale', 'zebra']})

Viewing the first 5 lines

```python
>>> df.head()
   animal
0  alligator
1     bee
2   falcon
3     lion
4   monkey
5  parrot
6    shark
7   whale
8  zebra
```

Viewing the first $n$ lines (three in this case)

```python
>>> df.head(3)
   animal
0  alligator
1     bee
2   falcon
```

For negative values of $n
```python
>>> df.head(-3)
   animal
 0  alligator
 1      bee
 2    falcon
 3     lion
 4  monkey
 5  parrot
```

**pandas.DataFrame.hist**

DataFrame.hist(column=None, by=None, grid=True, xlabelsize=None, xrot=None, ylabelsize=None, yrot=None, ax=None, sharex=False, sharey=False, figsize=None, layout=None, bins=10, backend=None, legend=False, **kwargs)

Make a histogram of the DataFrame’s.

A **histogram** is a representation of the distribution of data. This function calls `matplotlib.pyplot.hist()`, on each series in the DataFrame, resulting in one histogram per column.

**Parameters**

- **data** [DataFrame] The pandas object holding the data.
- **column** [str or sequence] If passed, will be used to limit data to a subset of columns.
- **by** [object, optional] If passed, then used to form histograms for separate groups.
- **grid** [bool, default True] Whether to show axis grid lines.
- **xlabelsize** [int, default None] If specified changes the x-axis label size.
- **xrot** [float, default None] Rotation of x axis labels. For example, a value of 90 displays the x labels rotated 90 degrees clockwise.
- **ylabelsize** [int, default None] If specified changes the y-axis label size.
- **yrot** [float, default None] Rotation of y axis labels. For example, a value of 90 displays the y labels rotated 90 degrees clockwise.
- **ax** [Matplotlib axes object, default None] The axes to plot the histogram on.
- **sharex** [bool, default True if ax is None else False] In case subplots=True, share x axis and set some x axis labels to invisible; defaults to True if ax is None otherwise False if an ax is passed in. Note that passing in both an ax and sharex=True will alter all x axis labels for all subplots in a figure.
- **sharey** [bool, default False] In case subplots=True, share y axis and set some y axis labels to invisible.
- **figsize** [tuple] The size in inches of the figure to create. Uses the value in `matplotlib.rcParams` by default.
- **layout** [tuple, optional] Tuple of (rows, columns) for the layout of the histograms.
- **bins** [int or sequence, default 10] Number of histogram bins to be used. If an integer is given, bins + 1 bin edges are calculated and returned. If bins is a sequence, gives bin edges, including left edge of first bin and right edge of last bin. In this case, bins is returned unmodified.
- **backend** [str, default None] Backend to use instead of the backend specified in the option `plotting.backend`. For instance, ‘matplotlib’. Alternatively, to
specify the `plotting.backend` for the whole session, set `pd.options.plotting.backend`.

New in version 1.0.0.

**legend** [bool, default False] Whether to show the legend.

New in version 1.1.0.

**kwargs** All other plotting keyword arguments to be passed to `matplotlib.pyplot.hist()`.

Returns

- `matplotlib.AxesSubplot` or `numpy.ndarray` of them

See also:

- `matplotlib.pylot.hist` Plot a histogram using matplotlib.

**Examples**

This example draws a histogram based on the length and width of some animals, displayed in three bins

```python
>>> df = pd.DataFrame({
...    'length': [1.5, 0.5, 1.2, 0.9, 3],
...    'width': [0.7, 0.2, 0.15, 0.2, 1.1]
...    }, index=['pig', 'rabbit', 'duck', 'chicken', 'horse'])

>>> hist = df.hist(bins=3)
```

### `pandas.DataFrame.idxmax`

`DataFrame.idxmax(axis=0, skipna=True)`

Return index of first occurrence of maximum over requested axis.

NA/null values are excluded.

**Parameters**

- **axis** [{0 or 'index', 1 or 'columns'}, default 0] The axis to use. 0 or 'index' for row-wise, 1 or 'columns' for column-wise.

- **skipna** [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

**Returns**

- **Series** Indexes of maxima along the specified axis.

**Raises**

- **ValueError**

  - If the row/column is empty

**See also:**

- `Series.idxmax` Return index of the maximum element.
Notes

This method is the DataFrame version of `ndarray.argmax`.

Examples

Consider a dataset containing food consumption in Argentina.

```python
>>> df = pd.DataFrame({'consumption': [10.51, 103.11, 55.48],
...                   'co2_emissions': [37.2, 19.66, 1712]})
...                   index=['Pork', 'Wheat Products', 'Beef'])

>>> df
consumption  co2_emissions
Pork         10.51        37.20
Wheat Products 103.11      19.66
Beef          55.48       1712.00

By default, it returns the index for the maximum value in each column.

```python
>>> df.idxmax()
consumption    Wheat Products
co2_emissions  Beef
```

To return the index for the maximum value in each row, use `axis="columns"`.

```python
>>> df.idxmax(axis="columns")
Pork       co2_emissions
Wheat Products consumption
Beef       co2_emissions
```

`pandas.DataFrame.idxmin`

`DataFrame.idxmin(axis=0, skipna=True)`

Return index of first occurrence of minimum over requested axis.

NA/null values are excluded.

Parameters

- `axis` [{0 or 'index', 1 or 'columns'}, default 0] The axis to use. 0 or ‘index’ for row-wise, 1 or ‘columns’ for column-wise.
- `skipna` [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

Returns

- `Series` Indexes of minima along the specified axis.

Raises

- `ValueError`
  - If the row/column is empty
See also:

*Series.idxmin* Return index of the minimum element.

**Notes**

This method is the DataFrame version of *ndarray.argmin*.

**Examples**

Consider a dataset containing food consumption in Argentina.

```python
>>> df = pd.DataFrame({'consumption': [10.51, 103.11, 55.48],
...                     'co2_emissions': [37.2, 19.66, 1712]},
...                    index=['Pork', 'Wheat Products', 'Beef'])
```

```
>>> df
consumption   co2_emissions
Pork          10.51   37.20
Wheat Products 103.11  19.66
Beef          55.48  1712.00
```

By default, it returns the index for the minimum value in each column.

```python
>>> df.idxmin()
consumption    Pork
co2_emissions  Wheat Products
dtype: object
```

To return the index for the minimum value in each row, use *axis="columns"*.

```python
>>> df.idxmin(axis="columns")
Pork consumtion
Wheat Products co2_emissions
Beef           consumption
dtype: object
```

---

**pandas.DataFrame.infer_objects**

*DataFrame.infer_objects()*

Attempt to infer better dtypes for object columns.

Attempts soft conversion of object-dtyped columns, leaving non-object and unconvertible columns unchanged. The inference rules are the same as during normal Series/DataFrame construction.

**Returns**

converted [same type as input object]

**See also:**

*to_datetime* Convert argument to datetime.

*to_timedelta* Convert argument to timedelta.

*to_numeric* Convert argument to numeric type.
**convert_dtypes** Convert argument to best possible dtype.

### Examples

```python
>>> df = pd.DataFrame({'A': ['a', 1, 2, 3]})
>>> df = df.iloc[1:]
>>> df
   A
0  1
1  2
2  3
```

```python
>>> df.dtypes
A    object
dtype: object
```

```python
>>> df.infer_objects().dtypes
A    int64
dtype: object
```

#### pandas.DataFrame.info

**DataFrame.info** *(verbose=None, buf=None, max_cols=None, memory_usage=None, null_counts=None)*

Print a concise summary of a DataFrame.

This method prints information about a DataFrame including the index dtype and columns, non-null values and memory usage.

**Parameters**

- **data** [DataFrame] DataFrame to print information about.
- **verbose** [bool, optional] Whether to print the full summary. By default, the setting in pandas.options.display.max_info_columns is followed.
- **buf** [writable buffer, defaults to sys.stdout] Where to send the output. By default, the output is printed to sys.stdout. Pass a writable buffer if you need to further process the output.
- **max_cols** [int, optional] When to switch from the verbose to the truncated output. If the DataFrame has more than max_cols columns, the truncated output is used. By default, the setting in pandas.options.display.max_info_columns is used.
- **memory_usage** [bool, str, optional] Specifies whether total memory usage of the DataFrame elements (including the index) should be displayed. By default, this follows the pandas.options.display.memory_usage setting.

True always show memory usage. False never shows memory usage. A value of ‘deep’ is equivalent to “True with deep introspection”. Memory usage is shown in human-readable units (base-2 representation). Without deep introspection a memory estimation is made based in column dtype and number of rows assuming values consume the same memory amount for corresponding dtypes. With deep memory introspection, a real memory usage calculation is performed at the cost of computational resources.
null_counts [bool, optional] Whether to show the non-null counts. By default, this is shown only if the DataFrame is smaller than pandas.options.display.max_info_rows and pandas.options.display.max_info_columns. A value of True always shows the counts, and False never shows the counts.

Returns

None This method prints a summary of a DataFrame and returns None.

See also:

DataFrame.describe Generate descriptive statistics of DataFrame columns.

DataFrame.memory_usage Memory usage of DataFrame columns.

Examples

>>> int_values = [1, 2, 3, 4, 5]
>>> text_values = ['alpha', 'beta', 'gamma', 'delta', 'epsilon']
>>> float_values = [0.0, 0.25, 0.5, 0.75, 1.0]
>>> df = pd.DataFrame({'int_col': int_values, 'text_col': text_values, ...
"float_col": float_values})
>>> df
   int_col  text_col  float_col
0     1     alpha    0.00
1     2      beta    0.25
2     3    gamma    0.50
3     4     delta    0.75
4     5   epsilon    1.00

Prints information of all columns:

>>> df.info(verbose=True)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5 entries, 0 to 4
Data columns (total 3 columns):
   # Column    Non-Null Count  Dtype
   ---        -------------- -----
0  int_col    5 non-null     int64
1  text_col   5 non-null     object
2  float_col  5 non-null     float64
dtypes: float64(1), int64(1), object(1)
memory usage: 248.0+ bytes

Prints a summary of columns count and its dtypes but not per column information:

>>> df.info(verbose=False)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5 entries, 0 to 4
Columns: 3 entries, int_col to float_col
dtypes: float64(1), int64(1), object(1)
memory usage: 248.0+ bytes

Pipe output of DataFrame.info to buffer instead of sys.stdout, get buffer content and writes to a text file:
The `memory_usage` parameter allows deep introspection mode, specially useful for big DataFrames and fine-tune memory optimization:

```python
>>> random_strings_array = np.random.choice(['a', 'b', 'c'], 10 ** 6)
>>> df = pd.DataFrame(
    ... 'column_1': np.random.choice(['a', 'b', 'c'], 10 ** 6),
    ... 'column_2': np.random.choice(['a', 'b', 'c'], 10 ** 6),
    ... 'column_3': np.random.choice(['a', 'b', 'c'], 10 ** 6)
    ...
)
>>> df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000000 entries, 0 to 999999
Data columns (total 3 columns):
# Column    Non-Null Count   Dtype
--- ------ -------------- ----- 
0 column_1  1000000 non-null object
1 column_2  1000000 non-null object
2 column_3  1000000 non-null object
dtypes: object(3)
memory usage: 22.9+ MB

>>> df.info(memory_usage='deep')
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000000 entries, 0 to 999999
Data columns (total 3 columns):
# Column    Non-Null Count   Dtype
--- ------ -------------- ----- 
0 column_1  1000000 non-null object
1 column_2  1000000 non-null object
2 column_3  1000000 non-null object
dtypes: object(3)
memory usage: 188.8 MB
```

### `DataFrame.insert`

DataFrame.insert(loc, column, value, allow_duplicates=False)

Insert column into DataFrame at specified location.

Raises a ValueError if column is already contained in the DataFrame, unless allow_duplicates is set to True.

**Parameters**

- **loc** [int] Insertion index. Must verify 0 <= loc <= len(columns).
- **column** [str, number, or hashable object] Label of the inserted column.
- **value** [int, Series, or array-like]
allow_duplicates [bool, optional]

pandas.DataFrame.interpolate

Dataframe.interpolate(method='linear', axis=0, limit=None, inplace=False, limit_direction=None, limit_area=None, downcast=None, **kwargs)

Please note that only method='linear' is supported for DataFrame/Series with a MultiIndex.

Parameters

method [str, default ‘linear’] Interpolation technique to use. One of:

• ‘linear’: Ignore the index and treat the values as equally spaced. This is the only method supported on MultiIndexes.
• ‘time’: Works on daily and higher resolution data to interpolate given length of interval.
• ‘index’, ‘values’: use the actual numerical values of the index.
• ‘pad’: Fill in NaNs using existing values.
• ‘nearest’, ‘zero’, ‘slinear’, ‘quadratic’, ‘cubic’, ‘spline’, ‘barycentric’, ‘polynomial’. Passed to scipy.interpolate.interp1d. These methods use the numerical values of the index. Both ‘polynomial’ and ‘spline’ require that you also specify an order (int), e.g. df.interpolate(method='polynomial', order=5).
• ‘from_derivatives’: Refers to scipy.interpolate.BPoly.from_derivatives which replaces ‘piecewise_polynomial’ interpolation method in scipy 0.18.

axis [{0 or ‘index’, 1 or ‘columns’, None}, default None] Axis to interpolate along.

limit [int, optional] Maximum number of consecutive NaNs to fill. Must be greater than 0.

inplace [bool, default False] Update the data in place if possible.

limit_direction [{‘forward’, ‘backward’, ‘both’}], Optional] Consecutive NaNs will be filled in this direction.

If limit is specified:

• If ‘method’ is ‘pad’ or ‘ffill’, ‘limit_direction’ must be ‘forward’.
• If ‘method’ is ‘backfill’ or ‘bfill’, ‘limit_direction’ must be ‘backwards’.

If ‘limit’ is not specified:

• If ‘method’ is ‘backfill’ or ‘bfill’, the default is ‘backward’
• else the default is ‘forward’

Changed in version 1.1.0: raises ValueError if limit_direction is ‘forward’ or ‘both’ and method is ‘backfill’ or ‘bfill’, raises ValueError if limit_direction is ‘backward’ or ‘both’ and method is ‘pad’ or ‘ffill’.

limit_area [{None, ‘inside’, ‘outside’}], default None] If limit is specified, consecutive NaNs will be filled with this restriction.

• None: No fill restriction.
• ‘inside’: Only fill NaNs surrounded by valid values (interpolate).
• ‘outside’: Only fill NaNs outside valid values (extrapolate).

New in version 0.23.0.

downcast  [optional, ‘infer’ or None, defaults to None] Downcast dtypes if possible.

**kwargs  Keyword arguments to pass on to the interpolating function.

Returns

Series or DataFrame  Returns the same object type as the caller, interpolated at some or all NaN values.

See also:

fillna  Fill missing values using different methods.

scipy.interpolate.Akima1DInterpolator  Piecewise cubic polynomials (Akima interpolator).

scipy.interpolate.BPoly.from_derivatives  Piecewise polynomial in the Bernstein basis.

scipy.interpolate.interp1d  Interpolate a 1-D function.

scipy.interpolate.KroghInterpolator  Interpolate polynomial (Krogh interpolator).

scipy.interpolate.PchipInterpolator  PCHIP 1-d monotonic cubic interpolation.

scipy.interpolate.CubicSpline  Cubic spline data interpolator.

Notes

The ‘krogh’, ‘piecewise_polynomial’, ‘spline’, ‘pchip’ and ‘akima’ methods are wrappers around the respective SciPy implementations of similar names. These use the actual numerical values of the index. For more information on their behavior, see the SciPy documentation and SciPy tutorial.

Examples

Filling in NaN in a Series via linear interpolation.

```python
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s
0  0.0
1  1.0
2  NaN
3  3.0
dtype: float64

>>> s.interpolate()
0  0.0
1  1.0
2  2.0
3  3.0
dtype: float64
```

Filling in NaN in a Series by padding, but filling at most two consecutive NaN at a time.
Filling in NaN in a Series via polynomial interpolation or splines: Both ‘polynomial’ and ‘spline’ methods require that you also specify an order (int).

```
>>> s = pd.Series([0, 2, np.nan, 8])
>>> s.interpolate(method='polynomial', order=2)
0     0.000000
1     2.000000
2     4.666667
3     8.000000
dtype: float64
```

Fill the DataFrame forward (that is, going down) along each column using linear interpolation.

Note how the last entry in column ‘a’ is interpolated differently, because there is no entry after it to use for interpolation. Note how the first entry in column ‘b’ remains NaN, because there is no entry before it to use for interpolation.

```
>>> df = pd.DataFrame([(0.0, np.nan, -1.0, 1.0),
...                     (np.nan, 2.0, np.nan, np.nan),
...                     (2.0, 3.0, np.nan, 9.0),
...                     (np.nan, 4.0, -4.0, 16.0)],
...                    columns=list('abcd'))
>>> df.interpolate(method='linear', limit_direction='forward', axis=0)
0   NaN  -1.0   1.0
1  2.0     NaN     NaN
2  3.0     NaN    9.0
3  4.0    -4.0   16.0
```
Using polynomial interpolation.

```python
In [1]: df['d'].interpolate(method='polynomial', order=2)
Out[1]:
   0  1.0
   1  4.0
   2  9.0
   3 16.0
```

### pandas.DataFrame.isin

DataFrame.isin(values)

Whether each element in the DataFrame is contained in values.

**Parameters**

- `values` [iterable, Series, DataFrame or dict] The result will only be true at a location if all the labels match. If `values` is a Series, that’s the index. If `values` is a dict, the keys must be the column names, which must match. If `values` is a DataFrame, then both the index and column labels must match.

**Returns**

Dataframe Dataframe of booleans showing whether each element in the DataFrame is contained in values.

**See also:**

- DataFrame.eq Equality test for DataFrame.
- Series.isin Equivalent method on Series.
- Series.str.contains Test if pattern or regex is contained within a string of a Series or Index.

**Examples**

```python
In [2]: df = pd.DataFrame({'num_legs': [2, 4], 'num_wings': [2, 0]},
                    index=['falcon', 'dog'])
In [3]: df
   num_legs num_wings
  falcon    2        2
  dog       4        0

In [4]: df.isin([0, 2])
   num_legs num_wings
  falcon  True     True
  dog    False     True
```

When `values` is a list check whether every value in the DataFrame is present in the list (which animals have 0 or 2 legs or wings)

When `values` is a dict, we can pass values to check for each column separately:
pandas: powerful Python data analysis toolkit, Release 1.1.1

```python
>>> df.isin({'num_wings': [0, 3]})
  num_legs num_wings
falcon  False  False
dog  False  True
```

When `values` is a Series or DataFrame the index and column must match. Note that ‘falcon’ does not match based on the number of legs in df2.

```python
>>> other = pd.DataFrame({'num_legs': [8, 2], 'num_wings': [0, 2]},
                      index=['spider', 'falcon'])
>>> df.isin(other)
  num_legs num_wings
falcon  True  True
dog  False  False
```

### pandas.DataFrame.isna

DataFrame.isna()

Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as None or `numpy.NaN`, gets mapped to True values. Everything else gets mapped to False values. Characters such as empty strings '' or `numpy.inf` are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`).

**Returns**

DataFrame Mask of bool values for each element in DataFrame that indicates whether an element is not an NA value.

**See also:**

- `DataFrame.isnull` Alias of isna.
- `DataFrame.notna` Boolean inverse of isna.
- `DataFrame.dropna` Omit axes labels with missing values.
- `isna` Top-level isna.

#### Examples

Show which entries in a DataFrame are NA.

```python
>>> df = pd.DataFrame({'age': [5, 6, np.NaN],
...                     'born': [pd.NaT, pd.Timestamp('1939-05-27'),
...                             pd.Timestamp('1940-04-25')],
...                     'name': ['Alfred', 'Batman', ''],
...                     'toy': [None, 'Batmobile', 'Joker']})
>>> df
   age  born     name  toy
0  5.0  NaT  Alfred  None
1 6.0 1939-05-27  Batman Batmobile
2  NaT 1940-04-25  Joker
```
Show which entries in a Series are NA.

```
>>> ser = pd.Series([5, 6, np.NaN])
>>> ser
0   5.0
1   6.0
2   NaN
dtype: float64
```

```
>>> ser.isna()
0  False
1  False
2   True
dtype: bool
```

**pandas.DataFrame.isnull**

DataFrame.isnull()  
Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as None or numpy.nan, gets mapped to True values. Everything else gets mapped to False values. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.use_inf_as_na = True).

**Returns**

- DataFrame: Mask of bool values for each element in DataFrame that indicates whether an element is not an NA value.

**See also:**

- DataFrame.isnull: Alias of isna.
- DataFrame.notna: Boolean inverse of isna.
- DataFrame.dropna: Omit axes labels with missing values.
- isna: Top-level isna.

**Examples**

Show which entries in a DataFrame are NA.

```
>>> df = pd.DataFrame({'age': [5, 6, np.NaN],
...                     'born': [pd.NaT, pd.Timestamp('1939-05-27'),
...                              pd.Timestamp('1940-04-25')],
...                     'name': ['Alfred', 'Batman', ''],
...                     'toy': [None, 'Batmobile', 'Joker']})
```

(continues on next page)
pandas: powerful Python data analysis toolkit, Release 1.1.1

(continued from previous page)

<table>
<thead>
<tr>
<th>age</th>
<th>born</th>
<th>name</th>
<th>toy</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 5.0</td>
<td>NaT</td>
<td>Alfred</td>
<td>None</td>
</tr>
<tr>
<td>1 6.0</td>
<td>1939-05-27</td>
<td>Batman</td>
<td>Batmobile</td>
</tr>
<tr>
<td>2 NaN</td>
<td>1940-04-25</td>
<td>Joker</td>
<td></td>
</tr>
</tbody>
</table>

```python
>>> df.isna()
   age   born  name  toy
0  False  True  False  True
1  False  False  False  False
2   True  False  False  False
```

Show which entries in a Series are NA.

```python
>>> ser = pd.Series([5, 6, np.NaN])
>>> ser
0  5.0
1  6.0
2  NaN
dtype: float64

>>> ser.isna()
0  False
1  False
2   True
dtype: bool
```

pandas.DataFrame.items

DataFrame.items()

Iterate over (column name, Series) pairs.

Iterates over the DataFrame columns, returning a tuple with the column name and the content as a Series.

Yields

- **label** [object] The column names for the DataFrame being iterated over.
- **content** [Series] The column entries belonging to each label, as a Series.

See also:

- **DataFrame.iterrows** Iterate over DataFrame rows as (index, Series) pairs.
- **DataFrame.itertuples** Iterate over DataFrame rows as namedtuples of the values.

Examples

```python
>>> df = pd.DataFrame({'species': ['bear', 'bear', 'marsupial'],
...                    'population': [1864, 22000, 80000],
...                    'index': ['panda', 'polar', 'koala']})
>>> df
      species population
panda  bear     1864
polar bear    22000
```

(continues on next page)
koala marsupial 80000
>>> for label, content in df.items():
...     print(f'label: {label!r}')
...     print(f'content: {content!r}', sep='\n')
...     label: species
     content:
panda bear
polar bear
koala marsupial
Name: species, dtype: object
label: population
content:
panda 1864
polar 22000
koala 80000
Name: population, dtype: int64

pandas.DataFrame.items

DataFrame.items() Iterate over (column name, Series) pairs.

Iterates over the DataFrame columns, returning a tuple with the column name and the content as a Series.

Yields

label [object] The column names for the DataFrame being iterated over.
content [Series] The column entries belonging to each label, as a Series.

See also:

DataFrame.iterrows Iterate over DataFrame rows as (index, Series) pairs.
DataFrame.itertuples Iterate over DataFrame rows as namedtuples of the values.

Examples

>>> df = pd.DataFrame({'species': ['bear', 'bear', 'marsupial'],
...                     'population': [1864, 22000, 80000]},
...                     index=['panda', 'polar', 'koala'])
>>> df
    species      population
panda    bear          1864
polar    bear          22000
koala    marsupial     80000

>>> for label, content in df.items():
...     print(f'label: {label!r}')
...     print(f'content: {content!r}', sep='\n')
...     label: species
     content:
panda    bear
polar    bear
(continues on next page)
pandas.DataFrame.iterrows

DataFrame.iterrows()
Iterate over DataFrame rows as (index, Series) pairs.

Yields

index [label or tuple of label] The index of the row. A tuple for a MultiIndex.
data [Series] The data of the row as a Series.
it [generator] A generator that iterates over the rows of the frame.

See also:

DataFrame.itertuples Iterate over DataFrame rows as namedtuples of the values.
DataFrame.items Iterate over (column name, Series) pairs.

Notes

1. Because iterrows returns a Series for each row, it does not preserve dtypes across the rows (dtypes are preserved across columns for DataFrames). For example,

```python
>>> df = pd.DataFrame([[1, 1.5]], columns=['int', 'float'])
>>> row = next(df.iterrows())[1]
>>> row
int 1.0
float 1.5
Name: 0, dtype: float64
>>> print(row['int'].dtype)
float64
>>> print(df['int'].dtype)
int64
```

To preserve dtypes while iterating over the rows, it is better to use itertuples() which returns namedtuples of the values and which is generally faster than iterrows.

2. You should never modify something you are iterating over. This is not guaranteed to work in all cases. Depending on the data types, the iterator returns a copy and not a view, and writing to it will have no effect.
pandas.DataFrame.itertuples

DataFrame.itertuples (index=True, name='Pandas')
Iterate over DataFrame rows as namedtuples.

Parameters

- **index** [bool, default True] If True, return the index as the first element of the tuple.
- **name** [str or None, default “Pandas”] The name of the returned namedtuples or None to return regular tuples.

Returns

- **iterator** An object to iterate over namedtuples for each row in the DataFrame with the first field possibly being the index and following fields being the column values.

See also:

- **DataFrame.iterrows** Iterate over DataFrame rows as (index, Series) pairs.
- **DataFrame.items** Iterate over (column name, Series) pairs.

Notes

The column names will be renamed to positional names if they are invalid Python identifiers, repeated, or start with an underscore. On python versions < 3.7 regular tuples are returned for DataFrames with a large number of columns (>254).

Examples

```python
>>> df = pd.DataFrame({'num_legs': [4, 2], 'num_wings': [0, 2]},
                   index=['dog', 'hawk'])
>>> df
   num_legs  num_wings
dog       4          0
hawk      2          2
```

```python
>>> for row in df.itertuples():
...    print(row)
...Pandas(Index='dog', num_legs=4, num_wings=0)
Pandas(Index='hawk', num_legs=2, num_wings=2)
```

By setting the `index` parameter to False we can remove the index as the first element of the tuple:

```python
>>> for row in df.itertuples(index=False):
...    print(row)
...Pandas(num_legs=4, num_wings=0)
Pandas(num_legs=2, num_wings=2)
```

With the `name` parameter set we set a custom name for the yielded namedtuples:

```python
>>> for row in df.itertuples(name='Animal'):
...    print(row)
...```

(continues on next page)
pandas.DataFrame.join

DataFrame.join(other, on=None, how='left', lsuffix='', rsuffix='', sort=False)

Join columns of another DataFrame.

Join columns with other DataFrame either on index or on a key column. Efficiently join multiple DataFrame objects by index at once by passing a list.

Parameters

- **other** [DataFrame, Series, or list of DataFrame] Index should be similar to one of the columns in this one. If a Series is passed, its name attribute must be set, and that will be used as the column name in the resulting joined DataFrame.

- **on** [str, list of str, or array-like, optional] Column or index level name(s) in the caller to join on the index in other, otherwise joins index-on-index. If multiple values given, the other DataFrame must have a MultiIndex. Can pass an array as the join key if it is not already contained in the calling DataFrame. Like an Excel VLOOKUP operation.

- **how** [{‘left’, ‘right’, ‘outer’, ‘inner’}, default ‘left’] How to handle the operation of the two objects.

  - left: use calling frame’s index (or column if on is specified)
  - right: use other’s index.
  - outer: form union of calling frame’s index (or column if on is specified) with other’s index, and sort it lexicographically.
  - inner: form intersection of calling frame’s index (or column if on is specified) with other’s index, preserving the order of the calling’s one.

- **lsuffix** [str, default ‘’] Suffix to use from left frame’s overlapping columns.

- **rsuffix** [str, default ‘’] Suffix to use from right frame’s overlapping columns.

- **sort** [bool, default False] Order result DataFrame lexicographically by the join key. If False, the order of the join key depends on the join type (how keyword).

Returns

DataFrame A dataframe containing columns from both the caller and other.

See also:

- **DataFrame.merge** For column(s)-on-column(s) operations.
Notes

Parameters `on`, `lsuffix`, and `rsuffix` are not supported when passing a list of `DataFrame` objects.
Support for specifying index levels as the `on` parameter was added in version 0.23.0.

Examples

```python
>>> df = pd.DataFrame({'key': ['K0', 'K1', 'K2', 'K3', 'K4', 'K5'],
                    'A': ['A0', 'A1', 'A2', 'A3', 'A4', 'A5']})
>>> df
   key  A
0   K0  A0
1   K1  A1
2   K2  A2
3   K3  A3
4   K4  A4
5   K5  A5

>>> other = pd.DataFrame({'key': ['K0', 'K1', 'K2'],
                         'B': ['B0', 'B1', 'B2']})
>>> other
   key  B
0   K0  B0
1   K1  B1
2   K2  B2

Join DataFrames using their indexes.

```python
>>> df.join(other, lsuffix='_caller', rsuffix='_other')
   key_caller  A  key_other  B
0    K0    A0    K0  B0
1    K1    A1    K1  B1
2    K2    A2    K2  B2
3    K3    A3  NaN  NaN
4    K4    A4  NaN  NaN
5    K5    A5  NaN  NaN
```

If we want to join using the key columns, we need to set key to be the index in both `df` and `other`. The joined DataFrame will have key as its index.

```python
>>> df.set_index('key').join(other.set_index('key'))
      A  B
key
K0  A0  B0
K1  A1  B1
K2  A2  B2
K3  A3  NaN
K4  A4  NaN
K5  A5  NaN
```

Another option to join using the key columns is to use the `on` parameter. DataFrame.join always uses `other`'s index but we can use any column in `df`. This method preserves the original DataFrame's index in the result.

```python
>>> df.join(other, on='key')
      A  B
key
K0  A0  B0
K1  A1  B1
K2  A2  B2
K3  A3  NaN
K4  A4  NaN
K5  A5  NaN
```
>>> df.join(other.set_index('key'), on='key')
key  A  B
0  K0  A0  B0
1  K1  A1  B1
2  K2  A2  B2
3  K3  A3  NaN
4  K4  A4  NaN
5  K5  A5  NaN

pandas.DataFrame.keys

DataFrame.keys()

Get the ‘info axis’ (see Indexing for more).

This is index for Series, columns for DataFrame.

Returns

Index  Info axis.

pandas.DataFrame.kurt

DataFrame.kurt(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

Return unbiased kurtosis over requested axis.

Kurtosis obtained using Fisher’s definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1.

Parameters

axis  [[index (0), columns (1)]] Axis for the function to be applied on.

skipna  [bool, default True] Exclude NA/null values when computing the result.

level  [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

numeric_only  [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**kwargs  Additional keyword arguments to be passed to the function.

Returns

Series or DataFrame (if level specified)

pandas.DataFrame.kurtosis

DataFrame.kurtosis(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

Return unbiased kurtosis over requested axis.

Kurtosis obtained using Fisher’s definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1.

Parameters

axis  [[index (0), columns (1)]] Axis for the function to be applied on.

skipna  [bool, default True] Exclude NA/null values when computing the result.
**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

**numeric_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**kwargs** Additional keyword arguments to be passed to the function.

**Returns**

Series or DataFrame (if level specified)

---

**pandas.DataFrame.last**

**DataFrame.last**(offset)

Select final periods of time series data based on a date offset.

When having a DataFrame with dates as index, this function can select the last few rows based on a date offset.

**Parameters**

offset [str, DateOffset, dateutil.relativedelta] The offset length of the data that will be selected. For instance, ‘3D’ will display all the rows having their index within the last 3 days.

**Returns**

Series or DataFrame A subset of the caller.

**Raises**

TypeError If the index is not a DatetimeIndex

**See also:**

first Select initial periods of time series based on a date offset.
at_time Select values at a particular time of the day.
between_time Select values between particular times of the day.

**Examples**

```python
>>> i = pd.date_range('2018-04-09', periods=4, freq='2D')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
A
2018-04-09 1
2018-04-11 2
2018-04-13 3
2018-04-15 4

Get the rows for the last 3 days:

```python
>>> ts.last('3D')
A
2018-04-13 3
2018-04-15 4
```
Notice the data for 3 last calendar days were returned, not the last 3 observed days in the dataset, and therefore data for 2018-04-11 was not returned.

**pandas.DataFrame.last_valid_index**

Dataframe.last_valid_index()  
Return index for last non-NA/null value.

**Returns**

scalar [type of index]

**Notes**

If all elements are non-NA/null, returns None. Also returns None for empty Series/DataFrame.

**pandas.DataFrame.le**

Dataframe.le(other, axis='columns', level=None)  
Get Less than or equal to of dataframe and other, element-wise (binary operator le).

Among flexible wrappers (eq, ne, le, lt, ge, gt) to comparison operators.

Equivalent to ==, !=, <=, <, >=, > with support to choose axis (rows or columns) and level for comparison.

**Parameters**

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or ‘index’, 1 or ‘columns’}, default ‘columns’] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’).

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

**Returns**

DataFrame of bool  Result of the comparison.

See also:

- DataFrame.eq  Compare DataFrames for equality elementwise.
- DataFrame.ne  Compare DataFrames for inequality elementwise.
- DataFrame.le  Compare DataFrames for less than inequality or equality elementwise.
- DataFrame.lt  Compare DataFrames for strictly less than inequality elementwise.
- DataFrame.ge  Compare DataFrames for greater than inequality or equality elementwise.
- DataFrame.gt  Compare DataFrames for strictly greater than inequality elementwise.
Notes

Mismatched indices will be unioned together. NaN values are considered different (i.e. NaN != NaN).

Examples

```python
>>> df = pd.DataFrame({'cost': [250, 150, 100],
                    'revenue': [100, 250, 300]},
                    index=['A', 'B', 'C'])
>>> df
   cost revenue
A   250    100
B   150    250
C   100    300

Comparison with a scalar, using either the operator or method:

```python
>>> df == 100
   cost  revenue
A  False  True
B  False  False
C  True  False
```

```python
>>> df.eq(100)
   cost  revenue
A  False  True
B  False  False
C  True  False
```

When `other` is a `Series`, the columns of a DataFrame are aligned with the index of `other` and broadcast:

```python
>>> df != pd.Series([100, 250], index=['cost', 'revenue'])
   cost  revenue
A  True  True
B  True  False
C  False  True
```

Use the method to control the broadcast axis:

```python
>>> df.ne(pd.Series([100, 300], index=['A', 'D']), axis='index')
   cost  revenue
A  True  False
B  True  True
C  True  True
D  True  True
```

When comparing to an arbitrary sequence, the number of columns must match the number elements in `other`:

```python
>>> df == [250, 100]
   cost  revenue
A  True  True
B  False  False
C  False  False
```

Use the method to control the axis:
>>> df.eq([250, 250, 100], axis='index')
    cost  revenue
   A    True   False
   B   False    True
   C    True   False

Compare to a DataFrame of different shape.

```python
>>> other = pd.DataFrame({'revenue': [300, 250, 100, 150]},
                       index=['A', 'B', 'C', 'D'])
>>> other
     revenue
    A    300
    B    250
    C    100
    D    150
```

```python
>>> df.gt(other)
    cost  revenue
   A   False   False
   B   False   False
   C   False    True
   D   False   False
```

Compare to a MultiIndex by level.

```python
>>> df_multindex = pd.DataFrame({'cost': [250, 150, 100, 150, 300, 220],
                               'revenue': [100, 250, 300, 200, 175, 225],
                               index=[['Q1', 'Q1', 'Q1', 'Q2', 'Q2', 'Q2'],
                                      ['A', 'B', 'C', 'A', 'B', 'C']])
>>> df_multindex
     cost  revenue
    Q1   A    250    100
          B    150    250
          C    100    300
    Q2   A    150    200
          B    300    175
          C    220    225
```

```python
>>> df.le(df_multindex, level=1)
    cost  revenue
   Q1   A    True    True
       B    True    True
       C    True    True
   Q2   A   False    True
       B    True   False
       C    True   False
```
### pandas.DataFrame.lookup

**DataFrame.lookup**(row_labels, col_labels)

Label-based “fancy indexing” function for DataFrame.

Given equal-length arrays of row and column labels, return an array of the values corresponding to each (row, col) pair.

**Parameters**

- row_labels [sequence] The row labels to use for lookup.
- col_labels [sequence] The column labels to use for lookup.

**Returns**

- numpy.ndarray The found values.

### pandas.DataFrame.lt

**DataFrame.lt**(other, axis='columns', level=None)

Get Less than of dataframe and other, element-wise (binary operator lt).

Among flexible wrappers (eq, ne, le, lt, ge, gt) to comparison operators.

Equivalent to ==, !=, <=, <, >=, > with support to choose axis (rows or columns) and level for comparison.

**Parameters**

- other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.
- axis [{0 or ‘index’, 1 or ‘columns’}, default ‘columns’] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’).
- level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

**Returns**

- DataFrame of bool Result of the comparison.

**See also:**

- **DataFrame.eq** Compare DataFrames for equality elementwise.
- **DataFrame.ne** Compare DataFrames for inequality elementwise.
- **DataFrame.le** Compare DataFrames for less than inequality or equality elementwise.
- **DataFrame.lt** Compare DataFrames for strictly less than inequality elementwise.
- **DataFrame.ge** Compare DataFrames for greater than inequality or equality elementwise.
- **DataFrame.gt** Compare DataFrames for strictly greater than inequality elementwise.
Notes

Mismatched indices will be unioned together. NaN values are considered different (i.e. NaN != NaN).

Examples

```python
>>> df = pd.DataFrame({'cost': [250, 150, 100],  
                     'revenue': [100, 250, 300]},  
                     index=['A', 'B', 'C'])

>>> df
   cost  revenue
A  250     100
B  150     250
C  100     300

Comparison with a scalar, using either the operator or method:

```python
>>> df == 100
   cost  revenue
A   False    True
B   False    False
C    True    False
```  

```python
>>> df.eq(100)
   cost  revenue
A   False    True
B   False    False
C    True    False
```  

When `other` is a `Series`, the columns of a DataFrame are aligned with the index of `other` and broadcast:

```python
>>> df != pd.Series([100, 250], index=['cost', 'revenue'])
   cost  revenue
A   True    True
B   True    False
C  False    True

Use the method to control the broadcast axis:

```python
>>> df.ne(pd.Series([100, 300], index=['A', 'D']), axis='index')
   cost  revenue
A   True    False
B   True    True
C  True     True
D   True    True
```

When comparing to an arbitrary sequence, the number of columns must match the number elements in `other`:

```python
>>> df == [250, 100]
   cost  revenue
A   True    True
B  False    False
C  False    False
```

Use the method to control the axis:
```python
>>> df.eq([250, 250, 100], axis='index')
   cost  revenue
  A    True   False
  B   False    True
  C    True   False

Compare to a DataFrame of different shape.

```python
>>> other = pd.DataFrame({'revenue': [300, 250, 100, 150]},
                        index=['A', 'B', 'C', 'D'])
>>> other
     revenue
  A      300
  B      250
  C      100
  D      150

```python
>>> df.gt(other)
   cost  revenue
  A  False  False
  B  False  False
  C  False    True
  D  False  False

Compare to a MultiIndex by level.

```python
>>> df_multindex = pd.DataFrame({'cost': [250, 150, 100, 150, 300, 220],
                               'revenue': [100, 250, 300, 200, 175, 225],
                               index=[['Q1', 'Q1', 'Q1', 'Q2', 'Q2', 'Q2'],
                                      ['A', 'B', 'C', 'A', 'B', 'C']])
>>> df_multindex
     cost  revenue
  Q1 A   250    100
    B  150    250
    C  100    300
  Q2 A   150    200
    B  300    175
    C  220    225

```python
>>> df.le(df_multindex, level=1)
   cost  revenue
  Q1 A   True    True
    B   True    True
    C   True    True
  Q2 A  False    True
    B   True  False
    C   True  False
```
**pandas.DataFrame.mad**

DataFrame.mad(axis=None, skipna=None, level=None)

Return the mean absolute deviation of the values for the requested axis.

**Parameters**

- **axis** [{index (0), columns (1)}] Axis for the function to be applied on.
- **skipna** [bool, default None] Exclude NA/null values when computing the result.
- **level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

**Returns**

Series or DataFrame (if level specified)

**pandas.DataFrame.mask**

DataFrame.mask(cond, other=nan, inplace=False, axis=None, level=None, errors='raise', try_cast=False)

Replace values where the condition is True.

**Parameters**

- **cond** [bool Series/DataFrame, array-like, or callable] Where cond is False, keep the original value. Where True, replace with corresponding value from other. If cond is callable, it is computed on the Series/DataFrame and should return boolean Series/DataFrame or array. The callable must not change input Series/DataFrame (though pandas doesn’t check it).
- **other** [scalar, Series/DataFrame, or callable] Entries where cond is True are replaced with corresponding value from other. If other is callable, it is computed on the Series/DataFrame and should return scalar or Series/DataFrame. The callable must not change input Series/DataFrame (though pandas doesn’t check it).
- **inplace** [bool, default False] Whether to perform the operation in place on the data.
- **axis** [int, default None] Alignment axis if needed.
- **level** [int, default None] Alignment level if needed.
- **errors** [str, {'raise', 'ignore'}, default 'raise'] Note that currently this parameter won’t affect the results and will always coerce to a suitable dtype.
  - ‘raise’: allow exceptions to be raised.
  - ‘ignore’: suppress exceptions. On error return original object.
- **try_cast** [bool, default False] Try to cast the result back to the input type (if possible).

**Returns**

Same type as caller

**See also:**

DataFrame.where() Return an object of same shape as self.
Notes

The mask method is an application of the if-then idiom. For each element in the calling DataFrame, if \texttt{cond} is \texttt{False} the element is used; otherwise the corresponding element from the DataFrame \texttt{other} is used.

The signature for \texttt{DataFrame.where()} differs from \texttt{numpy.where()}. Roughly \texttt{df1.where(m, df2)} is equivalent to \texttt{np.where(m, df1, df2)}.

For further details and examples see the \texttt{mask} documentation in \texttt{indexing}.

Examples

```python
>>> s = pd.Series(range(5))
>>> s.where(s > 0)
0 NaN
1 1.0
2 2.0
3 3.0
4 4.0
dtype: float64
```

```python
>>> s.mask(s > 0)
0 0.0
1 NaN
2 NaN
3 NaN
4 NaN
dtype: float64
```

```python
>>> s.where(s > 1, 10)
0 10
1 10
2 2
3 3
4 4
dtype: int64
```

```python
>>> df = pd.DataFrame(np.arange(10).reshape(-1, 2), columns=['A', 'B'])
>>> df
        A   B
0      0   1
1      2   3
2      4   5
3      6   7
4      8   9
```

```python
>>> m = df % 3 == 0
>>> df.where(m, -df)
        A   B
0     -1   1
1      2  -3
2     -4  -5
3      6  -7
4     -8   9
```

```python
>>> df.where(m, -df) == np.where(m, df, -df)
```

(continues on next page)
**`pandas.DataFrame.max`**

`DataFrame.max` *(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)*

Return the maximum of the values for the requested axis.

If you want the index of the maximum, use `idxmax`. This is the equivalent of the `numpy.ndarray` method `argmax`.

**Parameters**

- **axis** [index (0), columns (1)] Axis for the function to be applied on.
- **skipna** [bool, default True] Exclude NA/null values when computing the result.
- **level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.
- **numeric_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.
- ****kwargs** Additional keyword arguments to be passed to the function.

**Returns**

Series or DataFrame (if level specified)

**See also:**

- `Series.sum` Return the sum.
- `Series.min` Return the minimum.
- `Series.max` Return the maximum.
- `Series.idxmin` Return the index of the minimum.
- `Series.idxmax` Return the index of the maximum.
- `DataFrame.sum` Return the sum over the requested axis.
- `DataFrame.min` Return the minimum over the requested axis.
- `DataFrame.max` Return the maximum over the requested axis.
- `DataFrame.idxmin` Return the index of the minimum over the requested axis.
- `DataFrame.idxmax` Return the index of the maximum over the requested axis.
Examples

```python
>>> idx = pd.MultiIndex.from_arrays([['warm', 'warm', 'cold', 'cold'],
...                         ['dog', 'falcon', 'fish', 'spider'],
...                         names=['blooded', 'animal'])
>>> s = pd.Series([4, 2, 0, 8], name='legs', index=idx)
>>> s
blooded    animal
  warm    dog  4
   falcon  2
  cold    fish  0
   spider  8
Name: legs, dtype: int64

>>> s.max()
8

Max using level names, as well as indices.

>>> s.max(level='blooded')
blooded
  warm  4
  cold  8
Name: legs, dtype: int64

>>> s.max(level=0)
blooded
  warm  4
  cold  8
Name: legs, dtype: int64

pandas.DataFrame.mean

DataFrame.mean (axis=None, skipna=None, level=None, numeric_only=None, **kwargs)
Return the mean of the values for the requested axis.

Parameters

axis         [{index (0), columns (1)}] Axis for the function to be applied on.
skipna       [bool, default True] Exclude NA/null values when computing the result.
level         [int or level name, default None] If the axis is a MultiIndex (hierarchical), count
              along a particular level, collapsing into a Series.
numeric_only  [bool, default None] Include only float, int, boolean columns. If None,
              will attempt to use everything, then use only numeric data. Not implemented for
              Series.
**kwargs Additional keyword arguments to be passed to the function.

Returns

Series or DataFrame (if level specified)
pandas.DataFrame.median

DataFrame.median (axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

Return the median of the values for the requested axis.

Parameters

axis [{index (0), columns (1)}] Axis for the function to be applied on.

skipna [bool, default True] Exclude NA/null values when computing the result.

level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

numeric_only [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**kwargs Additional keyword arguments to be passed to the function.

Returns

Series or DataFrame (if level specified)

pandas.DataFrame.melt

DataFrame.melt (id_vars=None, value_vars=None, var_name=None, value_name='value', col_level=None, ignore_index=True)

Unpivot a DataFrame from wide to long format, optionally leaving identifiers set.

This function is useful to massage a DataFrame into a format where one or more columns are identifier variables (id_vars), while all other columns, considered measured variables (value_vars), are “unpivoted” to the row axis, leaving just two non-identifier columns, ‘variable’ and ‘value’.

New in version 0.20.0.

Parameters

id_vars [tuple, list, or ndarray, optional] Column(s) to use as identifier variables.

value_vars [tuple, list, or ndarray, optional] Column(s) to unpivot. If not specified, uses all columns that are not set as id_vars.

var_name [scalar] Name to use for the ‘variable’ column. If None it uses frame.columns.name or ‘variable’.

value_name [scalar, default ‘value’] Name to use for the ‘value’ column.

col_level [int or str, optional] If columns are a MultiIndex then use this level to melt.

ignore_index [bool, default True] If True, original index is ignored. If False, the original index is retained. Index labels will be repeated as necessary.

New in version 1.1.0.

Returns

DataFrame Unpivoted DataFrame.

See also:

melt Identical method.

pivot_table Create a spreadsheet-style pivot table as a DataFrame.
**DataFrame.pivot** Return reshaped DataFrame organized by given index / column values.

**DataFrame.explode** Explode a DataFrame from list-like columns to long format.

### Examples

```python
>>> df = pd.DataFrame({'A': {0: 'a', 1: 'b', 2: 'c'},
                      'B': {0: 1, 1: 3, 2: 5},
                      'C': {0: 2, 1: 4, 2: 6}})
```

```plaintext
A   B   C  
0   a   1   2  
1   b   3   4  
2   c   5   6  
```

```python
>>> df.melt(id_vars=['A'], value_vars=['B'])
```

```plaintext
A  variable  value
0   a         B  1  
1   b         B  3  
2   c         B  5  
```

```python
>>> df.melt(id_vars=['A'], value_vars=['B', 'C'])
```

```plaintext
A  variable  value
0   a         B  1  
1   b         B  3  
2   c         B  5  
3   a         C  2  
4   b         C  4  
5   c         C  6  
```

The names of ‘variable’ and ‘value’ columns can be customized:

```python
>>> df.melt(id_vars=['A'], value_vars=['B', 'C'], var_name='myVarname', value_name='myValname')
```

```plaintext
A  myVarname  myValname
0   a         B  1  
1   b         B  3  
2   c         B  5  
```

Original index values can be kept around:

```python
>>> df.melt(id_vars=['A'], value_vars=['B', 'C'], ignore_index=False)
```

```plaintext
A  variable  value
0   a         B  1  
1   b         B  3  
2   c         B  5  
0   a         C  2  
1   b         C  4  
2   c         C  6  
```

If you have multi-index columns:

```python
>>> df.columns = [list('ABC'), list('DEF')]
```

```plaintext
A   B   C     
D   E   F
```

(continues on next page)
pandas.DataFrame.memory_usage

DataFrame memory_usage(index=True, deep=False)

Return the memory usage of each column in bytes.

The memory usage can optionally include the contribution of the index and elements of object dtype.

This value is displayed in DataFrame.info by default. This can be suppressed by setting pandas.options.display.memory_usage to False.

Parameters

- **index** [bool, default True] Specifies whether to include the memory usage of the DataFrame's index in returned Series. If index=True, the memory usage of the index is the first item in the output.

- **deep** [bool, default False] If True, introspect the data deeply by interrogating object dtypes for system-level memory consumption, and include it in the returned values.

Returns

Series A Series whose index is the original column names and whose values is the memory usage of each column in bytes.

See also:

- **numpy.ndarray.nbytes** Total bytes consumed by the elements of an ndarray.

- **Series.memory_usage** Bytes consumed by a Series.

- **Categorical** Memory-efficient array for string values with many repeated values.

- **DataFrame.info** Concise summary of a DataFrame.
Examples

```python
>>> dtypes = ['int64', 'float64', 'complex128', 'object', 'bool']
>>> data = dict([(t, np.ones(shape=5000).astype(t))
...               for t in dtypes])
>>> df = pd.DataFrame(data)
>>> df.head()
           int64  float64  complex128  object  bool
0         1.0     1.00 1.000000+0.000000j   1.0  True
1         1.0     1.00 1.000000+0.000000j   1.0  True
2         1.0     1.00 1.000000+0.000000j   1.0  True
3         1.0     1.00 1.000000+0.000000j   1.0  True
4         1.0     1.00 1.000000+0.000000j   1.0  True

>>> df.memory_usage()
Index 128
int64 40000
float64 40000
complex128 80000
object 40000
bool 5000
dtype: int64

>>> df.memory_usage(index=False)
int64 40000
float64 40000
complex128 80000
object 40000
bool 5000
dtype: int64

The memory footprint of object dtype columns is ignored by default:

>>> df.memory_usage(deep=True)
Index 128
int64 40000
float64 40000
complex128 80000
object 160000
bool 5000
dtype: int64

Use a Categorical for efficient storage of an object-dtype column with many repeated values.

>>> df['object'].astype('category').memory_usage(deep=True)
5216
```
pandas.DataFrame.merge

DataFrame.merge(right, how='inner', on=None, left_on=None, right_on=None, left_index=False, right_index=False, sort=False, suffixes='_x', '_y', copy=True, indicator=False, validate=None)

Merge DataFrame or named Series objects with a database-style join.

The join is done on columns or indexes. If joining columns on columns, the DataFrame indexes will be ignored. Otherwise if joining indexes on indexes or indexes on a column or columns, the index will be passed on.

Parameters

right [DataFrame or named Series] Object to merge with.

how [{'left', 'right', 'outer', 'inner'}, default 'inner'] Type of merge to be performed.

• left: use only keys from left frame, similar to a SQL left outer join; preserve key order.
• right: use only keys from right frame, similar to a SQL right outer join; preserve key order.
• outer: use union of keys from both frames, similar to a SQL full outer join; sort keys lexicographically.
• inner: use intersection of keys from both frames, similar to a SQL inner join; preserve the order of the left keys.

on [label or list] Column or index level names to join on. These must be found in both DataFrames. If on is None and not merging on indexes then this defaults to the intersection of the columns in both DataFrames.

left_on [label or list, or array-like] Column or index level names to join on in the left DataFrame. Can also be an array or list of arrays of the length of the left DataFrame. These arrays are treated as if they are columns.

right_on [label or list, or array-like] Column or index level names to join on in the right DataFrame. Can also be an array or list of arrays of the length of the right DataFrame. These arrays are treated as if they are columns.

left_index [bool, default False] Use the index from the left DataFrame as the join key(s). If it is a MultiIndex, the number of keys in the other DataFrame (either the index or a number of columns) must match the number of levels.

right_index [bool, default False] Use the index from the right DataFrame as the join key. Same caveats as left_index.

sort [bool, default False] Sort the join keys lexicographically in the result DataFrame. If False, the order of the join keys depends on the join type (how keyword).

suffixes [list-like, default is ("_x", "_y")]) A length-2 sequence where each element is optionally a string indicating the suffix to add to overlapping column names in left and right respectively. Pass a value of None instead of a string to indicate that the column name from left or right should be left as-is, with no suffix. At least one of the values must not be None.

copy [bool, default True] If False, avoid copy if possible.

indicator [bool or str, default False] If True, adds a column to the output DataFrame called “_merge” with information on the source of each row. The column can be given a different name by providing a string argument. The column will have a
Categorical type with the value of “left_only” for observations whose merge key only appears in the left DataFrame, “right_only” for observations whose merge key only appears in the right DataFrame, and “both” if the observation’s merge key is found in both DataFrames.

**validate** [str, optional] If specified, checks if merge is of specified type.
- “one_to_one” or “1:1”: check if merge keys are unique in both left and right datasets.
- “one_to_many” or “1:m”: check if merge keys are unique in left dataset.
- “many_to_one” or “m:1”: check if merge keys are unique in right dataset.
- “many_to_many” or “m:m”: allowed, but does not result in checks.

**Returns**

**DataFrame** A DataFrame of the two merged objects.

**See also:**

- **merge_ordered** Merge with optional filling/interpolation.
- **merge_asof** Merge on nearest keys.
- **DataFrame.join** Similar method using indices.

**Notes**

Support for specifying index levels as the `on, left_on, and right_on` parameters was added in version 0.23.0
Support for merging named Series objects was added in version 0.24.0

**Examples**

```python
>>> df1 = pd.DataFrame({'lkey': ['foo', 'bar', 'baz', 'foo'],
                      'value': [1, 2, 3, 5])
>>> df2 = pd.DataFrame({'rkey': ['foo', 'bar', 'baz', 'foo'],
                      'value': [5, 6, 7, 8])
```

Merge `df1` and `df2` on the `lkey` and `rkey` columns. The value columns have the default suffixes, `_x` and `_y`, appended.

```python
>>> df1.merge(df2, left_on='lkey', right_on='rkey')
lkey  value_x  rkey  value_y
0   foo       1  foo       5
1   bar       2  bar       6
2   baz       3  baz       7
3   foo       5  foo       8
```

(continues on next page)
Merge DataFrames df1 and df2 with specified left and right suffixes appended to any overlapping columns.

```python
>>> df1.merge(df2, left_on='lkey', right_on='rkey',
... suffixes=('left', 'right'))
```

<table>
<thead>
<tr>
<th>lkey</th>
<th>value_left</th>
<th>rkey</th>
<th>value_right</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>foo</td>
<td>1</td>
<td>foo 5</td>
</tr>
<tr>
<td>1</td>
<td>foo</td>
<td>1</td>
<td>foo 8</td>
</tr>
<tr>
<td>2</td>
<td>foo</td>
<td>5</td>
<td>foo 5</td>
</tr>
<tr>
<td>3</td>
<td>foo</td>
<td>5</td>
<td>foo 8</td>
</tr>
<tr>
<td>4</td>
<td>bar</td>
<td>2</td>
<td>bar 6</td>
</tr>
<tr>
<td>5</td>
<td>baz</td>
<td>3</td>
<td>baz 7</td>
</tr>
</tbody>
</table>

Merge DataFrames df1 and df2, but raise an exception if the DataFrames have any overlapping columns.

```python
>>> df1.merge(df2, left_on='lkey', right_on='rkey', suffixes=(False, False))
```

Traceback (most recent call last):
... 
ValueError: columns overlap but no suffix specified:
Index(['value'], dtype='object')

**pandas.DataFrame.min**

DataFrame.min *(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)*

Return the minimum of the values for the requested axis.

If you want the index of the minimum, use idxmin. This is the equivalent of the numpy.ndarray method argmin.

**Parameters**

- **axis** *(index (0), columns (1))| Axis for the function to be applied on.*
- **skipna** *[bool, default True] Exclude NA/null values when computing the result.*
- **level** *[int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.*
- **numeric_only** *[bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.*

**Returns**

Series or DataFrame (if level specified)

**See also:**

- **Series.sum** Return the sum.
- **Series.min** Return the minimum.
**Series.max**  Return the maximum.

**Series.idxmin**  Return the index of the minimum.

**Series.idxmax**  Return the index of the maximum.

**DataFrame.sum**  Return the sum over the requested axis.

**DataFrame.min**  Return the minimum over the requested axis.

**DataFrame.max**  Return the maximum over the requested axis.

**DataFrame.idxmin**  Return the index of the minimum over the requested axis.

**DataFrame.idxmax**  Return the index of the maximum over the requested axis.

### Examples

```python
>>> idx = pd.MultiIndex.from_arrays([
    ... ['warm', 'warm', 'cold', 'cold'],
    ... ['dog', 'falcon', 'fish', 'spider'],
    ... names=['blooded', 'animal'])

>>> s = pd.Series([4, 2, 0, 8], name='legs', index=idx)

>>> s
blooded  animal
  warm   dog  4
       falcon  2
  cold   fish  0
       spider  8
Name: legs, dtype: int64

>>> s.min()
0

Min using level names, as well as indices.

>>> s.min(level='blooded')
blooded
  warm   2
  cold   0
Name: legs, dtype: int64

>>> s.min(level=0)
blooded
  warm   2
  cold   0
Name: legs, dtype: int64
```
pandas.DataFrame.mod

DataFrame.mod(other, axis='columns', level=None, fill_value=None)

Get Modulo of dataframe and other, element-wise (binary operator mod).

Equivalent to dataframe % other, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, rmod.

Among flexible wrappers (add, sub, mul, div, mod, pow) to arithmetic operators: +, -, *, /, //, %, **.

Parameters

- **other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.
- **axis** [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.
- **level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.
- **fill_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

DataFrame Result of the arithmetic operation.

See also:

- **DataFrame.add** Add DataFrames.
- **DataFrame.sub** Subtract DataFrames.
- **DataFrame.mul** Multiply DataFrames.
- **DataFrame.div** Divide DataFrames (float division).
- **DataFrame.truediv** Divide DataFrames (float division).
- **DataFrame.floordiv** Divide DataFrames (integer division).
- **DataFrame.mod** Calculate modulo (remainder after division).
- **DataFrame.pow** Calculate exponential power.

Notes

Mismatched indices will be unioned together.
Examples

```python
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
```

```
<table>
<thead>
<tr>
<th>angles</th>
<th>degrees</th>
</tr>
</thead>
<tbody>
<tr>
<td>circle</td>
<td>0</td>
</tr>
<tr>
<td>triangle</td>
<td>3</td>
</tr>
<tr>
<td>rectangle</td>
<td>4</td>
</tr>
</tbody>
</table>
```

Add a scalar with operator version which return the same results.

```python
>>> df + 1
```

```
<table>
<thead>
<tr>
<th>angles</th>
<th>degrees</th>
</tr>
</thead>
<tbody>
<tr>
<td>circle</td>
<td>1</td>
</tr>
<tr>
<td>triangle</td>
<td>4</td>
</tr>
<tr>
<td>rectangle</td>
<td>5</td>
</tr>
</tbody>
</table>
```

```python
>>> df.add(1)
```

```
<table>
<thead>
<tr>
<th>angles</th>
<th>degrees</th>
</tr>
</thead>
<tbody>
<tr>
<td>circle</td>
<td>1</td>
</tr>
<tr>
<td>triangle</td>
<td>4</td>
</tr>
<tr>
<td>rectangle</td>
<td>5</td>
</tr>
</tbody>
</table>
```

Divide by constant with reverse version.

```python
>>> df.div(10)
```

```
<table>
<thead>
<tr>
<th>angles</th>
<th>degrees</th>
</tr>
</thead>
<tbody>
<tr>
<td>circle</td>
<td>0.0</td>
</tr>
<tr>
<td>triangle</td>
<td>0.3</td>
</tr>
<tr>
<td>rectangle</td>
<td>0.4</td>
</tr>
</tbody>
</table>
```

```python
>>> df.rdiv(10)
```

```
<table>
<thead>
<tr>
<th>angles</th>
<th>degrees</th>
</tr>
</thead>
<tbody>
<tr>
<td>circle</td>
<td>inf</td>
</tr>
<tr>
<td>triangle</td>
<td>0.027778</td>
</tr>
<tr>
<td>rectangle</td>
<td>0.027778</td>
</tr>
</tbody>
</table>
```

Subtract a list and Series by axis with operator version.

```python
>>> df - [1, 2]
```

```
<table>
<thead>
<tr>
<th>angles</th>
<th>degrees</th>
</tr>
</thead>
<tbody>
<tr>
<td>circle</td>
<td>-1</td>
</tr>
<tr>
<td>triangle</td>
<td>2</td>
</tr>
<tr>
<td>rectangle</td>
<td>3</td>
</tr>
</tbody>
</table>
```

```python
>>> df.sub([1, 2], axis='columns')
```

```
<table>
<thead>
<tr>
<th>angles</th>
<th>degrees</th>
</tr>
</thead>
<tbody>
<tr>
<td>circle</td>
<td>-1</td>
</tr>
<tr>
<td>triangle</td>
<td>2</td>
</tr>
<tr>
<td>rectangle</td>
<td>3</td>
</tr>
</tbody>
</table>
```

```python
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
          axis='index')
```

(continues on next page)
Multiply a DataFrame of different shape with operator version.

```python
other = pd.DataFrame({'angles': [0, 3, 4]},
                     index=['circle', 'triangle', 'rectangle'])
```

```python
other
```

```
angles
circle 0
triangle 3
rectangle 4
```

```python
df * other
```

```
angles degrees
circle 0 NaN
triangle 9 NaN
rectangle 16 NaN
```

```python
df.mul(other, fill_value=0)
```

```
angles degrees
circle 0 0.0
triangle 9 0.0
rectangle 16 0.0
```

Divide by a MultiIndex by level.

```python
df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6], 'degrees': [360, 180, 360, 360, 540, 720]},
                            index=['A', 'A', 'A', 'B', 'B', 'B',
                                   'circle', 'triangle', 'rectangle',
                                   'square', 'pentagon', 'hexagon'])
```

```python
df_multindex
```

```
angles degrees
A circle 0 360
triangle 3 180
rectangle 4 360
B square 4 360
pentagon 5 540
hexagon 6 720
```

```python
df.div(df_multindex, level=1, fill_value=0)
```

```
angles degrees
A circle NaN 1.0
triangle 1.0 1.0
rectangle 1.0 1.0
B square 0.0 0.0
pentagon 0.0 0.0
hexagon 0.0 0.0
```
pandas.DataFrame.mode

DataFrame.mode (axis=0, numeric_only=False, dropna=True)
Get the mode(s) of each element along the selected axis.

The mode of a set of values is the value that appears most often. It can be multiple values.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] The axis to iterate over while searching for the mode:
- 0 or 'index' : get mode of each column
- 1 or 'columns' : get mode of each row.
numeric_only [bool, default False] If True, only apply to numeric columns.
dropna [bool, default True] Don’t consider counts of NaN/NaT.

New in version 0.24.0.

Returns

DataFrame The modes of each column or row.

See also:

Series.mode Return the highest frequency value in a Series.
Series.value_counts Return the counts of values in a Series.

Examples

```python
def = pd.DataFrame([('bird', 2, 2),
                     ('mammal', 4, np.nan),
                     ('arthropod', 8, 0),
                     ('bird', 2, np.nan)],
                    index=('falcon', 'horse', 'spider', 'ostrich'),
                    columns=('species', 'legs', 'wings'))
def.mode()
```

By default, missing values are not considered, and the mode of wings are both 0 and 2. The second row of species and legs contains NaN, because they have only one mode, but the DataFrame has two rows.

```python
def.mode(dropna=False)
```

Setting dropna=False NaN values are considered and they can be the mode (like for wings).
Setting `numeric_only=True`, only the mode of numeric columns is computed, and columns of other types are ignored.

```python
>>> df.mode(numeric_only=True)
   legs  wings
 0  2.0  0.0
 1  NaN  2.0
```

To compute the mode over columns and not rows, use the `axis` parameter:

```python
>>> df.mode(axis='columns', numeric_only=True)
     0  1
  falcon  2.0 NaN
  horse   4.0 NaN
  spider  0.0  8.0
 ostrich  2.0 NaN
```

**pandas.DataFrame.mul**

DataFrame.mul(other, axis='columns', level=None, fill_value=None)

Get Multiplication of dataframe and other, element-wise (binary operator mul).

Equivalent to `dataframe * other`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `rmul`.

Among flexible wrappers (`add`, `sub`, `mul`, `div`, `mod`, `pow`) to arithmetic operators: `+`, `-`, `*`, `/`, `//`, `%`, `**`.

**Parameters**

- **other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.
- **axis** [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.
- **level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.
- **fill_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

**Returns**

DataFrame Result of the arithmetic operation.

**See also:**

- `DataFrame.add` Add DataFrames.
- `DataFrame.sub` Subtract DataFrames.
- `DataFrame.mul` Multiply DataFrames.
- `DataFrame.div` Divide DataFrames (float division).
- `DataFrame.truediv` Divide DataFrames (float division).
- `DataFrame.floordiv` Divide DataFrames (integer division).
- `DataFrame.mod` Calculate modulo (remainder after division).
**DataFrame.pow** Calculate exponential power.

**Notes**

Mismatched indices will be unioned together.

**Examples**

```python
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
```

Add a scalar with operator version which return the same results.

```python
>>> df + 1
```

```plaintext
angles  degrees
circle  1  361
triangle 4  181
rectangle 5  361
```

```python
>>> df.add(1)
```

```plaintext
angles  degrees
circle  1  361
triangle 4  181
rectangle 5  361
```

Divide by constant with reverse version.

```python
>>> df.div(10)
```

```plaintext
angles  degrees
circle  0.0 36.0
triangle 0.3 18.0
rectangle 0.4 36.0
```

```python
>>> df.rdiv(10)
```

```plaintext
angles  degrees
circle   inf  0.027778
triangle 3.333333  0.055556
rectangle 2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```python
>>> df - [1, 2]
```

```plaintext
angles  degrees
circle   -1 358
triangle  2  178
rectangle 3  358
```
```python
>>> df.sub([1, 2], axis='columns')
   angles  degrees
circle   -1     358
triangle   2     178
rectangle   3     358

>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
         axis='index')
   angles  degrees
circle   -1     359
triangle   2     179
rectangle   3     359

Multiply a DataFrame of different shape with operator version.

```python
>>> other = pd.DataFrame({'angles': [0, 3, 4],
                       'degrees': [360, 180, 360],
                       index=['circle', 'triangle', 'rectangle'])

```python
>>> df * other
   angles  degrees
circle    0      NaN
triangle   9      NaN
rectangle 16      NaN

```python
>>> df.mul(other, fill_value=0)
   angles  degrees
circle    0      0.0
triangle   9      0.0
rectangle 16      0.0

Divide by a MultiIndex by level.

```python
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
                               'degrees': [360, 180, 360, 360, 540, 720],
                               index=['A', 'A', 'A', 'B', 'B', 'B'],
                               columns=['circle', 'triangle', 'rectangle',
                                        'square', 'pentagon', 'hexagon'])

>>> df_multindex
   angles  degrees
A circle   0     360
triangle   3     180
rectangle  4     360
B square   4     360
pentagon   5     540
hexagon    6     720

>>> df.div(df_multindex, level=1, fill_value=0)
   angles  degrees
A circle  NaN      1.0
triangle  1.0      1.0
rectangle 1.0      1.0
```
(continues on next page)
pandas.DataFrame.multiply

DataFrame.multiply(other, axis='columns', level=None, fill_value=None)
Get Multiplication of dataframe and other, element-wise (binary operator mul).
Equivalent to dataframe * other, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, rmul.
Among flexible wrappers (add, sub, mul, div, mod, pow) to arithmetic operators: +, -, *, /, //, %, **.

Parameters
- **other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.
- **axis** [[0 or 'index', 1 or 'columns']] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.
- **level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.
- **fill_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns
- **DataFrame** Result of the arithmetic operation.

See also:
- DataFrame.add Add DataFrames.
- DataFrame.sub Subtract DataFrames.
- DataFrame.mul Multiply DataFrames.
- DataFrame.div Divide DataFrames (float division).
- DataFrame.truediv Divide DataFrames (float division).
- DataFrame.floordiv Divide DataFrames (integer division).
- DataFrame.mod Calculate modulo (remainder after division).
- DataFrame.pow Calculate exponential power.
Notes

Mismatched indices will be unioned together.

Examples

```python
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                   'degrees': [360, 180, 360],
...                   index=['circle', 'triangle', 'rectangle'])
>>> df
         angles  degrees
    circle     0       360
   triangle    3       180
  rectangle    4       360

Add a scalar with operator version which return the same results.

```python
>>> df + 1
         angles  degrees
    circle     1       361
   triangle    4       181
  rectangle    5       361

```python
>>> df.add(1)
         angles  degrees
    circle     1       361
   triangle    4       181
  rectangle    5       361

Divide by constant with reverse version.

```python
>>> df.div(10)
         angles  degrees
    circle   0.0     36.0
   triangle  0.3     18.0
  rectangle  0.4     36.0

```python
>>> df.rdiv(10)
         angles  degrees
    circle  inf     0.027778
   triangle  3.333333  0.055556
  rectangle  2.500000  0.027778

Subtract a list and Series by axis with operator version.

```python
>>> df - [1, 2]
         angles  degrees
    circle   -1     358
   triangle    2     178
  rectangle    3     358

>>> df.sub([1, 2], axis='columns')
         angles  degrees
    circle   -1     358
   triangle    2     178
  rectangle    3     358
```
Multiply a DataFrame of different shape with operator version.

```python
other = pd.DataFrame({'angles': [0, 3, 4]},
                     index=['circle', 'triangle', 'rectangle'])
other
```

```plaintext
angles
circle 0
triangle 3
rectangle 4
```

```python
df + other
```

```plaintext
angles degrees
circle 0 NaN
triangle 9 NaN
rectangle 16 NaN
```

```python
df.mul(other, fill_value=0)
```

```plaintext
angles degrees
circle 0 0.0
triangle 9 0.0
rectangle 16 0.0
```

Divide by a MultiIndex by level.

```python
df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
                              'degrees': [360, 180, 360, 360, 540, 720]},
                              index=[['A', 'A', 'A', 'B', 'B', 'B'],
                                     ['circle', 'triangle', 'rectangle',
                                    'square', 'pentagon', 'hexagon']])
```

```python
df_multindex
```

```plaintext
angles degrees
A circle 0 360
triangle 3 180
rectangle 4 360
B square 4 360
pentagon 5 540
hexagon 6 720
```

```python
df.div(df_multindex, level=1, fill_value=0)
```

```plaintext
angles degrees
A circle NaN 1.0
triangle 1.0 1.0
rectangle 1.0 1.0
B square 0.0 0.0
pentagon 0.0 0.0
hexagon 0.0 0.0
```
pandas.DataFrame.ne

DataFrame.ne (other, axis='columns', level=None)
Get Not equal to of dataframe and other, element-wise (binary operator ne).

Among flexible wrappers (eq, ne, le, lt, ge, gt) to comparison operators.
Equivalent to ==, !=, <=, <, >=, > with support to choose axis (rows or columns) and level for comparison.

Parameters

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.
axis [[0 or `index`, 1 or `columns`], default `columns`] Whether to compare by the index (0 or `index`) or columns (1 or `columns`).
level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

Returns

DataFrame of bool Result of the comparison.

See also:

DataFrame.eq Compare DataFrames for equality elementwise.
DataFrame.ne Compare DataFrames for inequality elementwise.
DataFrame.le Compare DataFrames for less than inequality or equality elementwise.
DataFrame.lt Compare DataFrames for strictly less than inequality elementwise.
DataFrame.ge Compare DataFrames for greater than inequality or equality elementwise.
DataFrame.gt Compare DataFrames for strictly greater than inequality elementwise.

Notes

Mismatched indices will be unioned together. NaN values are considered different (i.e. NaN != NaN).

Examples

```python
>>> df = pd.DataFrame({'cost': [250, 150, 100],
...                    'revenue': [100, 250, 300]},
...                   index=['A', 'B', 'C'])
>>> df
     cost  revenue
    A  250     100
    B  150     250
    C  100     300
```

Comparison with a scalar, using either the operator or method:

```python
>>> df == 100
     cost  revenue
    A   False    True
    B    True    False
    C    True    True
```
When `other` is a `Series`, the columns of a DataFrame are aligned with the index of `other` and broadcast:

```python
>>> df != pd.Series([100, 250], index=['cost', 'revenue'])
cost  revenue
A     True   True
B     True   False
C     False  True
```

Use the method to control the broadcast axis:

```python
>>> df.ne(pd.Series([100, 300], index=['A', 'D']), axis='index')
cost  revenue
A     True   False
B     True   True
C     True   True
D     True   True
```

When comparing to an arbitrary sequence, the number of columns must match the number elements in `other`:

```python
>>> df == [250, 100]
cost  revenue
A     True   True
B     False  False
C     False  False
```

Use the method to control the axis:

```python
>>> df.eq([250, 250, 100], axis='index')
cost  revenue
A     True   False
B     False  True
C     True   False
```

Compare to a DataFrame of different shape.

```python
>>> other = pd.DataFrame({'revenue': [300, 250, 100, 150],
                        ...
                        index=['A', 'B', 'C', 'D'])
>>> other
revenue
A  300
B  250
C  100
D  150
```

```python
>>> df.gt(other)
cost  revenue
(continues on next page)
```
Compare to a MultiIndex by level.

```python
>>> df_multindex = pd.DataFrame({'cost': [250, 150, 100, 150, 300, 220],
...                            'revenue': [100, 250, 300, 200, 175, 225],
...                            index=[['Q1', 'Q1', 'Q1', 'Q2', 'Q2', 'Q2'],
...                                  ['A', 'B', 'C', 'A', 'B', 'C']])
```

```python
>>> df_multindex
   cost  revenue
Q1 A   250     100
   B   150     250
   C   100     300
Q2 A   150     200
   B   300     175
   C   220     225
```

```python
>>> df.le(df_multindex, level=1)
   cost  revenue
Q1 A   True    True
   B   True    True
   C   True    True
Q2 A   False   True
   B   True    False
   C   True    False
```

### `pandas.DataFrame.nlargest`

Dataframe.nlargest(n, columns, keep='first')

Return the first n rows ordered by columns in descending order.

Return the first n rows with the largest values in columns, in descending order. The columns that are not specified are returned as well, but not used for ordering.

This method is equivalent to df.sort_values(columns, ascending=False).head(n), but more performant.

**Parameters**

- **n** [int] Number of rows to return.
- **columns** [label or list of labels] Column label(s) to order by.
- **keep** [{‘first’, ‘last’, ‘all’}, default ‘first’] Where there are duplicate values:
  - **first** : prioritize the first occurrence(s)
  - **last** : prioritize the last occurrence(s)
  - **all** [do not drop any duplicates, even it means] selecting more than n items.

**Returns**

- **DataFrame** The first n rows ordered by the given columns in descending order.
See also:

*DataFrame.nsmallest* Return the first $n$ rows ordered by columns in ascending order.

*DataFrame.sort_values* Sort DataFrame by the values.

*DataFrame.head* Return the first $n$ rows without re-ordering.

Notes

This function cannot be used with all column types. For example, when specifying columns with *object* or *category* dtypes, *TypeError* is raised.

Examples

```python
>>> df = pd.DataFrame({'population': [59000000, 65000000, 4340000, 4340000, 337000, 11300], 'GDP': [1937894, 2583560, 12011, 4520, 12128, 17036, 182, 38, 311], 'alpha-2': ['IT', 'FR', 'MT', 'MV', 'BN', 'IS', 'NR', 'TV', 'AI']}, index=['Italy', 'France', 'Malta', 'Maldives', 'Brunei', 'Iceland', 'Nauru', 'Tuvalu', 'Anguilla'])
>>> df
    population  GDP  alpha-2
Italy  59000000  1937894  IT
France  65000000  2583560  FR
Malta  4340000   12011  MT
Maldives  434000  4520  MV
Brunei  434000   12128  BN
Iceland  337000  17036  IS
Nauru  11300    182  NR
Tuvalu  11300    38  TV
Anguilla  11300  311  AI
```

In the following example, we will use `nlargest` to select the three rows having the largest values in column “population”.

```python
>>> df.nlargest(3, 'population')
    population  GDP  alpha-2
France  65000000  2583560  FR
Italy  59000000  1937894  IT
Malta  4340000   12011  MT
```

When using `keep='last'`, ties are resolved in reverse order:

```python
>>> df.nlargest(3, 'population', keep='last')
    population  GDP  alpha-2
France  65000000  2583560  FR
Italy  59000000  1937894  IT
Brunei  4340000   12128  BN
```

When using `keep='all'`, all duplicate items are maintained:
To order by the largest values in column “population” and then “GDP”, we can specify multiple columns like in the next example.

```python
>>> df.nlargest(3, ['population', 'GDP'])
   population     GDP alpha-2
France 65000000 2583560   FR
Italy  59000000 1937894   IT
Brunei 434000   12128   BN
```

### pandas.DataFrame.notna

DataFrame.notna()  
Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to True. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.use_inf_as_na = True). NA values, such as None or numpy.NaN, get mapped to False values.

Returns  
- **DataFrame** Mask of bool values for each element in DataFrame that indicates whether an element is not an NA value.

See also:

- **DataFrame.notnull** Alias of notna.
- **DataFrame.isna** Boolean inverse of notna.
- **DataFrame.dropna** Omit axes labels with missing values.

**notna** Top-level notna.

#### Examples

Show which entries in a DataFrame are not NA.

```python
>>> df = pd.DataFrame({'age': [5, 6, np.NaN],
                     ...
                              pd.Timestamp('1940-04-25')],
                     ...
                     'name': ['Alfred', 'Batman', ''],
                     ...
                     'toy': [None, 'Batmobile', 'Joker']})
```

```python
>>> df
  age  born   name  toy
0  5.0  NaT     Alfred  None
1  6.0  1939-05-27 Batman  Batmobile
2  NaN  1940-04-25        Joker
```
Show which entries in a Series are not NA.

```python
>>> ser = pd.Series([5, 6, np.NaN])
>>> ser
0    5.0
1    6.0
2  NaN
dtype: float64
>>> ser.notna()
0   True
1   True
2  False
dtype: bool
```

**pandas.DataFrame.notnull**

`DataFrame.notnull()`

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to True. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.use_inf_as_na = True). NA values, such as None or numpy.NaN, get mapped to False values.

Returns

- **DataFrame** Mask of bool values for each element in DataFrame that indicates whether an element is not an NA value.

See Also:

- **DataFrame.notnull** Alias of notna.
- **DataFrame.isna** Boolean inverse of notna.
- **DataFrame.dropna** Omit axes labels with missing values.
- **notna** Top-level notna.

Examples

Show which entries in a DataFrame are not NA.

```python
>>> df = pd.DataFrame({'age': [5, 6, np.NaN],
...                    'born': [pd.NaT, pd.Timestamp('1939-05-27'),
...                             pd.Timestamp('1940-04-25')],
...                    'name': ['Alfred', 'Batman', ''],
...                    'toy': [None, 'Batmobile', 'Joker']})
>>> df
```

(continues on next page)
```python
>>> df.notna()
age born name toy
0 True False True False
1 True True True True
2 False True True True
```

Show which entries in a Series are not NA.

```python
>>> ser = pd.Series([5, 6, np.NaN])
>>> ser
0    5.0
1    6.0
2     NaN
dtype: float64

>>> ser.notna()
0 True
1 True
2 False
dtype: bool
```

**pandas.DataFrame.nsmallest**

`DataFrame.nsmallest(n, columns, keep='first')`

Return the first `n` rows ordered by `columns` in ascending order.

Return the first `n` rows with the smallest values in `columns`, in ascending order. The columns that are not specified are returned as well, but not used for ordering.

This method is equivalent to `df.sort_values(columns, ascending=True).head(n)`, but more performant.

**Parameters**

- `n` [int] Number of items to retrieve.
- `columns` [list or str] Column name or names to order by.
- `keep` [{‘first’, ‘last’, ‘all’}, default ‘first’] Where there are duplicate values:
  - `first`: take the first occurrence.
  - `last`: take the last occurrence.
  - `all`: do not drop any duplicates, even it means selecting more than `n` items.

New in version 0.24.0.

**Returns**

- `DataFrame`

**See also:**
**DataFrame.nlargest**  Return the first $n$ rows ordered by columns in descending order.

**DataFrame.sort_values**  Sort DataFrame by the values.

**DataFrame.head**  Return the first $n$ rows without re-ordering.

**Examples**

```python
>>> df = pd.DataFrame({'population': [59000000, 65000000, 4340000, 4340000, 337000, 337000, 11300, 11300, 11300, 11300], 'GDP': [1937894, 2583560, 12011, 4520, 12128, 17036, 182, 38, 38, 311], 'alpha-2': ['IT', 'FR', 'MT', 'MV', 'BN', 'IS', 'NR', 'TV', 'AI']}, index=['Italy', 'France', 'Malta', 'Maldives', 'Brunei', 'Iceland', 'Nauru', 'Tuvalu', 'Anguilla'])

In the following example, we will use `nsmallest` to select the three rows having the smallest values in column “population”.

```python
>>> df.nsmallest(3, 'population')
   population  GDP  alpha-2
Tuvalu      11300  38   TV
Anguilla    11300  311  AI
Iceland    337000 17036 IS
```

When using `keep='last'`, ties are resolved in reverse order:

```python
>>> df.nsmallest(3, 'population', keep='last')
   population  GDP  alpha-2
Anguilla    11300  311  AI
Tuvalu      11300  38   TV
Nauru       337000 182  NR
```

When using `keep='all'`, all duplicate items are maintained:

```python
>>> df.nsmallest(3, 'population', keep='all')
   population  GDP  alpha-2
Tuvalu      11300  38   TV
Anguilla    11300  311  AI
Iceland    337000 17036 IS
Nauru       337000 182  NR
```

To order by the smallest values in column “population” and then “GDP”, we can specify multiple columns like in the next example.
```python
>>> df.nsmallest(3, ['population', 'GDP'])
     population  GDP  alpha-2
Tuvalu     11300  38   TV
Anguilla   11300  311  AI
Nauru     337000 182  NR
```

**pandas.DataFrame.nunique**

DataFrame.nunique(*axis=0, dropna=True*)

Count distinct observations over requested axis.

Return Series with number of distinct observations. Can ignore NaN values.

**Parameters**

- **axis** [{0 or 'index', 1 or 'columns'}, default 0] The axis to use. 0 or ‘index’ for row-wise, 1 or ‘columns’ for column-wise.
- **dropna** [bool, default True] Don’t include NaN in the counts.

**Returns**

Series

**See also:**

- Series.nunique Method nunique for Series.
- DataFrame.count Count non-NA cells for each column or row.

**Examples**

```python
>>> df = pd.DataFrame({'A': [1, 2, 3], 'B': [1, 1, 1]})
>>> df.nunique()
A     3
B     1
dtype: int64
```

```python
>>> df.nunique(axis=1)
0  1
1  2
2  2
dtype: int64
```

**pandas.DataFrame.pad**

DataFrame.pad(*axis=None, inplace=False, limit=None, downcast=None*)

Synonym for DataFrame.fillna() with method='ffill'.

**Returns**

{klass} or None Object with missing values filled or None if inplace=True.
pandas.DataFrame.pct_change

DataFrame\.pct_change(periods=1, fill_method='pad', limit=None, freq=None, **kwargs)

Percentage change between the current and a prior element.

Computes the percentage change from the immediately previous row by default. This is useful in comparing the percentage of change in a time series of elements.

**Parameters**

- **periods**: [int, default 1] Periods to shift for forming percent change.
- **fill_method**: [str, default ‘pad’] How to handle NAs before computing percent changes.
- **limit**: [int, default None] The number of consecutive NAs to fill before stopping.
- **freq**: [DateOffset, timedelta, or str, optional] Increment to use from time series API (e.g. ‘M’ or BDay()).
- **kwargs**: Additional keyword arguments are passed into DataFrame.shift or Series.shift.

**Returns**

chg [Series or DataFrame] The same type as the calling object.

See also:

- **Series.diff** Compute the difference of two elements in a Series.
- **DataFrame.diff** Compute the difference of two elements in a DataFrame.
- **Series.shift** Shift the index by some number of periods.
- **DataFrame.shift** Shift the index by some number of periods.

**Examples**

**Series**

```python
>>> s = pd.Series([90, 91, 85])
>>> s
0  90
1  91
2  85
dtype: int64

>>> s.pct_change()
0   NaN
1  0.011111
2 -0.065934
dtype: float64

>>> s.pct_change(periods=2)
0   NaN
1   NaN
2 -0.055556
dtype: float64
```

See the percentage change in a Series where filling NAs with last valid observation forward to next valid.

---

3.4. DataFrame
% >>> s = pd.Series([90, 91, None, 85])
% >>> s
% 0    90.0
% 1    91.0
% 2     NaN
% 3    85.0
% dtype: float64
% >>> s.pct_change(fill_method='ffill')
% 0   NaN
% 1  0.011111
% 2  0.000000
% 3 -0.065934
% dtype: float64

**DataFrame**

Percentage change in French franc, Deutsche Mark, and Italian lira from 1980-01-01 to 1980-03-01.

% >>> df = pd.DataFrame({
% ... 'FR': [4.0405, 4.0963, 4.3149],
% ... 'GR': [1.7246, 1.7482, 1.8519],
% ... 'IT': [804.74, 810.01, 860.13]},
% ... index=['1980-01-01', '1980-02-01', '1980-03-01'])
% >>> df
%            FR    GR     IT
% 1980-01-01  4.0405  1.7246  804.74
% 1980-02-01  4.0963  1.7482  810.01
% 1980-03-01  4.3149  1.8519  860.13
% >>> df.pct_change()
%            FR    GR     IT
% 1980-01-01  NaN  NaN   NaN
% 1980-02-01  0.013810  0.013684  0.006549
% 1980-03-01  0.053365  0.059318  0.061876

Percentage of change in GOOG and APPL stock volume. Shows computing the percentage change between columns.

% >>> df = pd.DataFrame({
% ... '2016': [1769950, 30586265],
% ... '2015': [1500923, 40912316],
% ... '2014': [1371819, 41403351]},
% ... index=['GOOG', 'APPL'])
% >>> df
%            GOOG      APPL
% 2016   1769950  30586265
% 2015   1500923  40912316
% 2014   1371819  41403351
% >>> df.pct_change(axis='columns')
%            GOOG     APPL
% 2016  NaN -0.151997
% 2015  NaN  0.337604
% 2014  NaN  0.012002
**DataFrame.pipe**

DataFrame.pipe(func, *args, **kwargs)

Apply func(self, *args, **kwargs).

**Parameters**

- **func** [function] Function to apply to the Series/DataFrame. args, and kwargs are passed into func. Alternatively a (callable, data_keyword) tuple where data_keyword is a string indicating the keyword of callable that expects the Series/DataFrame.

- **args** [iterable, optional] Positional arguments passed into func.

- **kwargs** [mapping, optional] A dictionary of keyword arguments passed into func.

**Returns**

- **object** [the return type of func.]

**See also:**

- **DataFrame.apply** Apply a function along input axis of DataFrame.
- **DataFrame.applymap** Apply a function elementwise on a whole DataFrame.
- **Series.map** Apply a mapping correspondence on a Series.

**Notes**

Use .pipe when chaining together functions that expect Series, DataFrames or GroupBy objects. Instead of writing

```python
def g(df):
    return df['A']

def h(df):
    return df.where(df['A'] > 0)

def func(arg1, arg2, arg3):
    return arg1 + arg2 + arg3
```

You can write

```python
>>> (df.pipe(h)
...     .pipe(g, arg1=10)
...     .pipe(func, arg2=20, arg3=30)
... )
```

If you have a function that takes the data as (say) the second argument, pass a tuple indicating which keyword expects the data. For example, suppose f takes its data as arg2:

```python
>>> (df.pipe(h)
...     .pipe(g, arg1=10)
...     .pipe(f, (func, 'arg2'), arg1=10, arg3=30)
... )
```
pandas.DataFrame.pivot

DataFrame.pivot(index=None, columns=None, values=None)

Return reshaped DataFrame organized by given index / column values.

Reshape data (produce a “pivot” table) based on column values. Uses unique values from specified index / columns to form axes of the resulting DataFrame. This function does not support data aggregation, multiple values will result in a MultiIndex in the columns. See the User Guide for more on reshaping.

Parameters

index [str or object or a list of str, optional] Column to use to make new frame’s index.
If None, uses existing index.
Changed in version 1.1.0: Also accept list of index names.

columns [str or object or a list of str] Column to use to make new frame’s columns.
Changed in version 1.1.0: Also accept list of columns names.

values [str, object or a list of the previous, optional] Column(s) to use for populating new frame’s values. If not specified, all remaining columns will be used and the result will have hierarchically indexed columns.
Changed in version 0.23.0: Also accept list of column names.

Returns

DataFrame Returns reshaped DataFrame.

Raises

ValueError: When there are any index, columns combinations with multiple values.
DataFrame.pivot_table when you need to aggregate.

See also:

DataFrame.pivot_table Generalization of pivot that can handle duplicate values for one index/column pair.

DataFrame.unstack Pivot based on the index values instead of a column.

Notes

For finer-tuned control, see hierarchical indexing documentation along with the related stack/unstack methods.

Examples

```python
>>> df = pd.DataFrame({'foo': ['one', 'one', 'one', 'two', 'two', ...
...     'two'],
...     'bar': ['A', 'B', 'C', 'A', 'B', 'C'],
...     'baz': [1, 2, 3, 4, 5, 6],
...     'zoo': ['x', 'y', 'z', 'q', 'w', 't']})
```

```python
0 one A 1 x
1 one B 2 y
2 one C 3 z
```
(continues on next page)
pandas: powerful Python data analysis toolkit, Release 1.1.1

3 two A  4    q
4 two B  5    w
5 two C  6    t

>>> df.pivot(index='foo', columns='bar', values='baz')
bar   A B C
foo
one  1 2 3
two  4 5 6

>>> df.pivot(index='foo', columns='bar')['baz']
bar   A B C
foo
one  1 2 3
two  4 5 6

>>> df.pivot(index='foo', columns='bar', values=['baz', 'zoo'])
baz zoo
bar   A B C A B C
foo
one  1 2 3 x y z
two  4 5 6 q w t

You could also assign a list of column names or a list of index names.

>>> df = pd.DataFrame({'
...     "lev1": [1, 1, 1, 2, 2, 2],
...     "lev2": [1, 1, 2, 1, 1, 2],
...     "lev3": [1, 2, 1, 2, 1, 2],
...     "lev4": [1, 2, 3, 4, 5, 6],
...     "values": [0, 1, 2, 3, 4, 5])

>>> df
lev1  lev2  lev3  lev4  values
0 1 1 1 1 1 0
1 1 1 2 2 1
2 1 2 1 3 2
3 2 1 2 4 3
4 2 1 1 5 4
5 2 2 2 6 5

>>> df.pivot(index="lev1", columns=["lev2", "lev3"],values="values")
lev2  lev3
lev1
1   0.0 1.0 2.0 NaN
2   4.0 3.0 NaN 5.0

>>> df.pivot(index="lev1", "lev2", columns="lev3",values="values")
lev3  lev1  lev2
1   1 0.0 1.0
    2 2.0 NaN
2   1 4.0 3.0
    2 NaN 5.0

A ValueError is raised if there are any duplicates.
```
>>> df = pd.DataFrame({"foo": ['one', 'one', 'two', 'two'],
... "bar": ['A', 'A', 'B', 'C'],
... "baz": [1, 2, 3, 4]})

>>> df
  foo bar baz
0  one A  1
1  one A  2
2  two B  3
3  two C  4
```

Notice that the first two rows are the same for our `index` and `columns` arguments.

```
>>> df.pivot(index='foo', columns='bar', values='baz')
Traceback (most recent call last):
...
ValueError: Index contains duplicate entries, cannot reshape
```

`pandas.DataFrame.pivot_table`

`DataFrame.pivot_table`(*values=None, index=None, columns=None, aggfunc='mean', fill_value=None, margins=False, dropna=True, margins_name='All', observed=False*)

Create a spreadsheet-style pivot table as a DataFrame.

The levels in the pivot table will be stored in MultiIndex objects (hierarchical indexes) on the index and columns of the result DataFrame.

**Parameters**

- **values** [column to aggregate, optional]
- **index** [column, Grouper, array, or list of the previous] If an array is passed, it must be the same length as the data. The list can contain any of the other types (except list). Keys to group by on the pivot table index. If an array is passed, it is being used as the same manner as column values.
- **columns** [column, Grouper, array, or list of the previous] If an array is passed, it must be the same length as the data. The list can contain any of the other types (except list). Keys to group by on the pivot table column. If an array is passed, it is being used as the same manner as column values.
- **aggfunc** [function, list of functions, dict, default `numpy.mean`] If list of functions passed, the resulting pivot table will have hierarchical columns whose top level are the function names (inferred from the function objects themselves) If dict is passed, the key is column to aggregate and value is function or list of functions.
- **fill_value** [scalar, default `None`] Value to replace missing values with (in the resulting pivot table, after aggregation).
- **margins** [bool, default `False`] Add all row / columns (e.g. for subtotal / grand totals).
- **dropna** [bool, default `True`] Do not include columns whose entries are all NaN.
- **margins_name** [str, default ‘All’] Name of the row / column that will contain the totals when margins is `True`.
- **observed** [bool, default `False`] This only applies if any of the groupers are Categoricals. If True: only show observed values for categorical groupers. If False: show all values for categorical groupers.
Changed in version 0.25.0.

Returns

DataFrame An Excel style pivot table.

See also:

DataFrame.pivot Pivot without aggregation that can handle non-numeric data.

Examples

```python
>>> df = pd.DataFrame(
    {"A": ["foo", "foo", "foo", "foo", "foo", "bar", "bar", "bar", "bar"],
     "B": ["one", "one", "one", "two", "two", "one", "two", "two"],
     "C": ["small", "large", "large", "small", "small", "large", "small", "large"],
     "D": [1, 2, 2, 3, 3, 4, 5, 6, 7],
     "E": [2, 4, 5, 5, 6, 6, 8, 9, 9]})
```

This first example aggregates values by taking the sum.

```python
>>> table = pd.pivot_table(df, values='D', index=['A', 'B'],
                         columns=['C'], aggfunc=np.sum)
```

We can also fill missing values using the `fill_value` parameter.

```python
>>> table = pd.pivot_table(df, values='D', index=['A', 'B'],
                         columns=['C'], aggfunc=np.sum, fill_value=0)
```

The next example aggregates by taking the mean across multiple columns.
```python
>>> table = pd.pivot_table(df, values=['D', 'E'], index=['A', 'C'],
...                        aggfunc={'D': np.mean,
...                                'E': np.mean})
>>> table

D   E
A  C
---  ---
bar large 5.500000 7.500000
     small 5.500000 8.500000
foo large 2.000000 4.500000
     small 2.333333 4.333333

We can also calculate multiple types of aggregations for any given value column.

```n
code-block:: python

```py
>>> table = pd.pivot_table(df, values=['D', 'E'], index=['A', 'C'],
...                        aggfunc={'D': np.mean,
...                                'E': [min, max, np.mean]})
>>> table

D    E
mean  max  mean  min
A  C
---  ---  ---  ---
bar large  5.500000  9.0  7.500000  6.0
     small  5.500000  9.0  8.500000  8.0
foo large  2.000000  5.0  4.500000  4.0
     small  2.333333  6.0  4.333333  2.0
```

**pandas.DataFrame.plot**

Dataframe.plot(*args, **kwargs)

Make plots of Series or DataFrame.

Uses the backend specified by the option plottingbackend. By default, matplotlib is used.

**Parameters**

- `data` [Series or DataFrame] The object for which the method is called.
- `x` [label or position, default None] Only used if data is a DataFrame.
- `y` [label, position or list of label, positions, default None] Allows plotting of one column versus another. Only used if data is a DataFrame.
- `kind` [str] The kind of plot to produce:
  - ‘line’: line plot (default)
  - ‘bar’: vertical bar plot
  - ‘barh’: horizontal bar plot
  - ‘hist’: histogram
  - ‘box’: boxplot
  - ‘kde’: Kernel Density Estimation plot
  - ‘density’: same as ‘kde’
  - ‘area’: area plot
  - ‘pie’: pie plot
  - ‘scatter’: scatter plot
• ‘hexbin’: hexbin plot.

**ax** [matplotlib axes object, default None] An axes of the current figure.

**subplots** [bool, default False] Make separate subplots for each column.

**sharex** [bool, default True if ax is None else False] In case subplots=True, share x axis and set some x axis labels to invisible; defaults to True if ax is None otherwise False if an ax is passed in; Be aware, that passing in both an ax and sharex=True will alter all x axis labels for all axis in a figure.

**sharey** [bool, default False] In case subplots=True, share y axis and set some y axis labels to invisible.

**layout** [tuple, optional] (rows, columns) for the layout of subplots.

**figsize** [a tuple (width, height) in inches] Size of a figure object.

**use_index** [bool, default True] Use index as ticks for x axis.

**title** [str or list] Title to use for the plot. If a string is passed, print the string at the top of the figure. If a list is passed and subplots is True, print each item in the list above the corresponding subplot.

**grid** [bool, default None (matlab style default)] Axis grid lines.

**legend** [bool or {‘reverse’}] Place legend on axis subplots.

**style** [list or dict] The matplotlib line style per column.

**logx** [bool or ‘sym’, default False] Use log scaling or symlog scaling on x axis. .. versionchanged:: 0.25.0

**logy** [bool or ‘sym’ default False] Use log scaling or symlog scaling on y axis. .. versionchanged:: 0.25.0

**loglog** [bool or ‘sym’, default False] Use log scaling or symlog scaling on both x and y axes. .. versionchanged:: 0.25.0

**xticks** [sequence] Values to use for the xticks.

**yticks** [sequence] Values to use for the yticks.

**xlim** [2-tuple/list] Set the x limits of the current axes.

**ylim** [2-tuple/list] Set the y limits of the current axes.

**xlabel** [label, optional] Name to use for the xlabel on x-axis. Default uses index name as xlabel.

New in version 1.1.0.

**ylabel** [label, optional] Name to use for the ylabel on y-axis. Default will show no ylabel.

New in version 1.1.0.

**rot** [int, default None] Rotation for ticks (xticks for vertical, yticks for horizontal plots).

**fontsize** [int, default None] Font size for xticks and yticks.

**colormap** [str or matplotlib colormap object, default None] Colormap to select colors from. If string, load colormap with that name from matplotlib.

**colorbar** [bool, optional] If True, plot colorbar (only relevant for ‘scatter’ and ‘hexbin’ plots).
position [float] Specify relative alignments for bar plot layout. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center).

table [bool, Series or DataFrame, default False] If True, draw a table using the data in the DataFrame and the data will be transposed to meet matplotlib’s default layout. If a Series or DataFrame is passed, use passed data to draw a table.

eyerr [DataFrame, Series, array-like, dict and str] See Plotting with Error Bars for detail.

xerr [DataFrame, Series, array-like, dict and str] Equivalent to yerr.

stacked [bool, default False in line and bar plots, and True in area plot] If True, create stacked plot.

sort_columns [bool, default False] Sort column names to determine plot ordering.

secondary_y [bool or sequence, default False] Whether to plot on the secondary y-axis if a list/tuple, which columns to plot on secondary y-axis.

mark_right [bool, default True] When using a secondary_y axis, automatically mark the column labels with “(right)” in the legend.

include_bool [bool, default is False] If True, boolean values can be plotted.

backend [str, default None] Backend to use instead of the backend specified in the option plotting.backend. For instance, ‘matplotlib’. Alternatively, to specify the plotting.backend for the whole session, set pd.options.plotting.backend. New in version 1.0.0.

**kwargs Options to pass to matplotlib plotting method.

Returns

matplotlib.axes.Axes or numpy.ndarray of them If the backend is not the default matplotlib one, the return value will be the object returned by the backend.

Notes

• See matplotlib documentation online for more on this subject

• If kind = ‘bar’ or ‘barh’, you can specify relative alignments for bar plot layout by position keyword. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)

pandas.DataFrame.pop

DataFrame.pop(item)

Return item and drop from frame. Raise KeyError if not found.

Parameters

item [label] Label of column to be popped.

Returns

Series
Examples

```python
>>> df = pd.DataFrame([('falcon', 'bird', 389.0),
...                    ('parrot', 'bird', 24.0),
...                    ('lion', 'mammal', 80.5),
...                    ('monkey', 'mammal', np.nan)],
...                    columns=('name', 'class', 'max_speed'))
```

```python
>>> df
    name   class  max_speed
0  falcon  bird     389.0
1  parrot  bird      24.0
2    lion  mammal    80.5
3   monkey  mammal     NaN
```

```python
>>> df.pop('class')
0    bird
1    bird
2  mammal
3  mammal
Name: class, dtype: object
```

```python
>>> df
    name  max_speed
0  falcon     389.0
1  parrot     24.0
2    lion     80.5
3   monkey     NaN
```

pandas.DataFrame.pow

DataFrame.pow(other, axis='columns', level=None, fill_value=None)

Get Exponential power of dataframe and other, element-wise (binary operator pow).

Equivalent to dataframe ** other, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, rpow.

Among flexible wrappers (add, sub, mul, div, mod, pow) to arithmetic operators: +, -, *, /, //, %, **.

Parameters

- **other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

- **axis** [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.

- **level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

- **fill_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

- **DataFrame** Result of the arithmetic operation.
See also:

- `DataFrame.add` Add DataFrames.
- `DataFrame.sub` Subtract DataFrames.
- `DataFrame.mul` Multiply DataFrames.
- `DataFrame.div` Divide DataFrames (float division).
- `DataFrame.truediv` Divide DataFrames (float division).
- `DataFrame.floordiv` Divide DataFrames (integer division).
- `DataFrame.mod` Calculate modulo (remainder after division).
- `DataFrame.pow` Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```python
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360],
...                    index=['circle', 'triangle', 'rectangle'])
>>> df
   angles  degrees
circle     0      360
triangle   3      180
rectangle  4      360
```

Add a scalar with operator version which return the same results.

```python
>>> df + 1
   angles  degrees
circle     1      361
triangle   4      181
rectangle  5      361
```

```python
>>> df.add(1)
   angles  degrees
circle     1      361
triangle   4      181
rectangle  5      361
```

Divide by constant with reverse version.

```python
>>> df.div(10)
   angles  degrees
circle    0.0    36.0
triangle  0.3    18.0
rectangle 0.4    36.0
```
Subtract a list and Series by axis with operator version.

```python
>>> df - [1, 2]
angles  degrees
circle   -1   358
triangle  2    178
rectangle 3    358
```

```python
>>> df.sub([1, 2], axis='columns')
angles  degrees
circle   -1   358
triangle  2    178
rectangle 3    358
```

```python
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']), axis='index')
angles  degrees
circle   -1   359
triangle  2    179
rectangle 3    359
```

Multiply a DataFrame of different shape with operator version.

```python
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
                        index=['circle', 'triangle', 'rectangle'])
```

```python
>>> df * other
angles  degrees
circle   0    NaN
triangle  9    NaN
rectangle 16   NaN
```

```python
>>> df.mul(other, fill_value=0)
angles  degrees
circle   0    0.0
triangle  9    0.0
rectangle 16   0.0
```

Divide by a MultiIndex by level.

```python
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
                               'degrees': [360, 180, 360, 360, 540, 720],
                               'index': ['circle', 'triangle', 'rectangle', 'square', 'pentagon', 'hexagon']})
```

(continues on next page)
pandas: powerful Python data analysis toolkit, Release 1.1.1

```
>>> df_multindex
angles  degrees
A  circle  0  360
triangle  3  180
rectangle  4  360
B  square  4  360
pentagon  5  540
hexagon  6  720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
angles  degrees
A  circle  NaN  1.0
triangle  1.0  1.0
rectangle  1.0  1.0
B  square  0.0  0.0
pentagon  0.0  0.0
hexagon  0.0  0.0
```

**pandas.DataFrame.prod**

Dataframe `.prod` (axis=None, skipna=None, level=None, numeric_only=None, min_count=0, **kwargs)

Return the product of the values for the requested axis.

**Parameters**

- **axis** ([index (0), columns (1)]) Axis for the function to be applied on.
- **skipna** (bool, default True) Exclude NA/null values when computing the result.
- **level** (int or level name, default None) If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.
- **numeric_only** (bool, default None) Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.
- **min_count** (int, default 0) The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

New in version 0.22.0: Added with the default being 0. This means the sum of an all-NA or empty Series is 0, and the product of an all-NA or empty Series is 1.

- **kwargs** Additional keyword arguments to be passed to the function.

**Returns**

- Series or DataFrame (if level specified)
**Examples**

By default, the product of an empty or all-NA Series is 1

```python
>>> pd.Series([]).prod()
1.0
```

This can be controlled with the `min_count` parameter

```python
>>> pd.Series([]).prod(min_count=1)
nan
```

Thanks to the `skipna` parameter, `min_count` handles all-NA and empty series identically.

```python
>>> pd.Series([np.nan]).prod()
1.0

>>> pd.Series([np.nan]).prod(min_count=1)
nan
```

---

**pandas.DataFrame.product**

`DataFrame.product` *(axis=None, skipna=None, level=None, numeric_only=None, min_count=0, **kwargs)*

Return the product of the values for the requested axis.

**Parameters**

- `axis` [{index (0), columns (1)}] Axis for the function to be applied on.
- `skipna` [bool, default True] Exclude NA/null values when computing the result.
- `level` [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.
- `numeric_only` [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.
- `min_count` [int, default 0] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

New in version 0.22.0: Added with the default being 0. This means the sum of an all-NA or empty Series is 0, and the product of an all-NA or empty Series is 1.

- `**kwargs` Additional keyword arguments to be passed to the function.

**Returns**

- Series or DataFrame (if level specified)
Examples

By default, the product of an empty or all-NA Series is 1

```python
>>> pd.Series([]).prod()
1.0
```

This can be controlled with the `min_count` parameter

```python
>>> pd.Series([]).prod(min_count=1)
nan
```

Thanks to the `skipna` parameter, `min_count` handles all-NA and empty series identically.

```python
>>> pd.Series([np.nan]).prod()
1.0
```
```python
>>> pd.Series([np.nan]).prod(min_count=1)
nan
```

pandas.DataFrame.quantile

DataFrame.quantile(q=0.5, axis=0, numeric_only=True, interpolation='linear')

Return values at the given quantile over requested axis.

**Parameters**

- **q** [float or array-like, default 0.5 (50% quantile)] Value between 0 <= q <= 1, the quantile(s) to compute.
- **axis** [[0, 1, ‘index’, ‘columns’], default 0] Equals 0 or ‘index’ for row-wise, 1 or ‘columns’ for column-wise.
- **numeric_only** [bool, default True] If False, the quantile of datetime and timedelta data will be computed as well.
- **interpolation** [{‘linear’, ‘lower’, ‘higher’, ‘midpoint’, ‘nearest’}] This optional parameter specifies the interpolation method to use, when the desired quantile lies between two data points \( i \) and \( j \):
  - linear: \( i + (j - i) \times \text{fraction} \), where \( \text{fraction} \) is the fractional part of the index surrounded by \( i \) and \( j \).
  - lower: \( i \).
  - higher: \( j \).
  - nearest: \( i \) or \( j \) whichever is nearest.
  - midpoint: \( (i + j) / 2 \).

**Returns**

Series or DataFrame

If \( q \) is an array, a DataFrame will be returned where the index is \( q \), the columns are the columns of self, and the values are the quantiles.

If \( q \) is a float, a Series will be returned where the index is the columns of self and the values are the quantiles.
See also:

**core.window.Rolling.quantile** Rolling quantile.

**numpy.percentile** Numpy function to compute the percentile.

**Examples**

```python
>>> df = pd.DataFrame(np.array([[1, 1], [2, 10], [3, 100], [4, 100]]),
                    columns=['a', 'b'])

>>> df.quantile(.1)
   a  1.3
   b  3.7
Name: 0.1, dtype: float64

>>> df.quantile([.1, .5])
   a  b
 0.1 1.3 3.7
 0.5 2.5 55.0
```

Specifying `numeric_only=False` will also compute the quantile of datetime and timedelta data.

```python
>>> df = pd.DataFrame({'A': [1, 2],
                     'B': [pd.Timestamp('2010'),
                           pd.Timestamp('2011')],
                     'C': [pd.Timedelta('1 days'),
                           pd.Timedelta('2 days')]})

>>> df.quantile(0.5, numeric_only=False)
   A  1.5
   B 2010-07-02 12:00:00
   C  1 days 12:00:00
Name: 0.5, dtype: object
```

**pandas.DataFrame.query**

`DataFrame.query(expr, inplace=False, **kwargs)`

Query the columns of a DataFrame with a boolean expression.

**Parameters**

- `expr` [str] The query string to evaluate.

  You can refer to variables in the environment by prefixing them with an `@` character like `@a + b`.

  You can refer to column names that contain spaces or operators by surrounding them in backticks. This way you can also escape names that start with a digit, or those that are a Python keyword. Basically when it is not valid Python identifier. See notes down for more details.

  For example, if one of your columns is called `a a` and you want to sum it with `b`, your query should be `@a + b`.

New in version 0.25.0: Backtick quoting introduced.

New in version 1.0.0: Expanding functionality of backtick quoting for more than only spaces.
inplace [bool] Whether the query should modify the data in place or return a modified copy.

**kwargs See the documentation for `eval()` for complete details on the keyword arguments accepted by `DataFrame.query()`.

**Returns**

*DataFrame* DataFrame resulting from the provided query expression.

**See also:**

*eval* Evaluate a string describing operations on DataFrame columns.

*DataFrame.eval* Evaluate a string describing operations on DataFrame columns.

**Notes**

The result of the evaluation of this expression is first passed to `DataFrame.loc` and if that fails because of a multidimensional key (e.g., a DataFrame) then the result will be passed to `DataFrame.__getitem__()`.

This method uses the top-level `eval()` function to evaluate the passed query.

The `query()` method uses a slightly modified Python syntax by default. For example, the & and | (bitwise) operators have the precedence of their boolean cousins, **and** and **or**. This is syntactically valid Python, however the semantics are different.

You can change the semantics of the expression by passing the keyword argument `parser='python'`. This enforces the same semantics as evaluation in Python space. Likewise, you can pass `engine='python'` to evaluate an expression using Python itself as a backend. This is not recommended as it is inefficient compared to using `numexpr` as the engine.

The `DataFrame.index` and `DataFrame.columns` attributes of the `DataFrame` instance are placed in the query namespace by default, which allows you to treat both the index and columns of the frame as a column in the frame. The identifier `index` is used for the frame index; you can also use the name of the index to identify it in a query. Please note that Python keywords may not be used as identifiers.

For further details and examples see the `query` documentation in `indexing`.

**Backtick quoted variables**

Backtick quoted variables are parsed as literal Python code and are converted internally to a Python valid identifier. This can lead to the following problems.

During parsing a number of disallowed characters inside the backtick quoted string are replaced by strings that are allowed as a Python identifier. These characters include all operators in Python, the space character, the question mark, the exclamation mark, the dollar sign, and the euro sign. For other characters that fall outside the ASCII range (U+0001..U+007F) and those that are not further specified in PEP 3131, the query parser will raise an error. This excludes whitespace different than the space character, but also the hashtag (as it is used for comments) and the backtick itself (backtick can also not be escaped).

In a special case, quotes that make a pair around a backtick can confuse the parser. For example, `it's > `that's` will raise an error, as it forms a quoted string ('s > `that`) with a backtick inside.

See also the Python documentation about lexical analysis (https://docs.python.org/3/reference/lexical_analysis.html) in combination with the source code in `pandas.core.computation.parsing`. 

1618 Chapter 3. API reference
Examples

```python
>>> df = pd.DataFrame({'A': range(1, 6),
                    'B': range(10, 0, -2),
                    'C C': range(10, 5, -1)})

>>> df
   A  B  C C
0  1  10 10
1  2  8  9
2  3  6  8
3  4  4  7
4  5  2  6

>>> df.query('A > B')
   A  B  C C
4  5  2  6
```

The previous expression is equivalent to

```python
>>> df[df.A > df.B]
   A  B  C C
4  5  2  6
```

For columns with spaces in their name, you can use backtick quoting.

```python
>>> df.query('B == `C C``')
   A  B  C C
0  1  10 10
```

The previous expression is equivalent to

```python
>>> df[df.B == df['C C']]  
   A  B  C C
0  1  10 10
```

---

**pandas.DataFrame.radd**

DataFrame .radd (other, axis='columns', level=None, fill_value=None)

Get Addition of dataframe and other, element-wise (binary operator radd).
Equivalent to other + dataframe, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, add.

Among flexible wrappers (add, sub, mul, div, mod, pow) to arithmetic operators: +, -, *, /, //, %, **.

**Parameters**

- **other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.
- **axis** [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.
- **level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.
- **fill_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before
computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns

**DataFrame** Result of the arithmetic operation.

See also:

*DataFrame.add* Add DataFrames.

*DataFrame.sub* Subtract DataFrames.

*DataFrame.mul* Multiply DataFrames.

*DataFrame.div* Divide DataFrames (float division).

*DataFrame.truediv* Divide DataFrames (float division).

*DataFrame.floordiv* Divide DataFrames (integer division).

*DataFrame.mod* Calculate modulo (remainder after division).

*DataFrame.pow* Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```python
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
>>> df
angles  degrees
circle     0      360
triangle   3      180
rectangle  4      360

Add a scalar with operator version which return the same results.

```python
>>> df + 1

<table>
<thead>
<tr>
<th>angles</th>
<th>degrees</th>
</tr>
</thead>
<tbody>
<tr>
<td>circle</td>
<td>1</td>
</tr>
<tr>
<td>triangle</td>
<td>4</td>
</tr>
<tr>
<td>rectangle</td>
<td>5</td>
</tr>
</tbody>
</table>
```

```python
>>> df.add(1)

<table>
<thead>
<tr>
<th>angles</th>
<th>degrees</th>
</tr>
</thead>
<tbody>
<tr>
<td>circle</td>
<td>1</td>
</tr>
<tr>
<td>triangle</td>
<td>4</td>
</tr>
<tr>
<td>rectangle</td>
<td>5</td>
</tr>
</tbody>
</table>
```
Divide by a MultiIndex by level.

3.4. DataFrame
pandas.DataFrame.rank

DataFrame.rank(axis=0, method='average', numeric_only=None, na_option='keep', ascending=True, pct=False)

Compute numerical data ranks (1 through n) along axis.
By default, equal values are assigned a rank that is the average of the ranks of those values.

Parameters

- **axis** ([0 or ‘index’, 1 or ‘columns’], default 0) Index to direct ranking.
- **method** ([‘average’, ‘min’, ‘max’, ‘first’, ‘dense’], default ‘average’) How to rank the group of records that have the same value (i.e. ties):
  - average: average rank of the group
  - min: lowest rank in the group
  - max: highest rank in the group
  - first: ranks assigned in order they appear in the array
  - dense: like ‘min’, but rank always increases by 1 between groups.
- **numeric_only** [bool, optional] For DataFrame objects, rank only numeric columns if set to True.
- **na_option** ([‘keep’, ‘top’, ‘bottom’], default ‘keep’) How to rank NaN values:
  - keep: assign NaN rank to NaN values
  - top: assign smallest rank to NaN values if ascending
  - bottom: assign highest rank to NaN values if ascending.
- **ascending** [bool, default True] Whether or not the elements should be ranked in ascending order.
**pct** [bool, default False] Whether or not to display the returned rankings in percentile form.

**Returns**

**same type as caller** Return a Series or DataFrame with data ranks as values.

**See also:**

**core.groupby.GroupBy.rank** Rank of values within each group.

**Examples**

```python
def = pd.DataFrame(data={'Animal': ['cat', 'penguin', 'dog', 'spider', 'snake'],
                         'Number_legs': [4, 2, 4, 8, np.nan]})
```

The following example shows how the method behaves with the above parameters:

- **default_rank**: this is the default behaviour obtained without using any parameter.
- **max_rank**: setting `method = 'max'` the records that have the same values are ranked using the highest rank (e.g.: since ‘cat’ and ‘dog’ are both in the 2nd and 3rd position, rank 3 is assigned.)
- **NA_bottom**: choosing `na_option = 'bottom'`, if there are records with NaN values they are placed at the bottom of the ranking.
- **pct_rank**: when setting `pct = True`, the ranking is expressed as percentile rank.

```python
def['default_rank'] = df['Number_legs'].rank()
def['max_rank'] = df['Number_legs'].rank(method='max')
def['NA_bottom'] = df['Number_legs'].rank(na_option='bottom')
def['pct_rank'] = df['Number_legs'].rank(pct=True)
```

```plaintext
Animal   Number_legs  default_rank  max_rank  NA_bottom  pct_rank
        0     cat        4.0          2.5        3.0      2.5  0.625
        1    penguin    2.0          1.0        1.0      1.0  0.250
        2      dog      4.0          2.5        3.0      2.5  0.625
        3    spider     8.0          4.0        4.0      4.0  1.000
        4     snake     NaN         NaN        NaN      NaN  NaN
```
**pandas.DataFrame.rdiv**

`DataFrame.rdiv(other, axis='columns', level=None, fill_value=None)`

Get Floating division of dataframe and other, element-wise (binary operator `rtruediv`).

Equivalent to `other / dataframe`, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, `truediv`.

Among flexible wrappers (`add`, `sub`, `mul`, `div`, `mod`, `pow`) to arithmetic operators: `+`, `-`, `*`, `/`, `//`, `%`, `**`.

**Parameters**

- `other` [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.
- `axis` [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.
- `level` [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.
- `fill_value` [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

**Returns**

*Dataframe* Result of the arithmetic operation.

**See also:**

- `DataFrame.add` Add DataFrames.
- `DataFrame.sub` Subtract DataFrames.
- `DataFrame.mul` Multiply DataFrames.
- `DataFrame.div` Divide DataFrames (float division).
- `DataFrame.truediv` Divide DataFrames (float division).
- `DataFrame.floordiv` Divide DataFrames (integer division).
- `DataFrame.mod` Calculate modulo (remainder after division).
- `DataFrame.pow` Calculate exponential power.

**Notes**

Mismatched indices will be unioned together.
Examples

```python
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360],
...                    index=['circle', 'triangle', 'rectangle'])
>>> df
    angles  degrees
circle     0       360
triangle    3       180
rectangle   4       360

Add a scalar with operator version which return the same results.

```python
>>> df + 1
    angles  degrees
circle     1       361
triangle    4       181
rectangle   5       361
``` 

```python
>>> df.add(1)
    angles  degrees
circle     1       361
triangle    4       181
rectangle   5       361
``` 

Divide by constant with reverse version.

```python
>>> df.div(10)
    angles  degrees
circle     0.0      36.0
triangle    0.3      18.0
rectangle   0.4      36.0
``` 

```python
>>> df.rdiv(10)
    angles  degrees
circle     inf      0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
``` 

Subtract a list and Series by axis with operator version.

```python
>>> df - [1, 2]
    angles  degrees
circle     -1      358
triangle     2      178
rectangle    3      358
``` 

```python
>>> df.sub([1, 2], axis='columns')
    angles  degrees
circle     -1      358
triangle     2      178
rectangle    3      358
``` 

```python
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...         axis='index')
    angles  degrees
circle     -1      358
triangle     2      178
rectangle    3      358
``` 

(continues on next page)
Multiply a DataFrame of different shape with operator version.

```
other = pd.DataFrame({'angles': [0, 3, 4],
                     'index':['circle', 'triangle', 'rectangle'])
other
```
```
angles
circle 0
triangle 3
rectangle 4
```
```
other = pd.DataFrame({'angles': [0, 3, 4],
                     'index':['circle', 'triangle', 'rectangle'])
other
```
```
angles
circle 0
triangle 3
rectangle 4
```
```
other
```
```
angles
circle 0
triangle 3
rectangle 4
```
```
df * other
```
```
angles degrees
circle 0 NaN
triangle 9 NaN
rectangle 16 NaN
```
```
df * other
```
```
angles degrees
circle 0 NaN
triangle 9 NaN
rectangle 16 NaN
```
```
df.mul(other, fill_value=0)
```
```
angles degrees
circle 0 0.0
triangle 9 0.0
rectangle 16 0.0
```
```
df.mul(other, fill_value=0)
```
```
angles degrees
circle 0 0.0
triangle 9 0.0
rectangle 16 0.0
```
```
Divide by a MultiIndex by level.

```
df_multindex = pd.DataFrame({'angles': [0, 3, 4, 5, 6],
                          'degrees': [360, 180, 360, 360, 540, 720],
                          'index':['circle', 'triangle', 'rectangle',
                                    'square', 'pentagon', 'hexagon'])
```
```
df_multindex
```
```
angles degrees
A circle 0 360
triangle 3 180
rectangle 4 360
B square 4 360
pentagon 5 540
hexagon 6 720
```
```
df_multindex
```
```
angles degrees
A circle 0 360
triangle 3 180
rectangle 4 360
B square 4 360
pentagon 5 540
hexagon 6 720
```
```
df_multindex
```
```
angles degrees
A circle NaN 1.0
triangle 1.0 1.0
rectangle 1.0 1.0
B square 0.0 0.0
pentagon 0.0 0.0
hexagon 0.0 0.0
```
```
df.multindex, level=1, fill_value=0)
```
```
angles degrees
A circle NaN 1.0
triangle 1.0 1.0
rectangle 1.0 1.0
B square 0.0 0.0
pentagon 0.0 0.0
hexagon 0.0 0.0
```
```
df.multindex, level=1, fill_value=0)
```
```
angles degrees
A circle NaN 1.0
triangle 1.0 1.0
rectangle 1.0 1.0
B square 0.0 0.0
pentagon 0.0 0.0
hexagon 0.0 0.0
```
```
df.multindex, level=1, fill_value=0)
```
```
angles degrees
A circle NaN 1.0
triangle 1.0 1.0
rectangle 1.0 1.0
B square 0.0 0.0
pentagon 0.0 0.0
hexagon 0.0 0.0
```
DataFrame.reindex

DataFrame.reindex(**kwargs)
Conform Series/DataFrame to new index with optional filling logic.

Places NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and copy=False.

Parameters

keywords for axes [array-like, optional] New labels / index to conform to, should be specified using keywords. Preferably an Index object to avoid duplicating data.

method [{None, ‘backfill’/’bfill’ , ‘pad’/’ffill’, ‘nearest’}] Method to use for filling holes in reindexed DataFrame. Please note: this is only applicable to DataFrames/Series with a monotonically increasing/decreasing index.
  • None (default): don’t fill gaps
  • pad / ffill: Propagate last valid observation forward to next valid.
  • backfill / bfill: Use next valid observation to fill gap.
  • nearest: Use nearest valid observations to fill gap.

copy [bool, default True] Return a new object, even if the passed indexes are the same.

level [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [scalar, default np.NaN] Value to use for missing values. Defaults to NaN, but can be any “compatible” value.

limit [int, default None] Maximum number of consecutive elements to forward or backward fill.

tolerance [optional] Maximum distance between original and new labels for inexact matches. The values of the index at the matching locations most satisfy the equation abs(index[indexer] - target) <= tolerance.

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index’s type.

Returns

Series/DataFrame with changed index.

See also:

DataFrame.set_index Set row labels.

DataFrame.reset_index Remove row labels or move them to new columns.

DataFrame.reindex_like Change to same indices as other DataFrame.
Examples

**DataFrame.reindex** supports two calling conventions

- `(index=index_labels, columns=column_labels, ...)`
- `(labels, axis={'index', 'columns'}, ...)`

We highly recommend using keyword arguments to clarify your intent.

Create a dataframe with some fictional data.

```
>>> index = ['Firefox', 'Chrome', 'Safari', 'IE10', 'Konqueror']
>>> df = pd.DataFrame({'http_status': [200, 200, 404, 404, 301],
                     'response_time': [0.04, 0.02, 0.07, 0.08, 1.0]},
                     index=index)
>>> df
http_status response_time
Firefox 200 0.04
Chrome 200 0.02
Safari 404 0.07
IE10 404 0.08
Konqueror 301 1.00
```

Create a new index and reindex the dataframe. By default values in the new index that do not have corresponding records in the dataframe are assigned NaN.

```
>>> new_index = ['Safari', 'Iceweasel', 'Comodo Dragon', 'IE10',
               'Chrome']
>>> df.reindex(new_index)
http_status response_time
Safari 404 0.07
Iceweasel NaN NaN
Comodo Dragon NaN NaN
IE10 404 0.08
Chrome 200 0.02
```

We can fill in the missing values by passing a value to the keyword `fill_value`. Because the index is not monotonically increasing or decreasing, we cannot use arguments to the keyword `method` to fill the NaN values.

```
>>> df.reindex(new_index, fill_value=0)
http_status response_time
Safari 404 0.07
Iceweasel 0 0.00
Comodo Dragon 0 0.00
IE10 404 0.08
Chrome 200 0.02
```

```
>>> df.reindex(new_index, fill_value='missing')
http_status response_time
Safari 404 0.07
Iceweasel missing missing
Comodo Dragon missing missing
IE10 404 0.08
Chrome 200 0.02
```

We can also reindex the columns.
Or we can use “axis-style” keyword arguments

To further illustrate the filling functionality in `reindex`, we will create a dataframe with a monotonically increasing index (for example, a sequence of dates).

Suppose we decide to expand the dataframe to cover a wider date range.

The index entries that did not have a value in the original data frame (for example, ‘2009-12-29’) are by default filled with NaN. If desired, we can fill in the missing values using one of several options.

For example, to back-propagate the last valid value to fill the NaN values, pass `bfill` as an argument to the method keyword.
Please note that the NaN value present in the original dataframe (at index value 2010-01-03) will not be filled by any of the value propagation schemes. This is because filling while reindexing does not look at dataframe values, but only compares the original and desired indexes. If you do want to fill in the NaN values present in the original dataframe, use the `fillna()` method.

See the user guide for more.

**pandas.DataFrame.reindex_like**

`DataFrame.reindex_like` *(other, method=None, copy=True, limit=None, tolerance=None)*

Return an object with matching indices as other object.

Conform the object to the same index on all axes. Optional filling logic, placing NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and copy=False.

**Parameters**

- **other** [Object of the same data type] Its row and column indices are used to define the new indices of this object.

- **method** [{None, ‘backfill’/’bfill’, ‘pad’/’ffill’, ‘nearest’}] Method to use for filling holes in reindexed DataFrame. Please note: this is only applicable to DataFrames/Series with a monotonically increasing/decreasing index.
  - None (default): don’t fill gaps
  - pad / ffill: propagate last valid observation forward to next valid
  - backfill / bfill: use next valid observation to fill gap
  - nearest: use nearest valid observations to fill gap.

- **copy** [bool, default True] Return a new object, even if the passed indexes are the same.

- **limit** [int, default None] Maximum number of consecutive labels to fill for inexact matches.

- **tolerance** [optional] Maximum distance between original and new labels for inexact matches. The values of the index at the matching locations most satisfy the equation \( \text{abs(index[indexer] - target) <= tolerance} \).
  - Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index’s type.

**Returns**
**Series or DataFrame** Same type as caller, but with changed indices on each axis.

*See also:*

**DataFrame.set_index** Set row labels.

**DataFrame.reset_index** Remove row labels or move them to new columns.

**DataFrame.reindex** Change to new indices or expand indices.

**Notes**

Same as calling `.reindex(index=other.index, columns=other.columns,...)`.

**Examples**

```python
>>> df1 = pd.DataFrame([[24.3, 75.7, 'high'],
                      [31, 87.8, 'high'],
                      [22, 71.6, 'medium'],
                      [35, 95, 'medium']],
                     columns=['temp_celsius', 'temp_fahrenheit', 'windspeed'],
                     index=pd.date_range(start='2014-02-12',
                                         end='2014-02-15', freq='D'))

>>> df1
       temp_celsius  temp_fahrenheit  windspeed
2014-02-12     24.3              75.7     high
2014-02-13     31.0              87.8     high
2014-02-14     22.0              71.6    medium
2014-02-15     35.0              95.0    medium
```

```python
>>> df2 = pd.DataFrame([[28, 'low'],
                      [30, 'low'],
                      [35.1, 'medium']],
                     columns=['temp_celsius', 'windspeed'],
                     index=pd.DatetimeIndex(['2014-02-12', '2014-02-13',
                                              '2014-02-15']))

>>> df2
       temp_celsius  windspeed
2014-02-12     28.0     low
2014-02-13     30.0     low
2014-02-15     35.1    medium
```

```python
>>> df2.reindex_like(df1)
       temp_celsius  temp_fahrenheit  windspeed
2014-02-12     28.0            NaN     low
2014-02-13     30.0            NaN     low
2014-02-14       NaN            NaN     NaN
2014-02-15     35.1            NaN    medium
```
pandas.DataFrame.rename

DataFrame.rename(**kwargs)
Alter axes labels.

Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is. Extra labels listed don’t throw an error.

See the user guide for more.

Parameters

mapper [dict-like or function] Dict-like or functions transformations to apply to that axis’ values. Use either mapper and axis to specify the axis to target with mapper, or index and columns.

index [dict-like or function] Alternative to specifying axis (mapper, axis=0 is equivalent to index=mapper).

columns [dict-like or function] Alternative to specifying axis (mapper, axis=1 is equivalent to columns=mapper).

axis [[0 or ‘index’, 1 or ‘columns’], default 0] Axis to target with mapper. Can be either the axis name (‘index’, ‘columns’) or number (0, 1). The default is ‘index’.

copy [bool, default True] Also copy underlying data.

inplace [bool, default False] Whether to return a new DataFrame. If True then value of copy is ignored.

level [int or level name, default None] In case of a MultiIndex, only rename labels in the specified level.

errors [{‘ignore’, ‘raise’}, default ‘ignore’] If ‘raise’, raise a KeyError when a dict-like mapper, index, or columns contains labels that are not present in the Index being transformed. If ‘ignore’, existing keys will be renamed and extra keys will be ignored.

Returns

DataFrame DataFrame with the renamed axis labels.

Raises

KeyError If any of the labels is not found in the selected axis and “errors=’raise’”.

See also:

DataFrame.rename_axis Set the name of the axis.

Examples

DataFrame.rename supports two calling conventions

• (index=index_mapper, columns=columns_mapper, ...)
• (mapper, axis=['index', 'columns'], ...)

We highly recommend using keyword arguments to clarify your intent.

Rename columns using a mapping:
```python
>>> df = pd.DataFrame({"A": [1, 2, 3], "B": [4, 5, 6]})
>>> df.rename(columns={"A": "a", "B": "c"})
    a  c
0  1  4
1  2  5
2  3  6

Rename index using a mapping:
```n
```python
>>> df.rename(index={0: "x", 1: "y", 2: "z"})
    A  B
x  1  4
y  2  5
z  3  6

Cast index labels to a different type:
```n
```python
>>> df.index
RangeIndex(start=0, stop=3, step=1)
>>> df.rename(index=str).index
Index(["0", "1", "2"], dtype='object')

Using axis-style parameters
```n
```python
>>> df.rename(str.lower, axis='columns')
    a  b
0  1  4
1  2  5
2  3  6

>>> df.rename({1: 2, 2: 4}, axis='index')
    A  B
0  1  4
2  2  5
4  3  6
```

**pandas.DataFrame.rename_axis**

**DataFrame.rename_axis(**kwargs**)**

Set the name of the axis for the index or columns.

**Parameters**

mapper [scalar, list-like, optional] Value to set the axis name attribute.

index, columns [scalar, list-like, dict-like or function, optional] A scalar, list-like, dict-like or functions transformations to apply to that axis’ values. Note that the columns parameter is not allowed if the object is a Series. This parameter only apply for DataFrame type objects.

Use either mapper and axis to specify the axis to target with mapper, or index and/or columns.

3.4. DataFrame
Changed in version 0.24.0.

axis [[0 or ‘index’, 1 or ‘columns’], default 0] The axis to rename.

copy [bool, default True] Also copy underlying data.

inplace [bool, default False] Modifies the object directly, instead of creating a new Series or DataFrame.

Returns

Series, DataFrame, or None The same type as the caller or None if inplace is True.

See also:

Series.rename Alter Series index labels or name.

DataFrame.rename Alter DataFrame index labels or name.

Index.rename Set new names on index.

Notes

DataFrame.rename_axis supports two calling conventions

* (index=index_mapper, columns=columns_mapper, ...)
* (mapper, axis={'index', 'columns'}, ...)

The first calling convention will only modify the names of the index and/or the names of the Index object that is the columns. In this case, the parameter copy is ignored.

The second calling convention will modify the names of the the corresponding index if mapper is a list or a scalar. However, if mapper is dict-like or a function, it will use the deprecated behavior of modifying the axis labels.

We highly recommend using keyword arguments to clarify your intent.

Examples

Series

```python
>>> s = pd.Series(['dog', 'cat', 'monkey'])
>>> s
0   dog
1   cat
2  monkey
dtype: object
>>> s.rename_axis('animal')
animal
0   dog
1   cat
2  monkey
dtype: object
```

DataFrame
```python
>>> df = pd.DataFrame({"num_legs": [4, 4, 2], "num_arms": [0, 0, 2]},
                    index=["dog", "cat", "monkey"])
>>> df
   num_legs num_arms
dog      4        0
cat      4        0
monkey   2        2
>>> df = df.rename_axis("animal")
>>> df
   num_legs num_arms
animal
dog   4   0
cat   4   0
monkey   2   2
>>> df.rename_axis(index={'type': 'class'})
   num_legs num_arms
class
type
mammal
dog   4   0
cat   4   0
monkey   2   2
>>> df.rename_axis(columns=str.upper)
   LIMBS num_legs num_arms
type
name
mammal
dog   4   0
cat   4   0
monkey   2   2
```

**MultiIndex**

```python
>>> df.index = pd.MultiIndex.from_product([['mammal'], ['dog', 'cat', 'monkey']], names=['type', 'name'])
>>> df
   limbs num_legs num_arms
   type name
mammal
dog   4   0
cat   4   0
monkey   2   2
>>> df.rename_axis('class')
   num_legs num_arms
   type
   class
mammal
dog   4   0
cat   4   0
monkey   2   2
>>> df.rename_axis('str.upper')
   LIMBS num_legs num_arms
   type
   name
mammal
dog   4   0
cat   4   0
monkey   2   2
```
pandas.DataFrame.reorder_levels

DataFrame.reorder_levels(order, axis=0)
Rearrange index levels using input order. May not drop or duplicate levels.

Parameters

order [list of int or list of str] List representing new level order. Reference level by number (position) or by key (label).
axis [{0 or ‘index’, 1 or ‘columns’}, default 0] Where to reorder levels.

Returns
DataFrame

pandas.DataFrame.replace

DataFrame.replace(to_replace=None, value=None, inplace=False, limit=None, regex=False, method='pad')
Replace values given in to_replace with value.
Values of the DataFrame are replaced with other values dynamically. This differs from updating with .loc or .iloc, which require you to specify a location to update with some value.

Parameters

to_replace [str, regex, list, dict, Series, int, float, or None] How to find the values that will be replaced.
• numeric, str or regex:
  – numeric: numeric values equal to to_replace will be replaced with value
  – str: string exactly matching to_replace will be replaced with value
  – regex: regexs matching to_replace will be replaced with value
• list of str, regex, or numeric:
  – First, if to_replace and value are both lists, they must be the same length.
  – Second, if regex=True then all of the strings in both lists will be interpreted as regexs otherwise they will match directly. This doesn’t matter much for value since there are only a few possible substitution regexes you can use.
  – str, regex and numeric rules apply as above.
• dict:
  – Dicts can be used to specify different replacement values for different existing values. For example, {'a': 'b', 'y': 'z'} replaces the value ‘a’ with ‘b’ and ‘y’ with ‘z’. To use a dict in this way the value parameter should be None.
  – For a DataFrame a dict can specify that different values should be replaced in different columns. For example, {'a': 1, 'b': 'z'} looks for the value 1 in column ‘a’ and the value ‘z’ in column ‘b’ and replaces these values with whatever is specified in value. The value parameter should not be None in this case. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
For a DataFrame nested dictionaries, e.g., `{'a': {'b': np.nan}}`, are read as follows: look in column ‘a’ for the value ‘b’ and replace it with NaN. The value parameter should be None to use a nested dict in this way. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) cannot be regular expressions.

- None:
  - This means that the regex argument must be a string, compiled regular expression, or list, dict, ndarray or Series of such elements. If value is also None then this must be a nested dictionary or Series.

See the examples section for examples of each of these.

Parameter &Description &Notes
--- &--- &---
value &[scalar, dict, list, str, regex, default None] Value to replace any values matching to_replace with. For a DataFrame a dict of values can be used to specify which value to use for each column (columns not in the dict will not be filled). Regular expressions, strings and lists or dicts of such objects are also allowed.

inplace &[bool, default False] If True, in place. Note: this will modify any other views on this object (e.g. a column from a DataFrame). Returns the caller if this is True.

limit &[int, default None] Maximum size gap to forward or backward fill.

regex &[bool or same types as to_replace, default False] Whether to interpret to_replace and/or value as regular expressions. If this is True then to_replace must be a string. Alternatively, this could be a regular expression or a list, dict, or array of regular expressions in which case to_replace must be None.

method &[{'pad', 'ffill', 'bfill', None}] The method to use when for replacement, when to_replace is a scalar, list or tuple and value is None.

Returns

DataFrame Object after replacement.

Raises

AssertionError
- If regex is not a bool and to_replace is not None.

TypeError
- If to_replace is not a scalar, array-like, dict, or None
- If to_replace is a dict and value is not a list, dict, ndarray, or Series
- If to_replace is None and regex is not compilable into a regular expression or is a list, dict, ndarray, or Series.
- When replacing multiple bool or datetime64 objects and the arguments to to_replace does not match the type of the value being replaced

ValueError
- If a list or an ndarray is passed to to_replace and value but they are not the same length.

See also:

Dataframe.fillna Fill NA values.
DataFrame.where Replace values based on boolean condition.

Series.str.replace Simple string replacement.

Notes

• Regex substitution is performed under the hood with re.sub. The rules for substitution for re.sub are the same.

• Regular expressions will only substitute on strings, meaning you cannot provide, for example, a regular expression matching floating point numbers and expect the columns in your frame that have a numeric dtype to be matched. However, if those floating point numbers are strings, then you can do this.

• This method has a lot of options. You are encouraged to experiment and play with this method to gain intuition about how it works.

• When dict is used as the to_replace value, it is like key(s) in the dict are the to_replace part and value(s) in the dict are the value parameter.

Examples

Scalar `to_replace` and `value`

```python
>>> s = pd.Series([0, 1, 2, 3, 4])
>>> s.replace(0, 5)
0  5  
1  1  
2  2  
3  3  
4  4  
dtype: int64
```

```python
>>> df = pd.DataFrame({'A': [0, 1, 2, 3, 4],
...                    'B': [5, 6, 7, 8, 9],
...                    'C': ['a', 'b', 'c', 'd', 'e']})
>>> df.replace(0, 5)
   A  B  C
0  5  5  a
1  1  6  b
2  2  7  c
3  3  8  d
4  4  9  e
```

List-like `to_replace`

```python
>>> df.replace([0, 1, 2, 3], 4)
   A  B  C
0  4  5  a
1  4  6  b
2  4  7  c
3  4  8  d
4  4  9  e
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

```python
>>> df.replace([0, 1, 2, 3], [4, 3, 2, 1])
   A  B  C
0  4  5  a
1  3  6  b
2  2  7  c
3  1  8  d
4  4  9  e
```

```python
>>> s.replace([1, 2], method='bfill')
0  0
1  3
2  3
3  3
4  4
dtype: int64
```

**dict-like `to_replace`**

```python
>>> df.replace({0: 10, 1: 100})
   A  B  C
0 10  5  a
1 100  6  b
2  2  7  c
3  3  8  d
4  4  9  e
```

```python
>>> df.replace({'A': 0, 'B': 5}, 100)
   A  B  C
0  100 100 a
1   1  6  b
2   2  7  c
3   3  8  d
4   4  9  e
```

```python
>>> df.replace({'A': {0: 100, 4: 400}})
   A  B  C
0 100  5  a
1   1  6  b
2   2  7  c
3   3  8  d
4  400  9  e
```

**Regular expression `to_replace`**

```python
>>> df = pd.DataFrame({'A': ['bat', 'foo', 'bait'],
                    'B': ['abc', 'bar', 'xyz']})
```

```python
>>> df.replace(to_replace=r'^ba.$', value='new', regex=True)
   A  B
0 new abc
1 foo new
2 bait xyz
```

```python
>>> df.replace({'A': r'^ba.$'}, {'A': 'new'}, regex=True)
   A  B
0 new abc
```

(continues on next page)
1 foo bar
2 bait xyz

```python
>>> df.replace(regex=r'^ba.$', value='new')
   A   B
0  new abc
1  foo new
2  bait xyz
```

```python
>>> df.replace(regex={r'^ba.$': 'new', 'foo': 'xyz'})
   A   B
0  new abc
1  xyz new
2  bait xyz
```

```python
>>> df.replace(regex=[r'^ba.$', 'foo'], value='new')
   A   B
0  new abc
1  new new
2  bait xyz
```

Note that when replacing multiple bool or datetime64 objects, the data types in the `to_replace` parameter must match the data type of the value being replaced:

```python
>>> df = pd.DataFrame({'A': [True, False, True],
...                    'B': [False, True, False]})
>>> df.replace({'a string': 'new value', True: False})  # raises
Traceback (most recent call last):
  ...  
TypeError: Cannot compare types 'ndarray(dtype=bool)' and 'str'
```

This raises a `TypeError` because one of the dict keys is not of the correct type for replacement.

Compare the behavior of `s.replace({'a': None})` and `s.replace('a', None)` to understand the peculiarities of the `to_replace` parameter:

```python
>>> s = pd.Series([10, 'a', 'a', 'b', 'a'])
```

When one uses a dict as the `to_replace` value, it is like the value(s) in the dict are equal to the `value` parameter. `s.replace({'a': None})` is equivalent to `s.replace(to_replace={'a': None}, value=None, method=None):

```python
>>> s.replace({'a': None})
0  10
1  None
2  None
3   b
4  None
dtype: object
```

When `value=None` and `to_replace` is a scalar, list or tuple, `replace` uses the method parameter (default ‘pad’) to do the replacement. So this is why the ‘a’ values are being replaced by 10 in rows 1 and 2 and ‘b’ in row 4 in this case. The command `s.replace('a', None)` is actually equivalent to `s.replace(to_replace=['a'], value=None, method='pad'):`
```python
>>> s.replace('a', None)
0     10
1     10
2     10
3      b
4      b
dtype: object
```

**pandas.DataFrame.resample**

**DataFrame.resample**(rule, axis=0, closed=None, label=None, convention='start', kind=None, loffset=None, base=None, on=None, level=None, origin='start_day', offset=None)

Resample time-series data.

Convenience method for frequency conversion and resampling of time series. Object must have a datetime-like index (`DatetimeIndex`, `PeriodIndex`, or `TimedeltaIndex`), or pass datetime-like values to the `on` or `level` keyword.

**Parameters**

- **rule** [DateOffset, Timedelta or str] The offset string or object representing target conversion.
- **axis** [{0 or 'index', 1 or 'columns'}, default 0] Which axis to use for up- or down-sampling. For Series this will default to 0, i.e. along the rows. Must be `DateTimeIndex`, `TimedeltaIndex` or `PeriodIndex`.
- **label** [{‘right’, ‘left’}, default None] Which bin edge label to label bucket with. The default is ‘left’ for all frequency offsets except for ‘M’, ‘A’, ‘Q’, ‘BM’, ‘BA’, ‘BQ’, and ‘W’ which all have a default of ‘right’.
- **convention** [{‘start’, ‘end’, ‘s’, ‘e’}, default ‘start’] For `PeriodIndex` only, controls whether to use the start or end of `rule`.
- **kind** [{‘timestamp’, ‘period’}, optional, default None] Pass ‘timestamp’ to convert the resulting index to a `DateTimeIndex` or ‘period’ to convert it to a `PeriodIndex`. By default the input representation is retained.
- **loffset** [timedelta, default None] Adjust the resampled time labels.

Deprecated since version 1.1.0: You should add the loffset to the `df.index` after the resample. See below.

- **base** [int, default 0] For frequencies that evenly subdivide 1 day, the “origin” of the aggregated intervals. For example, for ‘5min’ frequency, base could range from 0 through 4. Defaults to 0.

    Deprecated since version 1.1.0: The new arguments that you should use are ‘offset’ or ‘origin’.

- **on** [str, optional] For a DataFrame, column to use instead of index for resampling. Column must be datetime-like.
- **level** [str or int, optional] For a MultiIndex, level (name or number) to use for resampling. `level` must be datetime-like.
origin [{‘epoch’, ‘start’, ‘start_day’}, Timestamp or str, default ‘start_day’] The times-
tamp on which to adjust the grouping. The timezone of origin must match the
timezone of the index. If a timestamp is not used, these values are also supported:

- ‘epoch’: origin is 1970-01-01
- ‘start’: origin is the first value of the timeseries
- ‘start_day’: origin is the first day at midnight of the timeseries

New in version 1.1.0.

offset [Timedelta or str, default is None] An offset timedelta added to the origin.

New in version 1.1.0.

Returns
Resampler object

See also:

groupby Group by mapping, function, label, or list of labels.
Series.resample Resample a Series.
DataFrame.resample Resample a DataFrame.

Notes
See the user guide for more.
To learn more about the offset strings, please see this link.

Examples
Start by creating a series with 9 one minute timestamps.

```python
>>> index = pd.date_range('1/1/2000', periods=9, freq='T')
>>> series = pd.Series(range(9), index=index)
```

Downsample the series into 3 minute bins and sum the values of the timestamps falling into a bin.

```python
>>> series.resample('3T').sum()
```

Downsample the series into 3 minute bins as above, but label each bin using the right edge instead of the left. Please note that the value in the bucket used as the label is not included in the bucket, which it labels. For example, in the original series the bucket 2000-01-01 00:03:00 contains the value 3, but the summed value in the resampled bucket with the label 2000-01-01 00:03:00 does not include 3 (if it did, the summed value would be 6, not 3). To include this value close the right side of the bin interval as illustrated in the example below this one.

```python
>>> series.resample('3T', label='right').sum()
2000-01-01 00:00:00   3
2000-01-01 00:03:00   12
2000-01-01 00:06:00   21
Freq: 3T, dtype: int64
```

Downsample the series into 3 minute bins as above, but close the right side of the bin interval.

```python
>>> series.resample('3T', label='right', closed='right').sum()
2000-01-01 00:00:00   0
2000-01-01 00:03:00   6
2000-01-01 00:06:00  15
2000-01-01 00:09:00  15
Freq: 3T, dtype: int64
```

Upsample the series into 30 second bins.

```python
>>> series.resample('30S').asfreq()[0:5]  # Select first 5 rows
2000-01-01 00:00:00   0.0
2000-01-01 00:00:30   NaN
2000-01-01 00:01:00   1.0
2000-01-01 00:01:30   NaN
2000-01-01 00:02:00   2.0
Freq: 30S, dtype: float64
```

Upsample the series into 30 second bins and fill the NaN values using the pad method.

```python
>>> series.resample('30S').pad()[0:5]
2000-01-01 00:00:00   0
2000-01-01 00:00:30   0
2000-01-01 00:01:00   1
2000-01-01 00:01:30   1
2000-01-01 00:02:00   2
Freq: 30S, dtype: int64
```

Upsample the series into 30 second bins and fill the NaN values using the bfill method.

```python
>>> series.resample('30S').bfill()[0:5]
2000-01-01 00:00:00   0
2000-01-01 00:00:30   1
2000-01-01 00:01:00   1
2000-01-01 00:01:30   2
2000-01-01 00:02:00   2
Freq: 30S, dtype: int64
```

Pass a custom function via apply

```python
>>> def custom_resampler(array_like):
...     return np.sum(array_like) + 5
...
```
For a Series with a PeriodIndex, the keyword convention can be used to control whether to use the start or end of rule.

Resample a year by quarter using 'start' convention. Values are assigned to the first quarter of the period.

```python
>>> s = pd.Series([1, 2], index=pd.period_range('2012-01-01', freq='A', periods=2))
>>> s
2012 1
2013 2
Freq: A-DEC, dtype: int64

>>> s.resample('Q', convention='start').asfreq()
2012Q1 1.0
2012Q2 NaN
2012Q3 NaN
2012Q4 NaN
2013Q1 2.0
2013Q2 NaN
2013Q3 NaN
2013Q4 NaN
Freq: Q-DEC, dtype: float64
```

Resample quarters by month using 'end' convention. Values are assigned to the last month of the period.

```python
>>> q = pd.Series([1, 2, 3, 4], index=pd.period_range('2018-01-01', freq='Q', periods=4))
>>> q
2018Q1 1
2018Q2 2
2018Q3 3
2018Q4 4
Freq: Q-DEC, dtype: int64

>>> q.resample('M', convention='end').asfreq()
2018-03 1.0
2018-04 NaN
2018-05 NaN
2018-06 2.0
2018-07 NaN
2018-08 NaN
2018-09 3.0
2018-10 NaN
2018-11 NaN
2018-12 4.0
Freq: M, dtype: float64
```

For DataFrame objects, the keyword on can be used to specify the column instead of the index for resampling.
>>> d = dict({'price': [10, 11, 9, 13, 14, 18, 17, 19],
...    'volume': [50, 60, 40, 100, 50, 100, 40, 50]})
>>> df = pd.DataFrame(d)
>>> df['week_starting'] = pd.date_range('01/01/2018',
...    periods=8,
...    freq='W')
>>> df

<table>
<thead>
<tr>
<th>price</th>
<th>volume</th>
<th>week_starting</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>50</td>
<td>2018-01-07</td>
</tr>
<tr>
<td>11</td>
<td>60</td>
<td>2018-01-14</td>
</tr>
<tr>
<td>9</td>
<td>40</td>
<td>2018-01-21</td>
</tr>
<tr>
<td>13</td>
<td>100</td>
<td>2018-01-28</td>
</tr>
<tr>
<td>14</td>
<td>50</td>
<td>2018-02-04</td>
</tr>
<tr>
<td>18</td>
<td>100</td>
<td>2018-02-11</td>
</tr>
<tr>
<td>17</td>
<td>40</td>
<td>2018-02-18</td>
</tr>
<tr>
<td>19</td>
<td>50</td>
<td>2018-02-25</td>
</tr>
</tbody>
</table>

>>> df.resample('M', on='week_starting').mean()

<table>
<thead>
<tr>
<th>week_starting</th>
<th>price</th>
<th>volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>2018-01-31</td>
<td>10.75</td>
<td>62.5</td>
</tr>
<tr>
<td>2018-02-28</td>
<td>17.00</td>
<td>60.0</td>
</tr>
</tbody>
</table>

For a DataFrame with MultiIndex, the keyword `level` can be used to specify on which level the resampling needs to take place.

>>> days = pd.date_range('1/1/2000', periods=4, freq='D')
>>> d2 = dict({'price': [10, 11, 9, 13, 14, 18, 17, 19],
...    'volume': [50, 60, 40, 100, 50, 100, 40, 50]})
>>> df2 = pd.DataFrame(d2, index=pd.MultiIndex.from_product([[days],
...    ['morning', 'afternoon']])
>>> df2

<table>
<thead>
<tr>
<th>price</th>
<th>volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01 morning</td>
<td>10</td>
</tr>
<tr>
<td>afternoon</td>
<td>11</td>
</tr>
<tr>
<td>2000-01-02 morning</td>
<td>9</td>
</tr>
<tr>
<td>afternoon</td>
<td>13</td>
</tr>
<tr>
<td>2000-01-03 morning</td>
<td>14</td>
</tr>
<tr>
<td>afternoon</td>
<td>18</td>
</tr>
<tr>
<td>2000-01-04 morning</td>
<td>17</td>
</tr>
<tr>
<td>afternoon</td>
<td>19</td>
</tr>
</tbody>
</table>

>>> df2.resample('D', level=0).sum()

<table>
<thead>
<tr>
<th>week_starting</th>
<th>price</th>
<th>volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01</td>
<td>21</td>
<td>110</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>22</td>
<td>140</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>32</td>
<td>150</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>36</td>
<td>90</td>
</tr>
</tbody>
</table>

If you want to adjust the start of the bins based on a fixed timestamp:

>>> start, end = '2000-10-01 23:30:00', '2000-10-02 00:30:00'
>>> rng = pd.date_range(start, end, freq='7min')
>>> ts = pd.Series(np.arange(len(rng)) * 3, index=rng)
>>> ts

(continues on next page)
If you want to adjust the start of the bins with an `offset` Timedelta, the two following lines are equivalent:

```python
>>> ts.resample('17min', origin='start').sum()
2000-10-01 23:30:00  9
2000-10-01 23:47:00  21
2000-10-02 00:04:00  54
2000-10-02 00:21:00  24
Freq: 17T, dtype: int64
```
```
>>> ts.resample('17min', offset='23h30min').sum()
2000-10-01 23:30:00  9
2000-10-01 23:47:00  21
2000-10-02 00:04:00  54
2000-10-02 00:21:00  24
Freq: 17T, dtype: int64
```

To replace the use of the deprecated `base` argument, you can now use `offset`, in this example it is equivalent to have `base=2`:

```python
>>> ts.resample('17min', offset='2min').sum()
2000-10-01 23:16:00  0
2000-10-01 23:33:00  9
```

To replace the use of the deprecated `loffset` argument:

```python
>>> from pandas.tseries.frequencies import to_offset
>>> loffset = '19min'
>>> ts_out = ts.resample('17min').sum()
>>> ts_out.index = ts_out.index + to_offset(loffset)
```

```
2000-10-01 23:33:00   0
2000-10-01 23:50:00   9
2000-10-02 00:07:00  21
2000-10-02 00:24:00  54
2000-10-02 00:41:00  24
Freq: 17T, dtype: int64
```

**pandas.DataFrame.reset_index**

DataFrame.reset_index (level=None, drop=False, inplace=False, col_level=0, col_fill='')

Reset the index, or a level of it.

Reset the index of the DataFrame, and use the default one instead. If the DataFrame has a MultiIndex, this method can remove one or more levels.

**Parameters**

- **level** [int, str, tuple, or list, default None] Only remove the given levels from the index. Removes all levels by default.
- **drop** [bool, default False] Do not try to insert index into dataframe columns. This resets the index to the default integer index.
- **inplace** [bool, default False] Modify the DataFrame in place (do not create a new object).
- **col_level** [int or str, default 0] If the columns have multiple levels, determines which level the labels are inserted into. By default it is inserted into the first level.
- **col_fill** [object, default ‘’] If the columns have multiple levels, determines how the other levels are named. If None then the index name is repeated.

**Returns**

- **DataFrame or None** DataFrame with the new index or None if inplace=True.

**See also:**

- **DataFrame.set_index** Opposite of reset_index.
- **DataFrame.reindex** Change to new indices or expand indices.
- **DataFrame.reindex_like** Change to same indices as other DataFrame.
Examples

```python
>>> df = pd.DataFrame([('bird', 389.0),
...                     ('bird', 24.0),
...                     ('mammal', 80.5),
...                     ('mammal', np.nan),
...                     index=['falcon', 'parrot', 'lion', 'monkey'],
...                     columns=('class', 'max_speed'))
>>> df
    class max_speed
falcon bird    389.0
parrot bird    24.0
lion mammal    80.5
monkey mammal  NaN

When we reset the index, the old index is added as a column, and a new sequential index is used:

```python
>>> df.reset_index()
    index class max_speed
       0  falcon bird    389.0
       1  parrot bird    24.0
       2    lion mammal    80.5
       3 monkey mammal   NaN
```

We can use the `drop` parameter to avoid the old index being added as a column:

```python
>>> df.reset_index(drop=True)
    class max_speed
       0  bird    389.0
       1  bird    24.0
       2  mammal    80.5
       3  mammal    NaN

You can also use `reset_index` with `MultiIndex`.

```python
>>> index = pd.MultiIndex.from_tuples([('bird', 'falcon'),
...                                     ('bird', 'parrot'),
...                                     ('mammal', 'lion'),
...                                     ('mammal', 'monkey')],
...                                     names=['class', 'name'])
>>> columns = pd.MultiIndex.from_tuples([('speed', 'max'),
...                                        ('species', 'type')])
>>> df = pd.DataFrame([(389.0, 'fly'),
...                     ( 24.0, 'fly'),
...                     ( 80.5, 'run'),
...                     (np.nan, 'jump')],
...                     index=index,
...                     columns=columns)
>>> df
    speed species
    max type
      class name
    bird falcon 389.0   fly
    parrot 24.0   fly
    mammal lion 80.5   run
    monkey NaN  NaN
```

If the index has multiple levels, we can reset a subset of them:
If we are not dropping the index, by default, it is placed in the top level. We can place it in another level:

```
>>> df.reset_index(level='class', col_level=1)
```

When the index is inserted under another level, we can specify under which one with the parameter `col_fill`:

```
>>> df.reset_index(level='class', col_level=1, col_fill='species')
```

If we specify a nonexistent level for `col_fill`, it is created:

```
>>> df.reset_index(level='class', col_level=1, col_fill='genus')
```

---

**pandas.DataFrame.rfloordiv**

Dataframe `.rfloordiv` (other, axis='columns', level=None, fill_value=None)

Get integer division of dataframe and other, element-wise (binary operator `rfloordiv`).

Equivalent to `other // dataframe`, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, `floordiv`.

Among flexible wrappers (`add`, `sub`, `mul`, `div`, `mod`, `pow`) to arithmetic operators: `+`, `-`, `*`, `/`, `//`, `%`, `**`.

**Parameters**

- `other` [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.
axis [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’)
or columns (1 or ‘columns’). For Series input, axis to match Series index on.

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [float or None, default None] Fill existing missing (NaN) values, and any
new element needed for successful DataFrame alignment, with this value before
computation. If data in both corresponding DataFrame locations is missing the
result will be missing.

Returns

DataFrame Result of the arithmetic operation.

See also:

DataFrame.add Add DataFrames.
DataFrame.sub Subtract DataFrames.
DataFrame.mul Multiply DataFrames.
DataFrame.div Divide DataFrames (float division).
DataFrame.truediv Divide DataFrames (float division).
DataFrame.floordiv Divide DataFrames (integer division).
DataFrame.mod Calculate modulo (remainder after division).
DataFrame.pow Calculate exponential power.

Notes

Mismatched indices will be unioned together.

Examples

```python
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                     'degrees': [360, 180, 360]},
...                     index=['circle', 'triangle', 'rectangle'])
>>> df
     angles  degrees
circle      0      360
triangle    3      180
rectangle   4      360

Add a scalar with operator version which return the same results.

```
divide by constant with reverse version.

```
>>> df.div(10)
   angles  degrees
circle     0.0   36.0
triangle   0.3   18.0
rectangle  0.4   36.0
```

```
>>> df.rdiv(10)
   angles  degrees
circle    inf   0.027778
triangle  3.333333  0.055556
rectangle 2.500000  0.027778
```

subtract a list and series by axis with operator version.

```
>>> df - [1, 2]
   angles  degrees
circle   -1   358
triangle   2   178
rectangle  3   358
```

```
>>> df.sub([1, 2], axis='columns')
   angles  degrees
circle   -1   358
triangle   2   178
rectangle  3   358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
         axis='index')
   angles  degrees
circle   -1   359
triangle   2   179
rectangle  3   359
```

multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
                        index=['circle', 'triangle', 'rectangle'])
>>> other
   angles
circle   0
triangle   3
rectangle   4
```

```
>>> df * other
   angles  degrees
circle     0   NaN
triangle    9   NaN
rectangle  16   NaN
```
>>> df.mul(other, fill_value=0)
   angles  degrees
   circle    0       0
   triangle   9       0
   rectangle 16       0

Divide by a MultiIndex by level.

>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 5, 6],
                               'degrees': [360, 180, 360, 360, 540, 720],
                               'index': [['A', 'A', 'A', 'B', 'B', 'B'],
                                         ['circle', 'triangle', 'rectangle', 'square', 'pentagon', 'hexagon']]})

>>> df_multindex
   angles  degrees
   A circle 0         360
        triangle 3       180
        rectangle 4       360
   B square 4         360
        pentagon 5        540
        hexagon 6        720

>>> df.div(df_multindex, level=1, fill_value=0)
   angles  degrees
   A circle NaN       1.0
        triangle 1.0    1.0
        rectangle 1.0    1.0
   B square 0.0       0.0
        pentagon 0.0    0.0
        hexagon 0.0    0.0

pandas.DataFrame.rmod

DataFrame.rmod(other, axis='columns', level=None, fill_value=None)

Get Modulo of dataframe and other, element-wise (binary operator rmod).

Equivalent to other % dataframe, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, mod.

Among flexible wrappers (add, sub, mul, div, mod, pow) to arithmetic operators: +, -, *, /, //, %, **.

Parameters

other  [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.
axis  [(0 or 'index', 1 or 'columns')] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.
level  [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.
fill_value  [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

Returns
**DataFrame**  Result of the arithmetic operation.

**See also:**

- *DataFrame.add*  Add DataFrames.
- *DataFrame.sub*  Subtract DataFrames.
- *DataFrame.mul*  Multiply DataFrames.
- *DataFrame.div*  Divide DataFrames (float division).
- *DataFrame.truediv*  Divide DataFrames (float division).
- *DataFrame.floordiv*  Divide DataFrames (integer division).
- *DataFrame.mod*  Calculate modulo (remainder after division).
- *DataFrame.pow*  Calculate exponential power.

**Notes**

Mismatched indices will be unioned together.

**Examples**

```python
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                    index=['circle', 'triangle', 'rectangle'])
>>> df
   angles  degrees
circle     0      360
triangle    3      180
rectangle   4      360
```

Add a scalar with operator version which return the same results.

```python
>>> df + 1
    angles  degrees
  circle    1      361
  triangle   4      181
  rectangle  5      361
```

```python
>>> df.add(1)
    angles  degrees
  circle    1      361
  triangle   4      181
  rectangle  5      361
```

Divide by constant with reverse version.

```python
>>> df.div(10)
    angles  degrees
  circle    0.0     36.0
  triangle  0.3      18.0
  rectangle 0.4     36.0
```

3.4. *DataFrame*  1653
Subtract a list and Series by axis with operator version.

```python
>>> df - [1, 2]
angles  degrees  
circle -1    358
triangle  2     178
rectangle 3     358
```

```python
>>> df.sub([1, 2], axis='columns')
angles  degrees  
circle -1    358
triangle  2     178
rectangle 3     358
```

```python
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']), axis='index')
angles  degrees  
circle -1    359
triangle  2     179
rectangle 3     359
```

Multiply a DataFrame of different shape with operator version.

```python
>>> other = pd.DataFrame({'angles': [0, 3, 4]}, index=['circle', 'triangle', 'rectangle'])
```

```python
>>> df * other
angles  degrees  
circle  0.0   NaN
triangle 9.0   NaN
rectangle 16.0  NaN
```

```python
>>> df.mul(other, fill_value=0)
angles  degrees  
circle  0.0   0.0
triangle 9.0   0.0
rectangle 16.0  0.0
```

Divide by a MultiIndex by level.

```python
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6], 'degrees': [360, 180, 360, 360, 540, 720]}, index=['A', 'A', 'A', 'B', 'B', 'B'], columns=['circle', 'triangle', 'rectangle', 'square', 'pentagon', 'hexagon'])
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

(continued from previous page)

```python
>>> df_multindex = pandas.DataFrame({
    'angles': [0, 3, 4, 5, 6],
    'degrees': [360, 180, 360, 540, 720]
    }, index=['circle', 'triangle', 'rectangle', 'square', 'pentagon', 'hexagon'])
```

```python
>>> df = df_multindex
```

```python
>>> df.div(df_multindex, level=1, fill_value=0)
```

```
angles  degrees
A circle   NaN   1.0
triangle  1.0   1.0
rectangle 1.0   1.0
B square  0.0   0.0
pentagon  0.0   0.0
hexagon  0.0   0.0
```

**pandas.DataFrame.rmul**

DataFrame.rmul (other, axis='columns', level=None, fill_value=None)

Get Multiplication of dataframe and other, element-wise (binary operator rmul).

Equivalent to other * dataframe, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, mul.

Among flexible wrappers (add, sub, mul, div, mod, pow) to arithmetic operators: +, -, *, /, //, %, **.

**Parameters**

- **other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.
- **axis** [{0 or 'index', 1 or 'columns'}] Whether to compare by the index (0 or 'index') or columns (1 or 'columns'). For Series input, axis to match Series index on.
- **level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.
- **fill_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

**Returns**

DataFrame Result of the arithmetic operation.

**See also:**

- DataFrame.add Add DataFrames.
- DataFrame.sub Subtract DataFrames.
- DataFrame.mul Multiply DataFrames.
- DataFrame.div Divide DataFrames (float division).
- DataFrame.truediv Divide DataFrames (float division).
**DataFrame.floordiv**  Divide DataFrames (integer division).

**DataFrame.mod**  Calculate modulo (remainder after division).

**DataFrame.pow**  Calculate exponential power.

### Notes

Mismatched indices will be unioned together.

### Examples

```python
gf = pd.DataFrame({'angles': [0, 3, 4],
                   'degrees': [360, 180, 360]},
                   index=['circle', 'triangle', 'rectangle'])

gf
angles  degrees
---  ------
circle   0  360
triangle  3  180
rectangle 4  360
```

Add a scalar with operator version which return the same results.

```python
>>> df + 1
angles  degrees
---  ------
circle   1  361
triangle  4  181
rectangle 5  361
```

```python
>>> df.add(1)
angles  degrees
---  ------
circle   1  361
triangle  4  181
rectangle 5  361
```

Divide by constant with reverse version.

```python
>>> df.div(10)
angles  degrees
---  ------
circle  0.0  36.0
triangle 0.3  18.0
rectangle 0.4  36.0
```

```python
>>> df.rdiv(10)
angles  degrees
---  ------
circle inf 0.027778
triangle 3.333333 0.055556
rectangle 2.500000 0.027778
```

Subtract a list and Series by axis with operator version.

```python
>>> df - [1, 2]
angles  degrees
---  ------
circle  -1  358
triangle   2  178
rectangle   3  358
```
Multiply a DataFrame of different shape with operator version.

```python
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
                      index=['circle', 'triangle', 'rectangle'])
```

```plaintext
>>>
```

```python
>>> df * other
>>>
```

```plaintext
    angles degrees
  circle    0      NaN
  triangle  9      NaN
  rectangle 16      NaN
```

```python
>>> df.mul(other, fill_value=0)
>>>
```

```plaintext
    angles degrees
  circle    0       0.0
  triangle  9       0.0
  rectangle 16      0.0
```

Divide by a MultiIndex by level.

```python
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 5, 6],
                               'degrees': [360, 180, 360, 360, 720],
                               index=['A', 'A', 'A', 'B', 'B', 'B'],
                               ...
                               })
```

```plaintext
>>>
```

```python
>>> df_multindex
>>>
```

```plaintext
   angles degrees
A circle    0      360
triangle  3      180
rectangle  4      360
B square  4      360
pentagon  5      540
hexagon  6      720
```

```python
>>> df.div(df_multindex, level=1, fill_value=0)
>>>
```

```plaintext
   angles degrees
A circle    NaN      1.0
triangle  1.0      1.0
rectangle  1.0      1.0
```

(continues on next page)
pandas: powerful Python data analysis toolkit, Release 1.1.1

(continued from previous page)

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>B square</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>pentagon</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>hexagon</td>
<td>0.0</td>
<td>0.0</td>
</tr>
</tbody>
</table>

pandas.DataFrame.rolling

DataFrame.rolling(window, min_periods=None, center=False, win_type=None, on=None, axis=0, closed=None)

Provide rolling window calculations.

Parameters

- **window** [int, offset, or BaseIndexer subclass] Size of the moving window. This is the number of observations used for calculating the statistic. Each window will be a fixed size.

  If its an offset then this will be the time period of each window. Each window will be a variable sized based on the observations included in the time-period. This is only valid for datetimelike indexes.

  If a BaseIndexer subclass is passed, calculates the window boundaries based on the defined `get_window_bounds` method. Additional rolling keyword arguments, namely `min_periods`, `center`, and `closed` will be passed to `get_window_bounds`.

- **min_periods** [int, default None] Minimum number of observations in window required to have a value (otherwise result is NA). For a window that is specified by an offset, `min_periods` will default to 1. Otherwise, `min_periods` will default to the size of the window.

- **center** [bool, default False] Set the labels at the center of the window.

- **win_type** [str, default None] Provide a window type. If `None`, all points are evenly weighted. See the notes below for further information.

- **on** [str, optional] For a DataFrame, a datetime-like column or MultiIndex level on which to calculate the rolling window, rather than the DataFrame’s index. Provided integer column is ignored and excluded from result since an integer index is not used to calculate the rolling window.

- **axis** [int or str, default 0]

- **closed** [str, default None] Make the interval closed on the ‘right’, ‘left’, ‘both’ or ‘neither’ endpoints. For offset-based windows, it defaults to ‘right’. For fixed windows, defaults to ‘both’. Remaining cases not implemented for fixed windows.

Returns

A Window or Rolling sub-classed for the particular operation

See also:

- **expanding** Provides expanding transformations.
- **ewm** Provides exponential weighted functions.
Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

To learn more about the offsets & frequency strings, please see this link.

The recognized `win_types` are:

- `boxcar`
- `triang`
- `blackman`
- `hamming`
- `bartlett`
- `parzen`
- `bohman`
- `blackmanharris`
- `nuttall`
- `barthann`
- `kaiser` (needs parameter: `beta`)
- `gaussian` (needs parameter: `std`)
- `general_gaussian` (needs parameters: `power`, `width`)
- `slepian` (needs parameter: `width`)
- `exponential` (needs parameter: `tau`), center is set to `None`.

If `win_type=None` all points are evenly weighted. To learn more about different window types see `scipy.signal window functions`.

Certain window types require additional parameters to be passed. Please see the third example below on how to add the additional parameters.

Examples

```python
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]})
>>> df
   B
0  0.0
1  1.0
2  2.0
3  NaN
4  4.0
```

Rolling sum with a window length of 2, using the ‘triang’ window type.

```python
>>> df.rolling(2, win_type='triang').sum()
   B
0  NaN
1  0.5
2  1.5
```

Rolling sum with a window length of 2, using the ‘gaussian’ window type (note how we need to specify std).

```python
>>> df.rolling(2, win_type='gaussian').sum(std=3)
B
0  NaN
1  0.986207
2  2.958621
3  NaN
4  NaN
```

Rolling sum with a window length of 2, min_periods defaults to the window length.

```python
>>> df.rolling(2).sum()
B
0  NaN
1  1.0
2  3.0
3  NaN
4  NaN
```

Same as above, but explicitly set the min_periods

```python
>>> df.rolling(2, min_periods=1).sum()
B
0  0.0
1  1.0
2  3.0
3  2.0
4  4.0
```

Same as above, but with forward-looking windows

```python
>>> indexer = pd.api.indexers.FixedForwardWindowIndexer(window_size=2)
>>> df.rolling(window=indexer, min_periods=1).sum()
B
0  1.0
1  3.0
2  2.0
3  4.0
4  4.0
```

A ragged (meaning not-a-regular frequency), time-indexed DataFrame

```python
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]},
...                   index = [pd.Timestamp('20130101 09:00:00'),
...                     pd.Timestamp('20130101 09:00:02'),
...                     pd.Timestamp('20130101 09:00:03'),
...                     pd.Timestamp('20130101 09:00:05'),
...                     pd.Timestamp('20130101 09:00:06')])
>>> df
     B
0  0.0
1  1.0
2  3.0
3  2.0
4  4.0
```

(continues on next page)
Contrasting to an integer rolling window, this will roll a variable length window corresponding to the time period. The default for min_periods is 1.

```python
>>> df.rolling('2s').sum()
```

```
B
2013-01-01 09:00:00 0.0  
2013-01-01 09:00:02 1.0  
2013-01-01 09:00:03 2.0  
2013-01-01 09:00:05 NaN  
2013-01-01 09:00:06 4.0  
```

**pandas.DataFrame.round**

DataFrame.round(decimals=0, *args, **kwargs)

Round a DataFrame to a variable number of decimal places.

**Parameters**

- **decimals** [int, dict, Series] Number of decimal places to round each column to. If an int is given, round each column to the same number of places. Otherwise dict and Series round to variable numbers of places. Column names should be in the keys if decimals is a dict-like, or in the index if decimals is a Series. Any columns not included in decimals will be left as is. Elements of decimals which are not columns of the input will be ignored.
- **args** Additional keywords have no effect but might be accepted for compatibility with numpy.
- **kwargs** Additional keywords have no effect but might be accepted for compatibility with numpy.

**Returns**

DataFrame A DataFrame with the affected columns rounded to the specified number of decimal places.

**See also:**

- **numpy.around** Round a numpy array to the given number of decimals.
- **Series.round** Round a Series to the given number of decimals.
Examples

```python
>>> df = pd.DataFrame([(0.21, 0.32), (0.01, 0.67), (0.66, 0.03), (0.21, 0.18)],
... columns=['dogs', 'cats'])
>>> df
dogs  cats
0  0.21  0.32
1  0.01  0.67
2  0.66  0.03
3  0.21  0.18
By providing an integer each column is rounded to the same number of decimal places
>>> df.round(1)
dogs  cats
0  0.2  0.3
1  0.0  0.7
2  0.7  0.0
3  0.2  0.2
With a dict, the number of places for specific columns can be specified with the column names as key and the number of decimal places as value
>>> df.round({'dogs': 1, 'cats': 0})
dogs  cats
0  0.2  0.0
1  0.0  1.0
2  0.7  0.0
3  0.2  0.0
Using a Series, the number of places for specific columns can be specified with the column names as index and the number of decimal places as value
>>> decimals = pd.Series([0, 1], index=['cats', 'dogs'])
>>> df.round(decimals)
dogs  cats
0  0.2  0.0
1  0.0  1.0
2  0.7  0.0
3  0.2  0.0
```

pandas.DataFrame.rpow

DataFrame.rpow(other, axis='columns', level=None, fill_value=None)

Get Exponential power of dataframe and other, element-wise (binary operator rpow).

Equivalent to other ** dataframe, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, pow.

Among flexible wrappers (add, sub, mul, div, mod, pow) to arithmetic operators: +, -, *, //, %, **.

Parameters

- other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

- axis [(0 or ‘index’, 1 or ‘columns’)] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.
**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

**fill_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

**Returns**

**DataFrame** Result of the arithmetic operation.

**See also:**

- `DataFrame.add` Add DataFrames.
- `DataFrame.sub` Subtract DataFrames.
- `DataFrame.mul` Multiply DataFrames.
- `DataFrame.div` Divide DataFrames (float division).
- `DataFrame.truediv` Divide DataFrames (float division).
- `DataFrame.floordiv` Divide DataFrames (integer division).
- `DataFrame.mod` Calculate modulo (remainder after division).
- `DataFrame.pow` Calculate exponential power.

**Notes**

Mismatched indices will be unioned together.

**Examples**

```python
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                    index=['circle', 'triangle', 'rectangle'])
>>> df
   angles  degrees
circle     0      360
triangle   3      180
rectangle  4      360
```

Add a scalar with operator version which return the same results.

```python
>>> df + 1
   angles  degrees
circle   1      361
triangle 4      181
rectangle 5      361
```

```python
>>> df.add(1)
   angles  degrees
circle   1      361
triangle 4      181
rectangle 5      361
```
Divide by constant with reverse version.

```python
>>> df.div(10)
angles   degrees
 circle   0.0    36.0
 triangle 0.3    18.0
 rectangle 0.4    36.0
```

```python
>>> df.rdiv(10)
angles   degrees
 circle   inf    0.027778
 triangle 3.333333 0.055556
 rectangle 2.500000 0.027778
```

Subtract a list and Series by axis with operator version.

```python
>>> df - [1, 2]
angles   degrees
 circle  -1    358
 triangle 2    178
 rectangle 3    358
```

```python
>>> df.sub([1, 2], axis='columns')
angles   degrees
 circle  -1    358
 triangle 2    178
 rectangle 3    358
```

```python
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']), axis='index')
angles   degrees
 circle  -1    359
 triangle 2    179
 rectangle 3    359
```

Multiply a DataFrame of different shape with operator version.

```python
other = pd.DataFrame({'angles': [0, 3, 4],
                      index=['circle', 'triangle', 'rectangle'])
```

```python
>>> df * other
angles   degrees
 circle  0.0    NaN
 triangle 9.0    NaN
 rectangle 16.0   NaN
```

```python
>>> df.mul(other, fill_value=0)
angles   degrees
 circle  0.0    0.0
 triangle 0.0    0.0
 rectangle 0.0    0.0
```
Divide by a MultiIndex by level.

```python
def_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
                             'degrees': [360, 180, 360, 360, 540, 720],
                             'index': ['circle', 'triangle', 'rectangle', 'square', 'pentagon', 'hexagon']})
```

```python
>>> df_multindex
angles  degrees
A circle  0   360
triangle  3   180
rectangle 4   360
B square  4   360
pentagon  5   540
hexagon  6   720
```

```python
>>> df.div(df_multindex, level=1, fill_value=0)
```

```
angles  degrees
A circle  NaN  1.0
triangle  1.0  1.0
rectangle 1.0  1.0
B square  0.0  0.0
pentagon  0.0  0.0
hexagon  0.0  0.0
```

**pandas.DataFrame.rsub**

Dataframe.rsub(\(\text{other, axis='columns', level=None, fill\_value=None}\))

Get Subtraction of dataframe and other, element-wise (binary operator \(\text{rsub}\)).

Equivalent to \(\text{other} - \text{dataframe}\), but with support to substitute a fill\_value for missing data in one of the inputs. With reverse version, \(\text{sub}\).

Among flexible wrappers (\(\text{add, sub, mul, div, mod, pow}\)) to arithmetic operators: +, -, *, /, //, %, **.

**Parameters**

- \(\text{other}\) [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.
- \(\text{axis}\) [0 or ‘index’, 1 or ‘columns’] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.
- \(\text{level}\) [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.
- \(\text{fill\_value}\) [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

**Returns**

Dataframe Result of the arithmetic operation.

**See also:**

- **DataFrame.add** Add DataFrames.
- **DataFrame.sub** Subtract DataFrames.
DataFrame.mul  Multiply DataFrames.
DataFrame.div  Divide DataFrames (float division).
DataFrame.truediv  Divide DataFrames (float division).
DataFrame.floordiv  Divide DataFrames (integer division).
DataFrame.mod  Calculate modulo (remainder after division).
DataFrame.pow  Calculate exponential power.

Notes
Mismatched indices will be unioned together.

Examples

```python
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                     'degrees': [360, 180, 360]},
...                     index=['circle', 'triangle', 'rectangle'])
```

```text
angles  degrees
circle  0  360
triangle  3  180
rectangle  4  360
```

Add a scalar with operator version which return the same results.

```python
>>> df + 1
```

```text
angles  degrees
circle  1  361
triangle  4  181
rectangle  5  361
```

```python
>>> df.add(1)
```

```text
angles  degrees
circle  1  361
triangle  4  181
rectangle  5  361
```

Divide by constant with reverse version.

```python
>>> df.div(10)
```

```text
angles  degrees
circle  0.0  36.0
triangle  0.3  18.0
rectangle  0.4  36.0
```

```python
>>> df.rdiv(10)
```

```text
angles  degrees
circle  inf  0.027778
triangle  3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.
```python
>>> df = [1, 2]
   angles  degrees
circle   -1   358
triangle   2   178
circle   3   358

>>> df.sub([1, 2], axis='columns')
   angles  degrees
circle   -1   358
triangle   2   178
circle   3   358

>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']), axis='index')
   angles  degrees
circle   -1   359
triangle   2   179
circle   3   359

Multiply a DataFrame of different shape with operator version.

>>> other = pd.DataFrame({'angles': [0, 3, 4]}, index=['circle', 'triangle', 'rectangle'])

>>> df * other
   angles  degrees
circle   0  NaN
triangle   9  NaN
rectangle 16  NaN

>>> df.mul(other, fill_value=0)
   angles  degrees
circle   0   0.0
triangle   9   0.0
rectangle 16   0.0

Divide by a MultiIndex by level.

>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
   'degrees': [360, 180, 360, 360, 540, 720],
   index=[['A', 'A', 'A', 'B', 'B', 'B'],
          ['circle', 'triangle', 'rectangle', 'square', 'pentagon', 'hexagon']])

>>> df_multindex
   angles  degrees
    A circle   0  360
      triangle   3  180
         rectangle   4  360
    B square   4  360
       pentagon   5  540
          hexagon   6  720
```

3.4. DataFrame
pandas: powerful Python data analysis toolkit, Release 1.1.1

```python
>>> df.div(df_multindex, level=1, fill_value=0)

<table>
<thead>
<tr>
<th>angles</th>
<th>degrees</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>NaN</td>
</tr>
<tr>
<td>triangle</td>
<td>1.0</td>
</tr>
<tr>
<td>rectangle</td>
<td>1.0</td>
</tr>
<tr>
<td>B</td>
<td>0.0</td>
</tr>
<tr>
<td>square</td>
<td>0.0</td>
</tr>
<tr>
<td>pentagon</td>
<td>0.0</td>
</tr>
<tr>
<td>hexagon</td>
<td>0.0</td>
</tr>
</tbody>
</table>
```

**pandas.DataFrame.rtruediv**

`DataFrame.rtruediv(other, axis='columns', level=None, fill_value=None)`

Get Floating division of dataframe and other, element-wise (binary operator `rtruediv`).

Equivalent to `other / dataframe`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `truediv`.

Among flexible wrappers (`add`, `sub`, `mul`, `div`, `mod`, `pow`) to arithmetic operators: `+`, `-`, `*`, `/`, `//`, `%`, `**`.

**Parameters**

- `other` [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.
- `axis` [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.
- `level` [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.
- `fill_value` [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

**Returns**

`DataFrame` Result of the arithmetic operation.

**See also:**

- `DataFrame.add` Add DataFrames.
- `DataFrame.sub` Subtract DataFrames.
- `DataFrame.mul` Multiply DataFrames.
- `DataFrame.div` Divide DataFrames (float division).
- `DataFrame.truediv` Divide DataFrames (float division).
- `DataFrame.floordiv` Divide DataFrames (integer division).
- `DataFrame.mod` Calculate modulo (remainder after division).
- `DataFrame.pow` Calculate exponential power.
Notes

Mismatched indices will be unioned together.

Examples

```python
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360],
...                    index=['circle', 'triangle', 'rectangle'])
>>> df
   angles  degrees
circle    0       360
triangle   3       180
rectangle  4       360
```

Add a scalar with operator version which return the same results.

```python
>>> df + 1
   angles  degrees
circle    1       361
triangle   4       181
rectangle  5       361
```

```python
>>> df.add(1)
   angles  degrees
circle    1       361
triangle   4       181
rectangle  5       361
```

Divide by constant with reverse version.

```python
>>> df.div(10)
   angles  degrees
circle  0.0       36.0
triangle 0.3       18.0
rectangle 0.4       36.0
```

```python
>>> df.rdiv(10)
   angles  degrees
circle  inf      0.027778
triangle  3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```python
>>> df - [1, 2]
   angles  degrees
circle   -1       358
triangle    2       178
rectangle   3       358
```

```python
>>> df.sub([1, 2], axis='columns')
   angles  degrees
circle   -1       358
triangle    2       178
rectangle   3       358
```
Multiply a DataFrame of different shape with operator version.

```python
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
                        index=['circle', 'triangle', 'rectangle'])
>>> other
angles
circle 0
triangle 3
rectangle 4
```

```python
>>> df + other
   angles  degrees
circle   0      NaN
triangle 9      NaN
rectangle 16     NaN
```

```python
>>> df.mul(other, fill_value=0)
   angles  degrees
circle   0       0.0
triangle 9       0.0
rectangle 16     0.0
```

Divide by a MultiIndex by level.

```python
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
                               'degrees': [360, 180, 360, 360, 540, 720],
                               'index': [['A', 'A', 'A', 'B', 'B', 'B'],
                                         ['circle', 'triangle', 'rectangle',
                                          'square', 'pentagon', 'hexagon']])
>>> df_multindex
    angles  degrees
A circle 0       360
triangle 3       180
rectangle 4      360
B square 4       360
pentagon 5       540
hexagon 6       720
```

```python
>>> df.div(df_multindex, level=1, fill_value=0)
   angles  degrees
A circle   NaN       1.0
triangle  1.0       1.0
rectangle 1.0       1.0
B square   0.0       0.0
pentagon   0.0       0.0
hexagon   0.0       0.0
```
DataFrame.sample

DataFrame.sample(n=None, frac=None, replace=False, weights=None, random_state=None, axis=None)

Return a random sample of items from an axis of object.

You can use random_state for reproducibility.

Parameters

- **n** [int, optional] Number of items from axis to return. Cannot be used with frac. Default = 1 if frac = None.
- **frac** [float, optional] Fraction of axis items to return. Cannot be used with n.
- **replace** [bool, default False] Allow or disallow sampling of the same row more than once.
- **weights** [str or ndarray-like, optional] Default ‘None’ results in equal probability weighting. If passed a Series, will align with target object on index. Index values in weights not found in sampled object will be ignored and index values in sampled object not in weights will be assigned weights of zero. If called on a DataFrame, will accept the name of a column when axis = 0. Unless weights are a Series, weights must be same length as axis being sampled. If weights do not sum to 1, they will be normalized to sum to 1. Missing values in the weights column will be treated as zero. Infinite values not allowed.
- **random_state** [int, array-like, BitGenerator, np.random.RandomState, optional] If int, array-like, or BitGenerator (NumPy>=1.17), seed for random number generator If np.random.RandomState, use as numpy RandomState object.

Changed in version 1.1.0: array-like and BitGenerator (for NumPy>=1.17) object now passed to np.random.RandomState() as seed

- **axis** [[0 or ‘index’, 1 or ‘columns’, None], default None] Axis to sample. Accepts axis number or name. Default is stat axis for given data type (0 for Series and DataFrames).

Returns

- **Series or DataFrame** A new object of same type as caller containing n items randomly sampled from the caller object.

See also:

- **DataFrameGroupBy.sample** Generates random samples from each group of a DataFrame object.
- **SeriesGroupBy.sample** Generates random samples from each group of a Series object.
- **numpy.random.choice** Generates a random sample from a given 1-D numpy array.
Notes

If \( \text{frac} > 1 \), replacement should be set to True.

Examples

```python
>>> df = pd.DataFrame({
    'num_legs': [2, 4, 8, 0],
    'num_wings': [2, 0, 0, 0],
    'num_specimen_seen': [10, 2, 1, 8],
}, index=['falcon', 'dog', 'spider', 'fish'])

>>> df
  num_legs num_wings num_specimen_seen
falcon     2         2            10
dog        4         0             2
spider     8         0             1
fish       0         0             8

Extract 3 random elements from the Series df['num_legs']: Note that we use random_state to ensure the reproducibility of the examples.

```python
>>> df['num_legs'].sample(n=3, random_state=1)
fish
spider
falcon
Name: num_legs, dtype: int64
```

A random 50% sample of the DataFrame with replacement:

```python
>>> df.sample(frac=0.5, replace=True, random_state=1)
  num_legs num_wings num_specimen_seen
dog        4         0             2
fish       0         0             8

An upsample sample of the DataFrame with replacement: Note that replace parameter has to be True for frac parameter > 1.

```python
>>> df.sample(frac=2, replace=True, random_state=1)
  num_legs num_wings num_specimen_seen
dog        4         0             2
fish       0         0             8
falcon     2         2             10
falcon     2         2             10
fish       0         0             8
dog        4         0             2
fish       0         0             8
dog        4         0             2

Using a DataFrame column as weights. Rows with larger value in the num_specimen_seen column are more likely to be sampled.

```python
>>> df.sample(n=2, weights='num_specimen_seen', random_state=1)
  num_legs num_wings num_specimen_seen
falcon     2         2             10
fish       0         0             8
```
**pandas.DataFrame.select_dtypes**

`DataFrame.select_dtypes(include=None, exclude=None)`

Return a subset of the DataFrame’s columns based on the column dtypes.

**Parameters**

- `include, exclude` [scalar or list-like] A selection of dtypes or strings to be included/excluded. At least one of these parameters must be supplied.

**Returns**

- `DataFrame` The subset of the frame including the dtypes in `include` and excluding the dtypes in `exclude`.

**Raises**

- `ValueError` • If both of `include` and `exclude` are empty
  • If `include` and `exclude` have overlapping elements
  • If any kind of string dtype is passed in.

**See also:**

- `DataFrame.dtypes` Return Series with the data type of each column.

**Notes**

- To select all numeric types, use `np.number` or `'number'`
- To select strings you must use the `object` dtype, but note that this will return all `object` dtype columns
- See the numpy dtype hierarchy
- To select datetimes, use `np.datetime64`, `'datetime'` or `'datetime64'`
- To select timedeltas, use `np.timedelta64`, `'timedelta'` or `'timedelta64'`
- To select Pandas categorical dtypes, use `'category'`
- To select Pandas datetimetz dtypes, use `'datetimetz'` (new in 0.20.0) or `'datetime64[ns, tz]'`

**Examples**

```python
>>> df = pd.DataFrame({'a': [1, 2] * 3,
...                    'b': [True, False] * 3,
...                    'c': [1.0, 2.0] * 3})
>>> df
      a   b   c
0  1.0  True  1.0
1  2.0   False  2.0
2  1.0  True  1.0
3  2.0   False  2.0
4  1.0  True  1.0
5  2.0   False  2.0
```
```python
>>> df.select_dtypes(include='bool')
   b
0  True
1  False
2  True
3  False
4  True
5  False

>>> df.select_dtypes(include=['float64'])
   c
0  1.0
1  2.0
2  1.0
3  2.0
4  1.0
5  2.0

>>> df.select_dtypes(exclude=['int64'])
   b   c
0  True  1.0
1  False 2.0
2  True  1.0
3  False 2.0
4  True  1.0
5  False 2.0
```

**pandas.DataFrame.sem**

`DataFrame.sem(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`

Return unbiased standard error of the mean over requested axis. Normalized by N-1 by default. This can be changed using the ddof argument.

**Parameters**

- **axis** [{index (0), columns (1)}]
- **skipna** [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.
- **level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.
- **ddof** [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.
- **numeric_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**Returns**

Series or DataFrame (if level specified)
DataFrame.set_axis

DataFrame.set_axis(labels, axis=0, inplace=False)
Assign desired index to given axis.
Indexes for column or row labels can be changed by assigning a list-like or Index.

Parameters

labels [list-like, Index] The values for the new index.
axis [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis to update. The value 0 identifies the rows, and 1 identifies the columns.
inplace [bool, default False] Whether to return a new DataFrame instance.

Returns

renamed [DataFrame or None] An object of type DataFrame if inplace=False, None otherwise.

See also:

DataFrame.rename_axis Alter the name of the index or columns.

Examples

```python
>>> df = pd.DataFrame({"A": [1, 2, 3], "B": [4, 5, 6]})
```
Change the row labels.
```python
>>> df.set_axis(['a', 'b', 'c'], axis='index')
```
```
   A  B
  a 1 4
  b 2 5
  c 3 6
```
Change the column labels.
```python
>>> df.set_axis(['I', 'II'], axis='columns')
```
```
   I  II
  0 1 4
  1 2 5
  2 3 6
```
Now, update the labels inplace.
```python
>>> df.set_axis(['i', 'ii'], axis='columns', inplace=True)
```
```python
   i  ii
  0 1 4
  1 2 5
  2 3 6
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.DataFrame.set_index

DataFrame.set_index (keys, drop=True, append=False, inplace=False, verify_integrity=False)
Set the DataFrame index using existing columns.
Set the DataFrame index (row labels) using one or more existing columns or arrays (of the correct length). The index can replace the existing index or expand on it.

Parameters
- keys [label or array-like or list of labels_arrays] This parameter can be either a single column key, a single array of the same length as the calling DataFrame, or a list containing an arbitrary combination of column keys and arrays. Here, “array” encompasses Series, Index, np.ndarray, and instances of Iterator.
- drop [bool, default True] Delete columns to be used as the new index.
- append [bool, default False] Whether to append columns to existing index.
- verify_integrity [bool, default False] Check the new index for duplicates. Otherwise defer the check until necessary. Setting to False will improve the performance of this method.

Returns
- DataFrame Changed row labels.

See also:
- DataFrame.reset_index Opposite of set_index.
- DataFrame.reindex Change to new indices or expand indices.
- DataFrame.reindex_like Change to same indices as other DataFrame.

Examples

```python
>>> df = pd.DataFrame({'month': [1, 4, 7, 10],
... 'year': [2012, 2014, 2013, 2014],
... 'sale': [55, 40, 84, 31]})
```
```
month year sale
0 1 2012 55
1 4 2014 40
2 7 2013 84
3 10 2014 31
```
Set the index to become the ‘month’ column:

```python
>>> df.set_index('month')
```
```
year sale
month
1 2012 55
4 2014 40
7 2013 84
10 2014 31
```
Create a MultiIndex using columns ‘year’ and ‘month’:

```python
>>> df.set_index(['year', 'month'])
   sale
year  month
2012   1  55
2014   4  40
2013   7  84
2014  10  31
```

Create a MultiIndex using an Index and a column:

```python
>>> df.set_index([pd.Index([1, 2, 3, 4]), 'year'])
   sale
month
year
1  2012   1  55
2  2014   4  40
3  2013   7  84
4  2014  10  31
```

Create a MultiIndex using two Series:

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> df.set_index([s, s**2])
   sale
month  year
1  1  2012   55
2  4  2014   40
3  9  2013   84
4 16  2014   31
```

**pandas.DataFrame.shift**

DataFrame.shift (periods=1, freq=None, axis=0, fill_value=None)

Shift index by desired number of periods with an optional time freq.

When freq is not passed, shift the index without realigning the data. If freq is passed (in this case, the index must be date or datetime, or it will raise a `NotImplementedError`), the index will be increased using the periods and the freq. freq can be inferred when specified as “infer” as long as either freq or inferred_freq attribute is set in the index.

**Parameters**

- **periods** [int] Number of periods to shift. Can be positive or negative.
- **freq** [DateOffset, tseries.offsets, timedelta, or str, optional] Offset to use from the tseries module or time rule (e.g. ‘EOM’). If freq is specified then the index values are shifted but the data is not realigned. That is, use freq if you would like to extend the index when shifting and preserve the original data. If freq is specified as “infer” then it will be inferred from the freq or inferred_freq attributes of the index. If neither of those attributes exist, a ValueError is thrown
- **axis** [{0 or ‘index’, 1 or ‘columns’, None}, default None] Shift direction.
- **fill_value** [object, optional] The scalar value to use for newly introduced missing values. the default depends on the dtype of self. For numeric data, np.nan is used. For datetime, timedelta, or period data, etc. NaT is used. For extension dtypes, self.dtype.na_value is used.
Changed in version 1.1.0.

Returns

DataFrame  Copy of input object, shifted.

See also:

Index.shift  Shift values of Index.
DateTimeIndex.shift  Shift values of DatetimeIndex.
PeriodIndex.shift  Shift values of PeriodIndex.
tshift  Shift the time index, using the index’s frequency if available.

Examples

```python
>>> df = pd.DataFrame({"Col1": [10, 20, 15, 30, 45],
...                     "Col2": [13, 23, 18, 33, 48],
...                     "Col3": [17, 27, 22, 37, 52]},
...                    index=pd.date_range("2020-01-01", "2020-01-05")
)

>>> df
  Col1  Col2  Col3
2020-01-01  10   13   17
2020-01-02  20   23   27
2020-01-03  15   18   22
2020-01-04  30   33   37
2020-01-05  45   48   52

>>> df.shift(periods=3)
  Col1  Col2  Col3
2020-01-01  NaN  NaN  NaN
2020-01-02  NaN  NaN  NaN
2020-01-03  NaN  NaN  NaN
2020-01-04  10.0  13.0  17.0
2020-01-05  20.0  23.0  27.0

>>> df.shift(periods=1, axis="columns")
  Col1  Col2  Col3
2020-01-01  NaN  10.0  13.0
2020-01-02  NaN  20.0  23.0
2020-01-03  NaN  15.0  18.0
2020-01-04  NaN  30.0  33.0
2020-01-05  NaN  45.0  48.0

>>> df.shift(periods=3, fill_value=0)
  Col1  Col2  Col3
2020-01-01   0    0    0
2020-01-02   0    0    0
2020-01-03   0    0    0
2020-01-04  10   13   17
2020-01-05  20   23   27

>>> df.shift(periods=3, freq="D")
  Col1  Col2  Col3
2020-01-04   10   13   17
```

(continues on next page)
pandas: powerful Python data analysis toolkit, Release 1.1.1

(continued from previous page)

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>2020-01-05</td>
<td>20</td>
<td>23</td>
</tr>
<tr>
<td>2020-01-06</td>
<td>15</td>
<td>18</td>
</tr>
<tr>
<td>2020-01-07</td>
<td>30</td>
<td>33</td>
</tr>
<tr>
<td>2020-01-08</td>
<td>45</td>
<td>48</td>
</tr>
</tbody>
</table>

```python
>>> df.shift(periods=3, freq="infer")
   Col1 Col2 Col3
2020-01-04  10  13  17
2020-01-05  20  23  27
2020-01-06  15  18  22
2020-01-07  30  33  37
2020-01-08  45  48  52
```

### pandas.DataFrame.skew

DataFrame.skew(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

Return unbiased skew over requested axis.

Normalized by N-1.

**Parameters**

- **axis** ([index (0), columns (1)]{index (0), columns (1)}) Axis for the function to be applied on.
- **skipna** [bool, default True] Exclude NA/null values when computing the result.
- **level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.
- **numeric_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**kwargs Additional keyword arguments to be passed to the function.

**Returns**

Series or DataFrame (if level specified)

### pandas.DataFrame.slice_shift

DataFrame.slice_shift(periods=1, axis=0)

Equivalent to shift without copying data.

The shifted data will not include the dropped periods and the shifted axis will be smaller than the original.

**Parameters**

- **periods** [int] Number of periods to move, can be positive or negative.

**Returns**

- **shifted** [same type as caller]
Notes

While the `slice_shift` is faster than `shift`, you may pay for it later during alignment.

### pandas.DataFrame.sort_index

`DataFrame.sort_index(axis=0, level=None, ascending=True, inplace=False, kind='quicksort', na_position='last', sort_remaining=True, ignore_index=False, key=None)`

Sort object by labels (along an axis).

Returns a new DataFrame sorted by label if `inplace` argument is `False`, otherwise updates the original DataFrame and returns None.

**Parameters**

- **axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis along which to sort. The value 0 identifies the rows, and 1 identifies the columns.
- **level** [int or level name or list of ints or list of level names] If not None, sort on values in specified index level(s).
- **ascending** [bool or list of bools, default True] Sort ascending vs. descending. When the index is a MultiIndex the sort direction can be controlled for each level individually.
- **inplace** [bool, default False] If True, perform operation in-place.
- **kind** [{‘quicksort’, ‘mergesort’, ‘heapsort’}, default ‘quicksort’] Choice of sorting algorithm. See also `ndarray.np.sort` for more information. `mergesort` is the only stable algorithm. For DataFrames, this option is only applied when sorting on a single column or label.
- **na_position** [{‘first’, ‘last’}, default ‘last’] Puts NaNs at the beginning if `first`; `last` puts NaNs at the end. Not implemented for MultiIndex.
- **sort_remaining** [bool, default True] If True and sorting by level and index is multi-level, sort by other levels too (in order) after sorting by specified level.
- **ignore_index** [bool, default False] If True, the resulting axis will be labeled 0, 1, …, n - 1.

New in version 1.0.0.

- **key** [callable, optional] If not None, apply the key function to the index values before sorting. This is similar to the `key` argument in the built-in `sorted()` function, with the notable difference that this `key` function should be `vectorized`. It should expect an Index and return an Index of the same shape. For MultiIndex inputs, the key is applied per level.

New in version 1.1.0.

**Returns**

`DataFrame` The original DataFrame sorted by the labels.

**See also:**

- `Series.sort_index` Sort Series by the index.
- `DataFrame.sort_values` Sort DataFrame by the value.
- `Series.sort_values` Sort Series by the value.
pandas: powerful Python data analysis toolkit, Release 1.1.1

Examples
>>> df = pd.DataFrame([1, 2, 3, 4, 5], index=[100, 29, 234, 1, 150],
...
columns=['A'])
>>> df.sort_index()
A
1
4
29
2
100 1
150 5
234 3

By default, it sorts in ascending order, to sort in descending order, use ascending=False
>>> df.sort_index(ascending=False)
A
234 3
150 5
100 1
29
2
1
4

A key function can be specified which is applied to the index before sorting. For a MultiIndex this is
applied to each level separately.
>>> df = pd.DataFrame({"a": [1, 2, 3, 4]}, index=['A', 'b', 'C', 'd'])
>>> df.sort_index(key=lambda x: x.str.lower())
a
A 1
b 2
C 3
d 4

pandas.DataFrame.sort_values
DataFrame.sort_values(by, axis=0, ascending=True, inplace=False,
na_position='last', ignore_index=False, key=None)
Sort by the values along either axis.

kind='quicksort',

Parameters
by [str or list of str] Name or list of names to sort by.
• if axis is 0 or ‘index’ then by may contain index levels and/or column labels.
• if axis is 1 or ‘columns’ then by may contain column levels and/or index labels.
Changed in version 0.23.0: Allow specifying index or column level names.
axis [{0 or ‘index’, 1 or ‘columns’}, default 0] Axis to be sorted.
ascending [bool or list of bool, default True] Sort ascending vs. descending. Specify
list for multiple sort orders. If this is a list of bools, must match the length of the
by.
inplace [bool, default False] If True, perform operation in-place.
kind [{‘quicksort’, ‘mergesort’, ‘heapsort’}, default ‘quicksort’] Choice of sorting algorithm. See also ndarray.np.sort for more information. mergesort is the only

3.4. DataFrame

1681


stable algorithm. For DataFrames, this option is only applied when sorting on a single column or label.

**na_position** [{‘first’, ‘last’}, default ‘last’] Puts NaNs at the beginning if first; last puts NaNs at the end.

**ignore_index** [bool, default False] If True, the resulting axis will be labeled 0, 1, ..., n - 1.

New in version 1.0.0.

**key** [callable, optional] Apply the key function to the values before sorting. This is similar to the key argument in the builtin sorted() function, with the notable difference that this key function should be vectorized. It should expect a Series and return a Series with the same shape as the input. It will be applied to each column in by independently.

New in version 1.1.0.

**Returns**

- **DataFrame or None** DataFrame with sorted values if inplace=False, None otherwise.

**See also:**

- **DataFrame.sort_index** Sort a DataFrame by the index.
- **Series.sort_values** Similar method for a Series.

**Examples**

```python
>>> df = pd.DataFrame(
...     {'col1': ['A', 'A', 'B', np.nan, 'D', 'C'],
...      'col2': [2, 1, 9, 8, 7, 4],
...      'col3': [0, 1, 9, 4, 2, 3],
...      'col4': ['a', 'B', 'c', 'D', 'e', 'F']
...     })
>>> df
   col1 col2 col3 col4
0    A   2   0   a
1    A   1   1   B
2    B   9   9   c
3  NaN   8   4   D
4    D   7   2   e
5    C   4   3   F
```

Sort by col1

```python
>>> df.sort_values(by=['col1'])
   col1  col2  col3  col4
0    A   2    0    a
1    A   1    1    B
2    B   9    9    c
3  NaN   8    4    D
4    D   7    2    e
5    C   4    3    F
```

Sort by multiple columns

```python
>>> df.sort_values(by=['col1', 'col2'])
   col1  col2  col3  col4
0    A   2    0    a
1    A   1    1    B
2    B   9    9    c
3  NaN   8    4    D
4    D   7    2    e
5    C   4    3    F
```
```python
>>> df.sort_values(by=['col1', 'col2'])
col1  col2  col3  col4
0   A     2   0   a
1   A     1   1   B
2   B     9   9   c
3   C     4   3   F
4   D     7   2   e
5  NaN    8   4   D

Sort Descending

```python
>>> df.sort_values(by='col1', ascending=False)
col1  col2  col3  col4
0   A     2   0   a
1   A     1   1   B
2   B     9   9   c
3   C     4   3   F
4   D     7   2   e
5  NaN    8   4   D

Putting NAs first

```python
>>> df.sort_values(by='col1', ascending=False, na_position='first')
col1  col2  col3  col4
0   A     2   0   a
1   A     1   1   B
2   B     9   9   c
3  NaN    8   4   D
4   D     7   2   e
5   C     4   3   F

Sorting with a key function

```python
>>> df.sort_values(by='col4', key=lambda col: col.str.lower())
col1  col2  col3  col4
0   A     2   0   a
1   A     1   1   B
2   B     9   9   c
3  NaN    8   4   D
4   D     7   2   e
5   C     4   3   F
```
**pandas.DataFrame.sparse**

DataFrame.sparse()

DataFrame accessor for sparse data.
New in version 0.25.0.

**pandas.DataFrame.squeeze**

DataFrame.squeeze(axis=None)

Squeeze 1 dimensional axis objects into scalars.
Series or DataFrames with a single element are squeezed to a scalar. DataFrames with a single column or a single row are squeezed to a Series. Otherwise the object is unchanged.

This method is most useful when you don’t know if your object is a Series or DataFrame, but you do know it has just a single column. In that case you can safely call `squeeze` to ensure you have a Series.

**Parameters**

- **axis** ([0 or ‘index’, 1 or ‘columns’, None], default None) A specific axis to squeeze. By default, all length-1 axes are squeezed.

**Returns**

- [DataFrame, Series, or scalar] The projection after squeezing `axis` or all the axes.

**See also:**

- `Series.iloc` Integer-location based indexing for selecting scalars.
- `DataFrame.iloc` Integer-location based indexing for selecting Series.
- `Series.to_frame` Inverse of `DataFrame.squeeze` for a single-column DataFrame.

**Examples**

```python
>>> primes = pd.Series([2, 3, 5, 7])

Slicing might produce a Series with a single value:

```python
>>> even_primes = primes[primes % 2 == 0]
```{.ipy}

```python
>>> even_primes
0 2
dtype: int64
```{.ipy}

```python
>>> even_primes.squeeze()
2
```{.ipy}

Squeezing objects with more than one value in every axis does nothing:

```python
>>> odd_primes = primes[primes % 2 == 1]
```{.ipy}

```python
>>> odd_primes
0 3
1 5
2 7
dtype: int64
```{.ipy}
Squeezing is even more effective when used with DataFrames.

```python
>>> df = pd.DataFrame([[1, 2], [3, 4]], columns=['a', 'b'])
>>> df
   a  b
0  1  2
1  3  4
```

Slicing a single column will produce a DataFrame with the columns having only one value:

```python
>>> df_a = df[['a']]
>>> df_a
   a
0  1
1  3
```

So the columns can be squeezed down, resulting in a Series:

```python
>>> df_a.squeeze('columns')
0  1
1  3
Name: a, dtype: int64
```

Slicing a single row from a single column will produce a single scalar DataFrame:

```python
>>> df_0a = df.loc[df.index < 1, ['a']]
>>> df_0a
   a
0  1
```

Squeezing the rows produces a single scalar Series:

```python
>>> df_0a.squeeze('rows')
a  1
Name: 0, dtype: int64
```

Squeezing all axes will project directly into a scalar:

```python
>>> df_0a.squeeze()
1
```
pandas.DataFrame.stack

`DataFrame.stack(level=-1, dropna=True)`

Stack the prescribed level(s) from columns to index.

Return a reshaped DataFrame or Series having a multi-level index with one or more new inner-most levels compared to the current DataFrame. The new inner-most levels are created by pivoting the columns of the current dataframe:

- if the columns have a single level, the output is a Series;
- if the columns have multiple levels, the new index level(s) is (are) taken from the prescribed level(s) and the output is a DataFrame.

**Parameters**

- `level` [int, str, list, default -1] Level(s) to stack from the column axis onto the index axis, defined as one index or label, or a list of indices or labels.
- `dropna` [bool, default True] Whether to drop rows in the resulting Frame/Series with missing values. Stacking a column level onto the index axis can create combinations of index and column values that are missing from the original dataframe. See Examples section.

**Returns**

- `DataFrame or Series` Stacked dataframe or series.

See also:

- `DataFrame.unstack` Unstack prescribed level(s) from index axis onto column axis.
- `DataFrame.pivot` Reshape dataframe from long format to wide format.
- `DataFrame.pivot_table` Create a spreadsheet-style pivot table as a DataFrame.

**Notes**

The function is named by analogy with a collection of books being reorganized from being side by side on a horizontal position (the columns of the dataframe) to being stacked vertically on top of each other (in the index of the dataframe).

**Examples**

**Single level columns**

```python
>>> df_single_level_cols = pd.DataFrame([[0, 1], [2, 3]],
                           index=['cat', 'dog'],
                           columns=['weight', 'height'])
```

Stacking a dataframe with a single level column axis returns a Series:

```python
>>> df_single_level_cols
              weight  height
          cat  0      1
          dog  2      3
```

```python
>>> df_single_level_cols.stack()  
```

(continues on next page)
Multi level columns: simple case

```python
>>> multicoll = pd.MultiIndex.from_tuples([('weight', 'kg'),
                                          ('height', 'm')])
>>> df_multi_level_cols2 = pd.DataFrame([[1.0, 2.0], [3.0, 4.0]],
                                       index=['cat', 'dog'],
                                       columns=multicoll)
```

Stacking a dataframe with a multi-level column axis:

```python
>>> df_multi_level_cols1
weight
kg pounds
cat 1 2
dog 2 4
```

```python
>>> df_multi_level_cols1.stack()
height weight
cat kg NaN 1.0
m 2.0 NaN
dog kg NaN 3.0
m 4.0 NaN
```

Missing values

```python
>>> multicoll2 = pd.MultiIndex.from_tuples([('weight', 'kg'),
                                          ('height', 'm'))
>>> df_multi_level_cols2 = pd.DataFrame([[1.0, 2.0], [3.0, 4.0]],
                                       index=['cat', 'dog'],
                                       columns=multicoll2)
```

It is common to have missing values when stacking a dataframe with multi-level columns, as the stacked dataframe typically has more values than the original dataframe. Missing values are filled with NaNs:

```python
>>> df_multi_level_cols2
weight height
kg m
cat 1.0 2.0
dog 3.0 4.0
```

```python
>>> df_multi_level_cols2.stack()
height weight
cat kg NaN 1.0
m 2.0 NaN
dog kg NaN 3.0
m 4.0 NaN
```

Prescribing the level(s) to be stacked

The first parameter controls which level or levels are stacked:

```python
>>> df_multi_level_cols2.stack(0)
kg m
```
cat height NaN 2.0  
weight 1.0 NaN  
dog height NaN 4.0  
weight 3.0 NaN  

>>> df_multi_level_cols2.stack([0, 1])  
cat height m 2.0  
weight kg 1.0  
dog height m 4.0  
weight kg 3.0  
dtype: float64

Dropping missing values

>>> df_multi_level_cols3 = pd.DataFrame([[None, 1.0], [2.0, 3.0]],  
index=['cat', 'dog'],  
columns=multicol2)

Note that rows where all values are missing are dropped by default but this behaviour can be controlled via the dropna keyword parameter:

>>> df_multi_level_cols3  
weight height  
kg m  
cat NaN 1.0  
dog 2.0 3.0  

>>> df_multi_level_cols3.stack(dropna=False)  
height weight  
kg NaN NaN  
m NaN 1.0  
dog kg NaN 2.0  
m NaN 3.0  

>>> df_multi_level_cols3.stack(dropna=True)  
height weight  
kg NaN NaN  
m NaN 1.0  
dog kg NaN 2.0  
m NaN 3.0

pandas.DataFrame.std

DataFrame.std((axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs))

Return sample standard deviation over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters

axis      [[index (0), columns (1)]]

skipna   [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

level    [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

ddof     [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is \( N - ddof \), where \( N \) represents the number of elements.
**numeric_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**Returns**
Series or DataFrame (if level specified)

**pandas.DataFrame.sub**

DataFrame.sub (other, axis='columns', level=None, fill_value=None)  
Get Subtraction of dataframe and other, element-wise (binary operator sub).

Equivalent to dataframe - other, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, rsub.

Among flexible wrappers (add, sub, mul, div, mod, pow) to arithmetic operators: +, -, *, /, //, %, **.

**Parameters**

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [[0 or ‘index’, 1 or ‘columns’]] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

**Returns**

DataFrame Result of the arithmetic operation.

**See also:**

DataFrame.add Add DataFrames.

DataFrame.sub Subtract DataFrames.

DataFrame.mul Multiply DataFrames.

DataFrame.div Divide DataFrames (float division).

DataFrame.truediv Divide DataFrames (float division).

DataFrame.floordiv Divide DataFrames (integer division).

DataFrame.mod Calculate modulo (remainder after division).

DataFrame.pow Calculate exponential power.
Notes

Mismatched indices will be unioned together.

Examples

```python
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                     'degrees': [360, 180, 360],
...                     index=['circle', 'triangle', 'rectangle'])
>>> df
   angles  degrees
circle    0      360
triangle   3      180
rectangle  4      360

Add a scalar with operator version which return the same results.

```python
>>> df + 1
   angles  degrees
circle    1      361
triangle   4      181
rectangle  5      361
```  
```python
>>> df.add(1)
   angles  degrees
circle    1      361
triangle   4      181
rectangle  5      361
```

Divide by constant with reverse version.

```python
>>> df.div(10)
   angles  degrees
circle   0.0     36.0
triangle 0.3     18.0
rectangle 0.4    36.0
```  
```python
>>> df.rdiv(10)
   angles  degrees
circle   inf    0.027778
triangle 3.333333 0.055556
rectangle 2.500000 0.027778
```

Subtract a list and Series by axis with operator version.

```python
>>> df - [1, 2]
   angles  degrees
circle   -1     358
triangle   2     178
rectangle  3     358
```  
```python
>>> df.sub([1, 2], axis='columns')
   angles  degrees
circle   -1     358
triangle   2     178
rectangle  3     358
```
Multiply a DataFrame of different shape with operator version.

```python
>>> other = pd.DataFrame({
    'angles': [0, 3, 4],
    'degrees': [360, 360, 540, 720]
},
index=['circle', 'triangle', 'rectangle', 'square', 'pentagon', 'hexagon'])
>>> df_multindex
  angles  degrees
A circle    0      360
triangle    3      360
rectangle   4      360
B square    4      360
pentagon    5      540
hexagon     6      720

>>> df_multindex.div(df_multindex, level=1, fill_value=0)
  angles  degrees
A circle      NaN      1.0
triangle     1.0      1.0
rectangle   1.0      1.0
B square     0.0      0.0
pentagon    0.0      0.0
hexagon     0.0      0.0
```

Divide by a MultiIndex by level.

```python
>>> df = df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']), axis='index')

<table>
<thead>
<tr>
<th>angles</th>
<th>degrees</th>
</tr>
</thead>
<tbody>
<tr>
<td>circle</td>
<td>-1</td>
</tr>
<tr>
<td>triangle</td>
<td>2</td>
</tr>
<tr>
<td>rectangle</td>
<td>3</td>
</tr>
</tbody>
</table>

>>> df
  angles  degrees
circle    -1      359
triangle    2      179
rectangle   3      359

>>> df * other
  angles  degrees
circle    0      NaN
triangle    9      NaN
rectangle  16      NaN

>>> df.mul(other, fill_value=0)
  angles  degrees
circle    0      0.0
triangle    9      0.0
rectangle  16      0.0
```

```python
>>> df_multindex.div(df_multindex, level=1, fill_value=0)
  angles  degrees
A circle      NaN      1.0
triangle     1.0      1.0
rectangle   1.0      1.0
B square     0.0      0.0
pentagon    0.0      0.0
hexagon     0.0      0.0
```
pandas.DataFrame.subtract

**DataFrame.subtract**(other, axis='columns', level=None, fill_value=None)

Get Subtraction of dataframe and other, element-wise (binary operator `sub`).

Equivalent to `dataframe - other`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `rsub`.

Among flexible wrappers (`add`, `sub`, `mul`, `div`, `mod`, `pow`) to arithmetic operators: `+`, `-`, `*`, `/`, `//`, `%`, `**`

**Parameters**

- **other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.
- **axis** [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.
- **level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.
- **fill_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

**Returns**

**DataFrame** Result of the arithmetic operation.

**See also:**

- `DataFrame.add` Add DataFrames.
- `DataFrame.sub` Subtract DataFrames.
- `DataFrame.mul` Multiply DataFrames.
- `DataFrame.div` Divide DataFrames (float division).
- `DataFrame.truediv` Divide DataFrames (float division).
- `DataFrame.floordiv` Divide DataFrames (integer division).
- `DataFrame.mod` Calculate modulo (remainder after division).
- `DataFrame.pow` Calculate exponential power.

**Notes**

Mismatched indices will be unioned together.
Examples

```python
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360]},
...                   index=['circle', 'triangle', 'rectangle'])
>>> df

    angles  degrees
circle     0      360
triangle   3      180
rectangle  4      360
```

Add a scalar with operator version which return the same results.

```python
>>> df + 1

    angles  degrees
circle     1      361
triangle   4      181
rectangle  5      361
```

```python
>>> df.add(1)

    angles  degrees
circle     1      361
triangle   4      181
rectangle  5      361
```

Divide by constant with reverse version.

```python
>>> df.div(10)

    angles  degrees
circle   0.0     36.0
triangle 0.3     18.0
rectangle 0.4    36.0
```

```python
>>> df.rdiv(10)

    angles   degrees
circle  inf    0.027778
triangle 3.333333  0.055556
rectangle 2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```python
>>> df - [1, 2]

    angles  degrees
circle   -1      358
triangle   2      178
rectangle  3      358
```

```python
>>> df.sub([1, 2], axis='columns')

    angles  degrees
circle   -1      358
triangle   2      178
rectangle  3      358
```

```python
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']), axis='index')

    angles  degrees
```

(continues on next page)
Multiply a DataFrame of different shape with operator version.

```python
other = pd.DataFrame({'angles': [0, 3, 4],
                     'index': ['circle', 'triangle', 'rectangle'])
other
```

```
angles
circle 0
triangle 3
rectangle 4
```

```python
df * other
```

```
angles  degrees
circle    0 NaN
triangle   9 NaN
rectangle 16 NaN
```

```python
df.mul(other, fill_value=0)
```

```
angles  degrees
circle    0  0.0
triangle   9  0.0
rectangle 16  0.0
```

Divide by a MultiIndex by level.

```python
df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
                             'degrees': [360, 180, 360, 360, 540, 720],
                             'index': ['A', 'A', 'A', 'B', 'B', 'B'],
                             ['circle', 'triangle', 'rectangle',
                              'square', 'pentagon', 'hexagon'])
```

```python
df_multindex
```

```
angles  degrees
A circle  0  360
triangle  3  180
rectangle 4  360
B square  4  360
pentagon  5  540
hexagon  6  720
```

```python
df.div(df_multindex, level=1, fill_value=0)
```

```
angles  degrees
A circle NaN  1.0
triangle  1.0  1.0
rectangle 1.0  1.0
B square  0.0  0.0
pentagon  0.0  0.0
hexagon  0.0  0.0
```
DataFrame\.sum\(\text{axis}=\text{None}, \text{skipna}=\text{None}, \text{level}=\text{None}, \text{numeric_only}=\text{None}, \text{min_count}=0, **\text{kwargs}\)\\
Return the sum of the values for the requested axis.\\
This is equivalent to the method \text{numpy}.sum.\\

**Parameters**\\
\begin{itemize}\\
\item \textbf{axis} [[index (0), columns (1)]] Axis for the function to be applied on.\\
\item \textbf{skipna} [bool, default True] Exclude NA/null values when computing the result.\\
\item \textbf{level} [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.\\
\item \textbf{numeric_only} [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.\\
\item \textbf{min_count} [int, default 0] The required number of valid values to perform the operation. If fewer than \text{min_count} non-NA values are present the result will be NA.\\
\end{itemize}\\
New in version 0.22.0: Added with the default being 0. This means the sum of an all-NA or empty Series is 0, and the product of an all-NA or empty Series is 1.\\

**\textbf{kwargs}** Additional keyword arguments to be passed to the function.\\

**Returns**\\
Series or DataFrame (if level specified)\\

**See also:**\\
\begin{itemize}\\
\item \textit{Series}.sum Return the sum.\\
\item \textit{Series}.min Return the minimum.\\
\item \textit{Series}.max Return the maximum.\\
\item \textit{Series}.idxmin Return the index of the minimum.\\
\item \textit{Series}.idxmax Return the index of the maximum.\\
\item \textit{DataFrame}.sum Return the sum over the requested axis.\\
\item \textit{DataFrame}.min Return the minimum over the requested axis.\\
\item \textit{DataFrame}.max Return the maximum over the requested axis.\\
\item \textit{DataFrame}.idxmin Return the index of the minimum over the requested axis.\\
\item \textit{DataFrame}.idxmax Return the index of the maximum over the requested axis.\\
\end{itemize}
Examples

```python
>>> idx = pd.MultiIndex.from_arrays([['warm', 'warm', 'cold', 'cold'], ...
... ['dog', 'falcon', 'fish', 'spider']], ...
... names=['blooded', 'animal'])
>>> s = pd.Series([4, 2, 0, 8], name='legs', index=idx)
>>> s
 blooded  animal
  warm  dog  4
         falcon 2
  cold  fish  0
         spider 8
Name: legs, dtype: int64

>>> s.sum()
14

Sum using level names, as well as indices.

```python
>>> s.sum(level='blooded')
 blooded
  warm  6
  cold  8
Name: legs, dtype: int64

>>> s.sum(level=0)
 blooded
  warm  6
  cold  8
Name: legs, dtype: int64
```

By default, the sum of an empty or all-NA Series is 0.

```python
>>> pd.Series([]).sum()  # min_count=0 is the default
0.0
```

This can be controlled with the `min_count` parameter. For example, if you’d like the sum of an empty series to be NaN, pass `min_count=1`.

```python
>>> pd.Series([]).sum(min_count=1)
nan
```

Thanks to the `skipna` parameter, `min_count` handles all-NA and empty series identically.

```python
>>> pd.Series([np.nan]).sum()
0.0

>>> pd.Series([np.nan]).sum(min_count=1)
nan
```
**pandas.DataFrame.swapaxes**

DataFrame.swapaxes(axis1, axis2, copy=True)

Interchange axes and swap values axes appropriately.

Returns

y [same as input]

**pandas.DataFrame.swaplevel**

DataFrame.swaplevel(i=-2, j=-1, axis=0)

Swap levels i and j in a MultiIndex on a particular axis.

Parameters

i, j [int or str] Levels of the indices to be swapped. Can pass level name as string.

axis [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis to swap levels on. 0 or ‘index’
for row-wise, 1 or ‘columns’ for column-wise.

Returns

DataFrame

**pandas.DataFrame.tail**

DataFrame.tail(n=5)

Return the last n rows.

This function returns last n rows from the object based on position. It is useful for quickly verifying data,
for example, after sorting or appending rows.

For negative values of n, this function returns all rows except the first n rows, equivalent to df[n:].

Parameters

n [int, default 5] Number of rows to select.

Returns

type of caller The last n rows of the caller object.

See also:

DataFrame.head The first n rows of the caller object.

**Examples**

```python
>>> df = pd.DataFrame({'animal': ['alligator', 'bee', 'falcon', 'lion',
...                            'monkey', 'parrot', 'shark', 'whale', 'zebra']})
>>> df
animal
0  alligator
1      bee
2     falcon
3      lion
4  monkey
```

(continues on next page)
5 parrot
6 shark
7 whale
8 zebra

Viewing the last 5 lines

```python
>>> df.tail()
   animal
4  monkey
5  parrot
6    shark
7  whale
8  zebra
```

Viewing the last $n$ lines (three in this case)

```python
>>> df.tail(3)
   animal
6    shark
7  whale
8  zebra
```

For negative values of $n$

```python
>>> df.tail(-3)
   animal
3    lion
4  monkey
5  parrot
6    shark
7  whale
8  zebra
```

pandas.DataFrame.take

Dataframe.take(indices, axis=0, is_copy=None, **kwargs)

Return the elements in the given positional indices along an axis.

This means that we are not indexing according to actual values in the index attribute of the object. We are indexing according to the actual position of the element in the object.

**Parameters**

- **indices** [array-like] An array of ints indicating which positions to take.
- **axis** [[0 or ‘index’, 1 or ‘columns’, None], default 0] The axis on which to select elements. 0 means that we are selecting rows, 1 means that we are selecting columns.
- **is_copy** [bool] Before pandas 1.0, is_copy=False can be specified to ensure that the return value is an actual copy. Starting with pandas 1.0, take always returns a copy, and the keyword is therefore deprecated. Deprecated since version 1.0.0.

**Returns**

For compatibility with numpy.take(). Has no effect on the output.
taken [same type as caller] An array-like containing the elements taken from the object.

See also:

DataFrame.loc Select a subset of a DataFrame by labels.

DataFrame.iloc Select a subset of a DataFrame by positions.

numpy.take Take elements from an array along an axis.

Examples

```python
def df = pd.DataFrame({'falcon': 'bird', 389.0},
... ('parrot', 'bird', 24.0),
... ('lion', 'mammal', 80.5),
... ('monkey', 'mammal', np.nan),
... columns=['name', 'class', 'max_speed'],
... index=[0, 2, 3, 1])
def take([0, 3])
    name class max_speed
0 falcon bird 389.0
2 parrot bird 24.0
3 lion mammal 80.5
1 monkey mammal NaN
def.take([1, 2], axis=1)
class max_speed
0  bird 389.0
2  bird 24.0
3 mammal 80.5
1 mammal NaN
def.take([-1, -2])
      name   class  max_speed
1      monkey mammal  NaN
3      lion     mammal  80.5
```

Take elements at positions 0 and 3 along the axis 0 (default).

Note how the actual indices selected (0 and 1) do not correspond to our selected indices 0 and 3. That's because we are selecting the 0th and 3rd rows, not rows whose indices equal 0 and 3.

We may take elements using negative integers for positive indices, starting from the end of the object, just like with Python lists.
**pandas.DataFrame.to_clipboard**

`DataFrame.to_clipboard(excel=True, sep=None, **kwargs)`

Copy object to the system clipboard.

Write a text representation of object to the system clipboard. This can be pasted into Excel, for example.

**Parameters**

- **excel** [bool, default True] Produce output in a csv format for easy pasting into excel.
  - True, use the provided separator for csv pasting.
  - False, write a string representation of the object to the clipboard.
- **sep** [str, default ' \t '] Field delimiter.
- **kwargs** These parameters will be passed to DataFrame.to_csv.

**See also:**

- `DataFrame.to_csv` Write a DataFrame to a comma-separated values (csv) file.
- `read_clipboard` Read text from clipboard and pass to read_table.

**Notes**

Requirements for your platform.

- Linux: xclip, or xsel (with PyQt4 modules)
- Windows: none
- OS X: none

**Examples**

Copy the contents of a DataFrame to the clipboard.

```python
>>> df = pd.DataFrame([[1, 2, 3], [4, 5, 6]], columns=['A', 'B', 'C'])
```

```python
>>> df.to_clipboard(sep=',')
... # Wrote the following to the system clipboard:
... # ,A,B,C
... # 0,1,2,3
... # 1,4,5,6
```

We can omit the index by passing the keyword `index` and setting it to false.

```python
>>> df.to_clipboard(sep=',', index=False)
... # Wrote the following to the system clipboard:
... # A,B,C
... # 1,2,3
... # 4,5,6
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.DataFrame.to_csv
DataFrame.to_csv(path_or_buf=None, sep=',', na_rep='', float_format=None, columns=None,
header=True, index=True, index_label=None, mode='w', encoding=None,
compression='infer', quoting=None, quotechar='"', line_terminator=None,
chunksize=None, date_format=None, doublequote=True, escapechar=None,
decimal='.', errors='strict')
Write object to a comma-separated values (csv) file.
Changed in version 0.24.0: The order of arguments for Series was changed.
Parameters
path_or_buf [str or file handle, default None] File path or object, if None is provided
the result is returned as a string. If a file object is passed it should be opened with
newline=”, disabling universal newlines.
Changed in version 0.24.0: Was previously named “path” for Series.
sep [str, default ‘,’] String of length 1. Field delimiter for the output file.
na_rep [str, default ‘’] Missing data representation.
float_format [str, default None] Format string for floating point numbers.
columns [sequence, optional] Columns to write.
header [bool or list of str, default True] Write out the column names. If a list of strings
is given it is assumed to be aliases for the column names.
Changed in version 0.24.0: Previously defaulted to False for Series.
index [bool, default True] Write row names (index).
index_label [str or sequence, or False, default None] Column label for index column(s)
if desired. If None is given, and header and index are True, then the index names
are used. A sequence should be given if the object uses MultiIndex. If False do not
print fields for index names. Use index_label=False for easier importing in R.
mode [str] Python write mode, default ‘w’.
encoding [str, optional] A string representing the encoding to use in the output file,
defaults to ‘utf-8’.
compression [str or dict, default ‘infer’] If str, represents compression mode. If dict,
value at ‘method’ is the compression mode. Compression mode may be any of the
following possible values: {‘infer’, ‘gzip’, ‘bz2’, ‘zip’, ‘xz’, None}. If compression mode is ‘infer’ and path_or_buf is path-like, then detect compression mode
from the following extensions: ‘.gz’, ‘.bz2’, ‘.zip’ or ‘.xz’. (otherwise no compression). If dict given and mode is one of {‘zip’, ‘gzip’, ‘bz2’}, or inferred as one of
the above, other entries passed as additional compression options.
Changed in version 1.0.0: May now be a dict with key ‘method’ as compression
mode and other entries as additional compression options if compression mode is
‘zip’.
Changed in version 1.1.0: Passing compression options as keys in dict is supported
for compression modes ‘gzip’ and ‘bz2’ as well as ‘zip’.
quoting [optional constant from csv module] Defaults to csv.QUOTE_MINIMAL.
If you have set a float_format then floats are converted to strings and thus
csv.QUOTE_NONNUMERIC will treat them as non-numeric.

3.4. DataFrame

1701


quotechar [str, default ‘”’] String of length 1. Character used to quote fields.

line_terminator [str, optional] The newline character or character sequence to use in
the output file. Defaults to os.linesep, which depends on the OS in which this
method is called (‘n’ for linux, ‘rn’ for Windows, i.e.).

Changed in version 0.24.0.

chunksize [int or None] Rows to write at a time.

date_format [str, default None] Format string for datetime objects.

doublequote [bool, default True] Control quoting of quotechar inside a field.

escapechar [str, default None] String of length 1. Character used to escape sep and
quotechar when appropriate.

decimal [str, default ‘.’] Character recognized as decimal separator. E.g. use ‘,’ for
European data.

doubleslashter [str, default ‘strict’] Specifies how encoding and decoding errors are to be han-
dled. See the errors argument for open() for a full list of options.

New in version 1.1.0.

Returns

None or str If path_or_buf is None, returns the resulting csv format as a string. Otherwise returns None.

See also:

read_csv Load a CSV file into a DataFrame.

to_excel Write DataFrame to an Excel file.

Examples

```python
>>> df = pd.DataFrame({
    'name': ['Raphael', 'Donatello'],
    'mask': ['red', 'purple'],
    'weapon': ['sai', 'bo staff']
})

>>> df.to_csv(index=False)
'name,mask,weapon
Raphael,red,sai
Donatello,purple,bo staff
'

Create ‘out.zip’ containing ‘out.csv’

```python
>>> compression_opts = dict(method='zip',
... archive_name='out.csv')

>>> df.to_csv('out.zip', index=False,
... compression=compression_opts)
```
pandas.DataFrame.to_dict

DataFrame.to_dict (orient='dict', into=<class 'dict'>)  
Convert the DataFrame to a dictionary.

The type of the key-value pairs can be customized with the parameters (see below).

Parameters

- **orient** [str {'dict', 'list', 'series', 'split', 'records', 'index'}] Determines the type of the values of the dictionary.
  - 'dict' (default): dict like {column -> {index -> value}}
  - 'list': dict like {column -> [values]}
  - 'series': dict like {column -> Series(values)}
  - 'split': dict like {'index' -> [index], 'columns' -> [columns], 'data' -> [values]}
  - 'records': list like [{column -> value}, ..., {column -> value}]
  - 'index': dict like {index -> {column -> value}}

Abbreviations are allowed. *s* indicates *series* and *sp* indicates *split*.

- **into** [class, default dict] The collections.abc.Mapping subclass used for all Mappings in the return value. Can be the actual class or an empty instance of the mapping type you want. If you want a collections.defaultdict, you must pass it initialized.

Returns

- **dict, list or collections.abc.Mapping** Return a collections.abc.Mapping object representing the DataFrame. The resulting transformation depends on the *orient* parameter.

See also:

- **DataFrame.from_dict** Create a DataFrame from a dictionary.
- **DataFrame.to_json** Convert a DataFrame to JSON format.

Examples

```python
>>> df = pd.DataFrame({'col1': [1, 2],
...                    'col2': [0.5, 0.75]},
...                   index=['row1', 'row2'])
>>> df
   col1  col2
row1   1   0.5
row2   2   0.75
>>> df.to_dict()
{'col1': {'row1': 1, 'row2': 2}, 'col2': {'row1': 0.5, 'row2': 0.75}}
```

You can specify the return orientation.

```python
>>> df.to_dict('series')
{'col1': row1 1
  row2 2
Name: col1, dtype: int64,
```

(continues on next page)
>>> df.to_dict('split')
{'index': ['row1', 'row2'], 'columns': ['col1', 'col2'],
'data': [[1, 0.5], [2, 0.75]]}

>>> df.to_dict('records')
[['col1': 1, 'col2': 0.5], ['col1': 2, 'col2': 0.75]]

>>> df.to_dict('index')
{'row1': {'col1': 1, 'col2': 0.5}, 'row2': {'col1': 2, 'col2': 0.75}}

You can also specify the mapping type.

>>> from collections import OrderedDict, defaultdict

>>> df.to_dict('records', into=OrderedDict)
OrderedDict([('col1', OrderedDict([('row1', 1), ('row2', 2)])),
('col2', OrderedDict([('row1', 0.5), ('row2', 0.75)]))])

If you want a defaultdict, you need to initialize it:

>>> dd = defaultdict(list)

>>> df.to_dict('records', into=dd)
[defaultdict(<class 'list'>, {'col1': 1, 'col2': 0.5}),
defaultdict(<class 'list'>, {'col1': 2, 'col2': 0.75})]

```
pandas.DataFrame.to_excel
```

DataFrame.to_excel(excel_writer, sheet_name='Sheet1', na_rep='', float_format=None, columns=None, header=True, index_label=None, startrow=0, startcol=0, engine=None, merge_cells=True, encoding=None, inf_rep='inf', verbose=True, freeze_panes=None)

Write object to an Excel sheet.

To write a single object to an Excel .xlsx file it is only necessary to specify a target file name. To write to multiple sheets it is necessary to create an ExcelWriter object with a target file name, and specify a sheet in the file to write to.

Multiple sheets may be written to by specifying unique sheet_name. With all data written to the file it is necessary to save the changes. Note that creating an ExcelWriter object with a file name that already exists will result in the contents of the existing file being erased.

Parameters

- **excel_writer** [str or ExcelWriter object] File path or existing ExcelWriter.
- **sheet_name** [str, default 'Sheet1'] Name of sheet which will contain DataFrame.
- **na_rep** [str, default `''`] Missing data representation.
- **float_format** [str, optional] Format string for floating point numbers. For example float_format="%.2f" will format 0.1234 to 0.12.
- **columns** [sequence or list of str, optional] Columns to write.
header [bool or list of str, default True] Write out the column names. If a list of string is given it is assumed to be aliases for the column names.

index [bool, default True] Write row names (index).

index_label [str or sequence, optional] Column label for index column(s) if desired. If not specified, and header and index are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

startrow [int, default 0] Upper left cell row to dump data frame.

startcol [int, default 0] Upper left cell column to dump data frame.


merge_cells [bool, default True] Write MultiIndex and Hierarchical Rows as merged cells.

encoding [str, optional] Encoding of the resulting excel file. Only necessary for xlwt, other writers support unicode natively.

inf_rep [str, default ‘inf’] Representation for infinity (there is no native representation for infinity in Excel).

verbose [bool, default True] Display more information in the error logs.

freeze_panes [tuple of int (length 2), optional] Specifies the one-based bottommost row and rightmost column that is to be frozen.

See also:

to_csv Write DataFrame to a comma-separated values (csv) file.

ExcelWriter Class for writing DataFrame objects into excel sheets.

read_excel Read an Excel file into a pandas DataFrame.

read_csv Read a comma-separated values (csv) file into DataFrame.

Notes

For compatibility with to_csv(), to_excel serializes lists and dicts to strings before writing.

Once a workbook has been saved it is not possible write further data without rewriting the whole workbook.

Examples

Create, write to and save a workbook:

```python
>>> df1 = pd.DataFrame([[\'a\', \'b\'], [\'c\', \'d\']],
                        index=['row 1', 'row 2'],
                        columns=['col 1', 'col 2'])
>>> df1.to_excel("output.xlsx")
```

To specify the sheet name:

```python
>>> df1.to_excel("output.xlsx",
                sheet_name='Sheet_name_1')
```
If you wish to write to more than one sheet in the workbook, it is necessary to specify an ExcelWriter object:

```python
>>> df2 = df1.copy()
>>> with pd.ExcelWriter('output.xlsx') as writer:
...    df1.to_excel(writer, sheet_name='Sheet_name_1')
...    df2.to_excel(writer, sheet_name='Sheet_name_2')
```

ExcelWriter can also be used to append to an existing Excel file:

```python
>>> with pd.ExcelWriter('output.xlsx', mode='a') as writer:
...    df.to_excel(writer, sheet_name='Sheet_name_3')
```

To set the library that is used to write the Excel file, you can pass the `engine` keyword (the default engine is automatically chosen depending on the file extension):

```python
>>> df1.to_excel('output1.xlsx', engine='xlsxwriter')
```

### pandas.DataFrame.to_feather

DataFrame.to_feather(**kwargs)

Write a DataFrame to the binary Feather format.

**Parameters**

- **path** [str] String file path.
- **kwargs** Additional keywords passed to pyarrow.feather.write_feather(). Starting with pyarrow 0.17, this includes the `compression`, `compression_level`, `chunksize` and `version` keywords.

New in version 1.1.0.

### pandas.DataFrame.to_gbq

DataFrame.to_gbq(destination_table, project_id=None, chunksize=None, reauth=False, if_exists='fail', auth_local_webserver=False, table_schema=None, location=None, progress_bar=True, credentials=None)

Write a DataFrame to a Google BigQuery table.

This function requires the pandas-gbq package.

See the [How to authenticate with Google BigQuery](https://pandas.pydata.org/pandas-docs/stable/guide/database.html#how-to-authenticate-with-google-bigquery) guide for authentication instructions.

**Parameters**

- **destination_table** [str] Name of table to be written, in the form dataset.tablename.
- **project_id** [str, optional] Google BigQuery Account project ID. Optional when available from the environment.
- **chunksize** [int, optional] Number of rows to be inserted in each chunk from the dataframe. Set to `None` to load the whole dataframe at once.
- **reauth** [bool, default False] Force Google BigQuery to re-authenticate the user. This is useful if multiple accounts are used.
if_exists [str, default ‘fail’] Behavior when the destination table exists. Value can be one of:

'fail' If table exists raise pandas_gbq.gbq.TableCreationError.
'replace' If table exists, drop it, recreate it, and insert data.
'append' If table exists, insert data. Create if does not exist.

auth_local_webserver [bool, default False] Use the local webserver flow instead of the console flow when getting user credentials.

New in version 0.2.0 of pandas-gbq.

table_schema [list of dicts, optional] List of BigQuery table fields to which according DataFrame columns conform to, e.g. [{'name': 'col1', 'type': 'STRING'}, ...]. If schema is not provided, it will be generated according to dtypes of DataFrame columns. See BigQuery API documentation on available names of a field.

New in version 0.3.1 of pandas-gbq.

location [str, optional] Location where the load job should run. See the BigQuery locations documentation for a list of available locations. The location must match that of the target dataset.

New in version 0.5.0 of pandas-gbq.

progress_bar [bool, default True] Use the library tqdm to show the progress bar for the upload, chunk by chunk.

New in version 0.5.0 of pandas-gbq.

credentials [google.auth.credentials.Credentials, optional] Credentials for accessing Google APIs. Use this parameter to override default credentials, such as to use Compute Engine google.auth.compute_engine.Credentials or Service Account google.oauth2.service_account.Credentials directly.

New in version 0.8.0 of pandas-gbq.

New in version 0.24.0.

See also:

pandas_gbq.to_gbq This function in the pandas-gbq library.
read_gbq Read a DataFrame from Google BigQuery.

pandas.DataFrame.to_hdf

DataFrame.to_hdf(path_or_buf, key, mode='a', complevel=None, complib=None, append=False, format=None, index=True, min_itemsize=None, nan_rep=None, dropna=None, data_columns=None, errors='strict', encoding='UTF-8')

Write the contained data to an HDF5 file using HDFStore.

Hierarchical Data Format (HDF) is self-describing, allowing an application to interpret the structure and contents of a file with no outside information. One HDF file can hold a mix of related objects which can be accessed as a group or as individual objects.

In order to add another DataFrame or Series to an existing HDF file please use append mode and a different a key.
For more information see the user guide.

Parameters

path_or_buf [str or pandas.HDFStore] File path or HDFStore object.

key [str] Identifier for the group in the store.

mode [{'a', 'w', 'r+'}, default 'a'] Mode to open file:
  • ‘w’: write, a new file is created (an existing file with the same name would be deleted).
  • ‘a’: append, an existing file is opened for reading and writing, and if the file does not exist it is created.
  • ‘r+’: similar to ‘a’, but the file must already exist.

complevel [{0-9}, optional] Specifies a compression level for data. A value of 0 disables compression.

complib [{'zlib', 'lzo', 'bzip2', 'blosc'}, default 'zlib'] Specifies the compression library to be used. As of v0.20.2 these additional compressors for Blosc are supported (default if no compressor specified: 'blosc:blosclz'): {'blosc:blosclz', 'blosc:lz4', 'blosc:lz4hc', 'blosc:snappy', 'blosc:zlib', 'blosc:zstd'}. Specifying a compression library which is not available issues a ValueError.

append [bool, default False] For Table formats, append the input data to the existing.

format [{'fixed', 'table', None}, default ‘fixed’] Possible values:
  • ‘table’: Table format. Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data.
  • If None, pd.get_option('io.hdf.default_format') is checked, followed by fallback to “fixed”

errors [str, default ‘strict’] Specifies how encoding and decoding errors are to be handled. See the errors argument for open() for a full list of options.

encoding [str, default “UTF-8”]

min_itemsize [dict or int, optional] Map column names to minimum string sizes for columns.


data_columns [list of columns or True, optional] List of columns to create as indexed data columns for on-disk queries, or True to use all columns. By default only the axes of the object are indexed. See Query via data columns. Applicable only to format=‘table’.

See also:

DataFrame.read_hdf Read from HDF file.

DataFrame.to_parquet Write a DataFrame to the binary parquet format.

DataFrame.to_sql Write to a sql table.

DataFrame.to_feather Write out feather-format for DataFrames.
**DataFrame.to_csv**  Write out to a csv file.

**Examples**

```python
>>> df = pd.DataFrame({'A': [1, 2, 3], 'B': [4, 5, 6]},
                    index=['a', 'b', 'c'])
>>> df.to_hdf('data.h5', key='df', mode='w')

We can add another object to the same file:

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s.to_hdf('data.h5', key='s')
```

Reading from HDF file:

```python
>>> pd.read_hdf('data.h5', 'df')
   A  B
a 1  4
b 2  5
c 3  6
```

```python
>>> pd.read_hdf('data.h5', 's')
0   1
1   2
2   3
3   4
dtype: int64
```

Deleting file with data:

```python
>>> import os
>>> os.remove('data.h5')
```

**pandas.DataFrame.to_html**

DataFrame.to_html(buf=None, columns=None, col_space=None, header=True, index=True, na_rep='NaN', formatters=None, float_format=None, sparsify=None, index_names=True, justify=None, max_rows=None, max_cols=None, show_dimensions=False, decimal='.', bold_rows=True, classes=None, escape=True, notebook=False, border=None, table_id=None, render_links=False, encoding=None)

Render a DataFrame as an HTML table.

**Parameters**

- **buf** [str, Path or StringIO-like, optional, default None] Buffer to write to. If None, the output is returned as a string.

- **columns** [sequence, optional, default None] The subset of columns to write. Writes all columns by default.

- **col_space** [str or int, list or dict of int or str, optional] The minimum width of each column in CSS length units. An int is assumed to be px units.

  New in version 0.25.0: Ability to use str.

- **header** [bool, optional] Whether to print column labels, default True.
index [bool, optional, default True] Whether to print index (row) labels.

na_rep [str, optional, default ‘NaN’] String representation of NAN to use.

formatters [list, tuple or dict of one-param. functions, optional] Formatter functions to apply to columns’ elements by position or name. The result of each function must be a unicode string. List/tuple must be of length equal to the number of columns.

float_format [one-parameter function, optional, default None] Formatter function to apply to columns’ elements if they are floats. The result of this function must be a unicode string.

sparsify [bool, optional, default True] Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row.

index_names [bool, optional, default True] Prints the names of the indexes.

justify [str, default None] How to justify the column labels. If None uses the option from the print configuration (controlled by set_option), ‘right’ out of the box. Valid values are

- left
- right
- center
- justify
- justify-all
- start
- end
- inherit
- match-parent
- initial
- unset.

max_rows [int, optional] Maximum number of rows to display in the console.

min_rows [int, optional] The number of rows to display in the console in a truncated repr (when number of rows is above max_rows).

max_cols [int, optional] Maximum number of columns to display in the console.

show_dimensions [bool, default False] Display DataFrame dimensions (number of rows by number of columns).

decimal [str, default ‘.’] Character recognized as decimal separator, e.g. ‘,’ in Europe.

bold_rows [bool, default True] Make the row labels bold in the output.

classes [str or list or tuple, default None] CSS class(es) to apply to the resulting html table.

escape [bool, default True] Convert the characters <, >, and & to HTML-safe sequences.

notebook [{True, False}, default False] Whether the generated HTML is for IPython Notebook.
border [int] A border=border attribute is included in the opening <table> tag. Default pd.options.display.html.border.

encoding [str, default “utf-8”] Set character encoding.

New in version 1.0.

table_id [str, optional] A css id is included in the opening <table> tag if specified.

New in version 0.23.0.

render_links [bool, default False] Convert URLs to HTML links.

New in version 0.24.0.

Returns

str or None If buf is None, returns the result as a string. Otherwise returns None.

See also:

to_string Convert DataFrame to a string.

pandas.DataFrame.to_json

DataFrame.to_json(path_or_buf=None, orient=None, date_format=None, double_precision=10, force_ascii=True, date_unit='ms', default_handler=None, lines=False, compression='infer', index=True, indent=None)

Convert the object to a JSON string.

Note NaN’s and None will be converted to null and datetime objects will be converted to UNIX timestamps.

Parameters

path_or_buf [str or file handle, optional] File path or object. If not specified, the result is returned as a string.

orient [str] Indication of expected JSON string format.

• Series:
  – default is ‘index’
  – allowed values are: {'split','records','index','table'}.

• DataFrame:
  – default is ‘columns’
  – allowed values are: {'split', ‘records’, ‘index’, ‘columns’, ‘values’, ‘table’}.

• The format of the JSON string:
  – ‘split’ : dict like {‘index’ -> [index], ‘columns’ -> [columns], ‘data’ -> [values]}
  – ‘records’ : list like [[column -> value], . . . , [column -> value]]
  – ‘index’ : dict like {index -> [column -> value]}
  – ‘columns’ : dict like {column -> [column -> value]}
  – ‘values’ : just the values array
Describing the data, where data component is like 
orient='records'.

Changed in version 0.20.0.

date_format [{None, ‘epoch’, ‘iso’}] Type of date conversion. ‘epoch’ = epoch milliseconds, ‘iso’ = ISO8601. The default depends on the orient. For orient='table', the default is ‘iso’. For all other orients, the default is ‘epoch’.

double_precision [int, default 10] The number of decimal places to use when encoding floating point values.

force_ascii [bool, default True] Force encoded string to be ASCII.

date_unit [str, default ‘ms’ (milliseconds)] The time unit to encode to, governs timestamp and ISO8601 precision. One of ‘s’, ‘ms’, ‘us’, ‘ns’ for second, millisecond, microsecond, and nanosecond respectively.

default_handler [callable, default None] Handler to call if object cannot otherwise be converted to a suitable format for JSON. Should receive a single argument which is the object to convert and return a serialisable object.

lines [bool, default False] If ‘orient’ is ‘records’ write out line delimited json format. Will throw ValueError if incorrect ‘orient’ since others are not list like.

compression [{‘infer’, ‘gzip’, ‘bz2’, ‘zip’, ‘xz’, None}] A string representing the compression to use in the output file, only used when the first argument is a filename. By default, the compression is inferred from the filename.

index [bool, default True] Whether to include the index values in the JSON string. Not including the index (index=False) is only supported when orient is ‘split’ or ‘table’.

indent [int, optional] Length of whitespace used to indent each record.

Returns

None or str If path_or_buf is None, returns the resulting json format as a string. Otherwise returns None.

See also:

read_json Convert a JSON string to pandas object.
Notes

The behavior of `indent=0` varies from the stdlib, which does not indent the output but does insert newlines. Currently, `indent=0` and the default `indent=None` are equivalent in pandas, though this may change in a future release.

Examples

```python
>>> import json
>>> df = pd.DataFrame(
...     [["a", "b"], ["c", "d"]],
...     index=["row 1", "row 2"],
...     columns=["col 1", "col 2"],
... )

>>> result = df.to_json(orient="split")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
{
    "columns": [
        "col 1",
        "col 2"
    ],
    "index": [
        "row 1",
        "row 2"
    ],
    "data": [
        ["a",
         "b"],
        ["c",
         "d"
    ]
}
```

Encoding/decoding a Dataframe using `records` formatted JSON. Note that index labels are not preserved with this encoding.

```python
>>> result = df.to_json(orient="records")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
[
    {
        "col 1": "a",
        "col 2": "b"
    },
    {
        "col 1": "c",
        "col 2": "d"
    }
]
```
Encoding/decoding a Dataframe using 'index' formatted JSON:

```python
>>> result = df.to_json(orient="index")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
{
  "row 1": {
    "col 1": "a",
    "col 2": "b"
  },
  "row 2": {
    "col 1": "c",
    "col 2": "d"
  }
}
```

Encoding/decoding a Dataframe using 'columns' formatted JSON:

```python
>>> result = df.to_json(orient="columns")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
{
  "col 1": {
    "row 1": "a",
    "row 2": "c"
  },
  "col 2": {
    "row 1": "b",
    "row 2": "d"
  }
}
```

Encoding/decoding a Dataframe using 'values' formatted JSON:

```python
>>> result = df.to_json(orient="values")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
[
  ["a", "b"],
  ["c", "d"]
]
```

Encoding with Table Schema:

```python
>>> result = df.to_json(orient="table")
>>> parsed = json.loads(result)
>>> json.dumps(parsed, indent=4)
{
  "schema": {
    "fields": [
    {
      "name": "index",
      ...
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

(continued from previous page)

```json
{
    "type": "string",
    "name": "col 1",
    "type": "string"
},
{
    "name": "col 2",
    "type": "string"
},
"primaryKey": [
    "index"
],
"pandas_version": "0.20.0"
},
"data": [
    {
        "index": "row 1",
        "col 1": "a",
        "col 2": "b"
    },
    {
        "index": "row 2",
        "col 1": "c",
        "col 2": "d"
    }
]
}
```

### pandas.DataFrame.to_latex

**DataFrame.to_latex** *(buf=None, columns=None, col_space=None, header=True, index=True, na_rep='NaN', formatters=None, float_format=None, sparse=None, index_names=True, bold_rows=False, column_format=None, longtable=None, escape=None, encoding=None, decimal='.', multicolumn=None, multicolumn_format=None, multirow=None, caption=None, label=None)*

Render object to a LaTeX tabular, longtable, or nested table/tabular.

Requires \usepackage{booktabs}. The output can be copy/pasted into a main LaTeX document or read from an external file with \input{table.tex}.

Changed in version 0.20.2: Added to Series.

Changed in version 1.0.0: Added caption and label arguments.

**Parameters**

- **buf** [str, Path or StringIO-like, optional, default None] Buffer to write to. If None, the output is returned as a string.
- **columns** [list of label, optional] The subset of columns to write. Writes all columns by default.
- **col_space** [int, optional] The minimum width of each column.
header [bool or list of str, default True] Write out the column names. If a list of strings is given, it is assumed to be aliases for the column names.

index [bool, default True] Write row names (index).

na_rep [str, default ‘NaN’] Missing data representation.

formatters [list of functions or dict of {str: function}, optional] Formatter functions to apply to columns’ elements by position or name. The result of each function must be a unicode string. List must be of length equal to the number of columns.

float_format [one-parameter function or str, optional, default None] Formatter for floating point numbers. For example float_format="%.2f" and float_format="{:0.2f}" will both result in 0.1234 being formatted as 0.12.

sparsify [bool, optional] Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row. By default, the value will be read from the config module.

index_names [bool, default True] Prints the names of the indexes.

bold_rows [bool, default False] Make the row labels bold in the output.

column_format [str, optional] The columns format as specified in LaTeX table format e.g. ‘rcl’ for 3 columns. By default, ‘l’ will be used for all columns except columns of numbers, which default to ‘r’.

longtable [bool, optional] By default, the value will be read from the pandas config module. Use a longtable environment instead of tabular. Requires adding a usepackage{longtable} to your LaTeX preamble.

escape [bool, optional] By default, the value will be read from the pandas config module. When set to False prevents from escaping latex special characters in column names.

encoding [str, optional] A string representing the encoding to use in the output file, defaults to ‘utf-8’.

decimal [str, default ‘.’] Character recognized as decimal separator, e.g. ‘,’ in Europe.

multicolumn [bool, default True] Use multicolumn to enhance MultiIndex columns. The default will be read from the config module.

multicolumn_format [str, default ‘l’] The alignment for multicolumns, similar to column_format. The default will be read from the config module.

multirow [bool, default False] Use multirow to enhance MultiIndex rows. Requires adding a usepackage{multirow} to your LaTeX preamble. Will print centered labels (instead of top-aligned) across the contained rows, separating groups via clines. The default will be read from the pandas config module.

caption [str, optional] The LaTeX caption to be placed inside \caption{} in the output.

New in version 1.0.0.

label [str, optional] The LaTeX label to be placed inside \label{} in the output. This is used with \ref{} in the main .tex file.

New in version 1.0.0.

Returns
str or None If buf is None, returns the result as a string. Otherwise returns None.

See also:

DataFrame.to_string Render a DataFrame to a console-friendly tabular output.

DataFrame.to_html Render a DataFrame as an HTML table.

Examples

```python
>>> df = pd.DataFrame({'name': ['Raphael', 'Donatello'],
                    'mask': ['red', 'purple'],
                    'weapon': ['sai', 'bo staff']})
>>> print(df.to_latex(index=False))
\begin{tabular}{lll}
\toprule
name & mask & weapon \\
\midrule
Raphael & red & sai \\
Donatello & purple & bo staff \\
\bottomrule
\end{tabular}
```

pandas.DataFrame.to_markdown

DataFrame.to_markdown (buf=None, mode=None, index=True, **kwargs)
Print DataFrame in Markdown-friendly format.

New in version 1.0.0.

Parameters

- **buf** [str, Path or StringIO-like, optional, default None] Buffer to write to. If None, the output is returned as a string.
- **mode** [str, optional] Mode in which file is opened.
- **index** [bool, optional, default True] Add index (row) labels.

New in version 1.1.0.

**kwargs These parameters will be passed to tabulate.

Returns

- **str** DataFrame in Markdown-friendly format.

Examples

```python
>>> s = pd.Series(['elk', 'pig', 'dog', 'quetzal'], name="animal")
>>> print(s.to_markdown())
<table>
<thead>
<tr>
<th></th>
<th>animal</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>elk</td>
</tr>
<tr>
<td>1</td>
<td>pig</td>
</tr>
<tr>
<td>2</td>
<td>dog</td>
</tr>
<tr>
<td>3</td>
<td>quetzal</td>
</tr>
</tbody>
</table>
```
Output markdown with a tabulate option.

```python
>>> print(s.to_markdown(tablefmt="grid"))
+----+----------+
| 0  | elk      |
| 1  | pig      |
| 2  | dog      |
| 3  | quetzal  |
+----+----------+
```

**pandas.DataFrame.to_numpy**

**DataFrame.to_numpy** *(dtype=None, copy=False, na_value=<object object>)*

Convert the DataFrame to a NumPy array.

New in version 0.24.0.

By default, the dtype of the returned array will be the common NumPy dtype of all types in the DataFrame. For example, if the dtypes are `float16` and `float32`, the results dtype will be `float32`. This may require copying data and coercing values, which may be expensive.

**Parameters**

- **dtype** [str or numpy.dtype, optional] The dtype to pass to numpy.asarray().
- **copy** [bool, default False] Whether to ensure that the returned value is not a view on another array. Note that copy=False does not ensure that to_numpy() is no-copy. Rather, copy=True ensure that a copy is made, even if not strictly necessary.
- **na_value** [Any, optional] The value to use for missing values. The default value depends on dtype and the dtypes of the DataFrame columns.

New in version 1.1.0.

**Returns**

numpy.ndarray

**See also:**

**Series.to_numpy** Similar method for Series.

**Examples**

```python
>>> pd.DataFrame({"A": [1, 2], "B": [3, 4]}).to_numpy()
array([[1, 2],
       [3, 4]])
```

With heterogeneous data, the lowest common type will have to be used.
For a mix of numeric and non-numeric types, the output array will have object dtype.

```python
>>> df['C'] = pd.date_range('2000', periods=2)
```
DataFrame.to_csv  Write a csv file.

DataFrame.to_sql  Write to a sql table.

DataFrame.to_hdf  Write to hdf.

Notes

This function requires either the fastparquet or pyarrow library.

Examples

```python
>>> df = pd.DataFrame(data={'col1': [1, 2], 'col2': [3, 4]})
>>> df.to_parquet('df.parquet.gzip',
...    compression='gzip')
>>> pd.read_parquet('df.parquet.gzip')
  col1  col2
0    1    3
1    2    4
```

If you want to get a buffer to the parquet content you can use a io.BytesIO object, as long as you don’t use partition_cols, which creates multiple files.

```python
>>> import io

>>> f = io.BytesIO()

>>> df.to_parquet(f)

>>> f.seek(0)

>>> content = f.read()
```

pandas.DataFrame.to_period

DataFrame.to_period(freq=None, axis=0, copy=True)

Convert DataFrame from DatetimeIndex to PeriodIndex.

Convert DataFrame from DatetimeIndex to PeriodIndex with desired frequency (inferred from index if not passed).

Parameters

- freq [str, default] Frequency of the PeriodIndex.
- axis [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis to convert (the index by default).
- copy [bool, default True] If False then underlying input data is not copied.

Returns

DataFrame with PeriodIndex
pandas.DataFrame.to_pickle

DataFrame.to_pickle(path, compression='infer', protocol=5)
Pickle (serialize) object to file.

Parameters

    path [str] File path where the pickled object will be stored.


    protocol [int] Int which indicates which protocol should be used by the pickler, default HIGHEST_PROTOCOL (see [1] paragraph 12.1.2). The possible values are 0, 1, 2, 3, 4. A negative value for the protocol parameter is equivalent to setting its value to HIGHEST_PROTOCOL.

See also:

    read_pickle Load pickled pandas object (or any object) from file.

    DataFrame.to_hdf Write DataFrame to an HDF5 file.

    DataFrame.to_sql Write DataFrame to a SQL database.

    DataFrame.to_parquet Write a DataFrame to the binary parquet format.

Examples

```python
>>> original_df = pd.DataFrame({"foo": range(5), "bar": range(5, 10)})
>>> original_df
   foo  bar
0  0   5
1  1   6
2  2   7
3  3   8
4  4   9

>>> original_df.to_pickle("./dummy.pkl")

>>> unpickled_df = pd.read_pickle("./dummy.pkl")
>>> unpickled_df
   foo  bar
0  0   5
1  1   6
2  2   7
3  3   8
4  4   9

>>> import os
>>> os.remove("./dummy.pkl")
```
pandas.DataFrame.to_records

DataFrame.to_records (index=True, column_dtypes=None, index_dtypes=None)

Convert DataFrame to a NumPy record array.

Index will be included as the first field of the record array if requested.

Parameters

- **index** [bool, default True] Include index in resulting record array, stored in ‘index’ field or using the index label, if set.

- **column_dtypes** [str, type, dict, default None] New in version 0.24.0.
  
  If a string or type, the data type to store all columns. If a dictionary, a mapping of column names and indices (zero-indexed) to specific data types.

- **index_dtypes** [str, type, dict, default None] New in version 0.24.0.

  If a string or type, the data type to store all index levels. If a dictionary, a mapping of index level names and indices (zero-indexed) to specific data types.

  This mapping is applied only if index=True.

Returns

- **numpy.recarray** NumPy ndarray with the DataFrame labels as fields and each row of the DataFrame as entries.

See also:

- **DataFrame.from_records** Convert structured or record ndarray to DataFrame.

- **numpy.recarray** An ndarray that allows field access using attributes, analogous to typed columns in a spreadsheet.

Examples

```python
>>> df = pd.DataFrame({'A': [1, 2], 'B': [0.5, 0.75]},
    ...            index=['a', 'b'])
>>> df
   A  B
a 1  0.5
b 2  0.75
>>> df.to_records()
rec.array([(a', 1, 0.5), (b', 2, 0.75)],
          dtype=[('index', 'O'), (A', '<i8'), (B', '<f8')])
```

If the DataFrame index has no label then the recarray field name is set to ‘index’. If the index has a label then this is used as the field name:

```python
>>> df.index = df.index.rename("I")
>>> df.to_records()
rec.array([(a', 1, 0.5), (b', 2, 0.75)],
          dtype=[('I', 'O'), (A', '<i8'), (B', '<f8')])
```

The index can be excluded from the record array:

```python
>>> df.index = df.index.rename("I")
>>> df.to_records()
rec.array([(a', 1, 0.5), (b', 2, 0.75)],
          dtype=[('I', 'O'), (A', '<i8'), (B', '<f8')])
```
Data types can be specified for the columns:

```python
cols = {'A': 'int32'}
df.to_records(column_dtypes=cols)
```

As well as for the index:

```python
idx = df.index.str.len().max()
df.to_records(index_dtypes=f'<{idx}S')
```

### pandas.DataFrame.to_sql

DataFrame.to_sql(name, con, schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None, method=None)

Write records stored in a DataFrame to a SQL database.

Databases supported by SQLAlchemy [1] are supported. Tables can be newly created, appended to, or overwritten.

**Parameters**

- **name** [str] Name of SQL table.
- **con** [sqlalchemy.engine.(Engine or Connection) or sqlite3.Connection] Using SQLAlchemy makes it possible to use any DB supported by that library. Legacy support is provided for sqlite3.Connection objects. The user is responsible for engine disposal and connection closure for the SQLAlchemy connectable See here.
- **schema** [str, optional] Specify the schema (if database flavor supports this). If None, use default schema.
- **if_exists** ['fail', 'replace', 'append', 'fail'] How to behave if the table already exists.
  - fail: Raise a ValueError.
  - replace: Drop the table before inserting new values.
  - append: Insert new values to the existing table.
- **index** [bool, default True] Write DataFrame index as a column. Uses index_label as the column name in the table.
- **index_label** [str or sequence, default None] Column label for index column(s). If None is given (default) and index is True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.
chunksize [int, optional] Specify the number of rows in each batch to be written at a
time. By default, all rows will be written at once.

dtype [dict or scalar, optional] Specifying the datatype for columns. If a dict-
ionary is used, the keys should be the column names and the values should be the
SQLAlchemy types or strings for the sqlite3 legacy mode. If a scalar is provided,
it will be applied to all columns.

method [{None, ‘multi’, callable}, optional] Controls the SQL insertion clause used:
  • None : Uses standard SQL INSERT clause (one per row).
  • ‘multi’: Pass multiple values in a single INSERT clause.
  • callable with signature (pd_table, conn, keys, data_iter).

Details and a sample callable implementation can be found in the section insert
method.

New in version 0.24.0.

Raises

ValueError When the table already exists and if_exists is ‘fail’ (the default).

See also:

read_sql Read a DataFrame from a table.

Notes

Timezone aware datetime columns will be written as Timestamp with timezone type with
SQLAlchemy if supported by the database. Otherwise, the datetimes will be stored as timezone unaware
timestamps local to the original timezone.

New in version 0.24.0.

References

[1], [2]

Examples

Create an in-memory SQLite database.

```python
>>> from sqlalchemy import create_engine
>>> engine = create_engine('sqlite://', echo=False)
```

Create a table from scratch with 3 rows.

```python
>>> df = pd.DataFrame({'name' : ['User 1', 'User 2', 'User 3']})
>>> df
    name
0  User 1
1  User 2
2  User 3
```
An `sqlalchemy.engine.Connection` can also be passed to to `con`: >>> with engine.begin() as connection: ... df1 = pd.DataFrame({'name': ['User 4', 'User 5']}) ... df1.to_sql('users', con=connection, if_exists='append')

This is allowed to support operations that require that the same DBAPI connection is used for the entire operation.

Overwrite the table with just `df2`.

```python
>>> df2.to_sql('users', con=engine, if_exists='replace', ... index_label='id')
>>> engine.execute("SELECT * FROM users").fetchall()
[(0, 'User 6'), (1, 'User 7')]
```

Specify the `dtype` (especially useful for integers with missing values). Notice that while pandas is forced to store the data as floating point, the database supports nullable integers. When fetching the data with Python, we get back integer scalars.

```python
>>> df = pd.DataFrame({"A": [1, None, 2]})
>>> df
   A
0  1.0
1  NaN
2  2.0

>>> from sqlalchemy.types import Integer
>>> df.to_sql('integers', con=engine, index=False, ... dtype={"A": Integer()})
>>> engine.execute("SELECT * FROM integers").fetchall()
[(1,), (None,), (2,)]
```

### pandas.DataFrame.to_stata

DataFrame.to_stata(**kwargs)

Export DataFrame object to Stata dta format.

Writes the DataFrame to a Stata dataset file. “dta” files contain a Stata dataset.

**Parameters**

- `path` [str, buffer or path object] String, path object (pathlib.Path or py._path.local.LocalPath) or object implementing a binary write() function. If using a buffer then the buffer will not be automatically closed after the file data has been written.
Changed in version 1.0.0.

Previously this was “fname”

**convert_dates**  [dict] Dictionary mapping columns containing datetime types to stata internal format to use when writing the dates. Options are ‘tc’, ‘td’, ‘tm’, ‘tw’, ‘th’, ‘tq’, ‘ty’. Column can be either an integer or a name. Datetime columns that do not have a conversion type specified will be converted to ‘tc’. Raises **NotImplementedError** if a datetime column has timezone information.

**write_index**  [bool] Write the index to Stata dataset.

**byteorder**  [str] Can be “>”, “<”, “little”, or “big”. default is sys.byteorder.

**time_stamp**  [datetime] A datetime to use as file creation date. Default is the current time.

**data_label**  [str, optional] A label for the data set. Must be 80 characters or smaller.

**variable_labels**  [dict] Dictionary containing columns as keys and variable labels as values. Each label must be 80 characters or smaller.

**version**  [{114, 117, 118, 119, None}, default 114] Version to use in the output dta file. Set to None to let pandas decide between 118 or 119 formats depending on the number of columns in the frame. Version 114 can be read by Stata 10 and later. Version 117 can be read by Stata 13 or later. Version 118 is supported in Stata 14 and later. Version 119 is supported in Stata 15 and later. Version 114 limits string variables to 244 characters or fewer while versions 117 and later allow strings with lengths up to 2,000,000 characters. Versions 118 and 119 support Unicode characters, and version 119 supports more than 32,767 variables.

New in version 0.23.0.

Changed in version 1.0.0: Added support for formats 118 and 119.

**convert_strl**  [list, optional] List of column names to convert to string columns to Stata StrL format. Only available if version is 117. Storing strings in the StrL format can produce smaller dta files if strings have more than 8 characters and values are repeated.

New in version 0.23.0.

**compression**  [str or dict, default ‘infer’] For on-the-fly compression of the output dta. If string, specifies compression mode. If dict, value at key ‘method’ specifies compression mode. Compression mode must be one of {‘infer’, ‘gzip’, ‘bz2’, ‘zip’, ‘xz’, None}. If compression mode is ‘infer’ and **fname** is path-like, then detect compression from the following extensions: ‘.gz’, ‘.bz2’, ‘.zip’, or ‘.xz’ (otherwise no compression). If dict and compression mode is one of {‘zip’, ‘gzip’, ‘bz2’}, or inferred as one of the above, other entries passed as additional compression options.

New in version 1.1.0.

**Raises**

**NotImplementedError**

* If datetimes contain timezone information
* Column dtype is not representable in Stata

**ValueError**
• Columns listed in convert_dates are neither datetime64[ns] or datetime
• Column listed in convert_dates is not in DataFrame
• Categorical label contains more than 32,000 characters

See also:

read_stata Import Stata data files.
io.stata.StataWriter Low-level writer for Stata data files.
io.stata.StataWriter117 Low-level writer for version 117 files.

Examples

```python
>>> df = pd.DataFrame({'animal': ['falcon', 'parrot', 'falcon', ...
        'parrot'],
        ...
        'speed': [350, 18, 361, 15]})
>>> df.to_stata('animals.dta')
```

pandas.DataFrame.to_string

DataFrame.to_string(buf=None, columns=None, col_space=None, header=True, index=True, na_rep='NaN', formatters=None, float_format=None, sparsify=None, index_names=True, justify=None, max_rows=None, min_rows=None, max_cols=None, show_dimensions=False, decimal='.', line_width=None, max_colwidth=None, encoding=None)

Render a DataFrame to a console-friendly tabular output.

Parameters

buf [str, Path or StringIO-like, optional, default None] Buffer to write to. If None, the output is returned as a string.
columns [sequence, optional, default None] The subset of columns to write. Writes all columns by default.
col_space [int, list or dict of int, optional] The minimum width of each column.
header [bool or sequence, optional] Write out the column names. If a list of strings is given, it is assumed to be aliases for the column names.
index [bool, optional, default True] Whether to print index (row) labels.
na_rep [str, optional, default ‘NaN’] String representation of NAN to use.
formatters [list, tuple or dict of one-param. functions, optional] Formatter functions to apply to columns’ elements by position or name. The result of each function must be a unicode string. List/tuple must be of length equal to the number of columns.
float_format [one-parameter function, optional, default None] Formatter function to apply to columns’ elements if they are floats. The result of this function must be a unicode string.
sparsify [bool, optional, default True] Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row.
index_names [bool, optional, default True] Prints the names of the indexes.


**justifies**  [str, default None] How to justify the column labels. If None uses the option from the print configuration (controlled by set_option), 'right' out of the box. Valid values are

- left
- right
- center
- justify
- justify-all
- start
- end
- inherit
- match-parent
- initial
- unset.

**max_rows**  [int, optional] Maximum number of rows to display in the console.

**min_rows**  [int, optional] The number of rows to display in the console in a truncated repr (when number of rows is above max_rows).

**max_cols**  [int, optional] Maximum number of columns to display in the console.

**show_dimensions**  [bool, default False] Display DataFrame dimensions (number of rows by number of columns).

**decimal**  [str, default ‘.’] Character recognized as decimal separator, e.g. ‘,’ in Europe.

**line_width**  [int, optional] Width to wrap a line in characters.

**max_colwidth**  [int, optional] Max width to truncate each column in characters. By default, no limit.

New in version 1.0.0.

**encoding**  [str, default “utf-8”] Set character encoding.

New in version 1.0.

Returns

- **str or None** If buf is None, returns the result as a string. Otherwise returns None.

See also:

- **to_html** Convert DataFrame to HTML.
### Examples

```python
>>> d = {'col1': [1, 2, 3], 'col2': [4, 5, 6]}
>>> df = pd.DataFrame(d)
>>> print(df.to_string())
   col1  col2
0     1     4
1     2     5
2     3     6
```

#### pandas.DataFrame.to_timestamp

DataFrame.to_timestamp(freq=None, how='start', axis=0, copy=True)

Cast to DatetimeIndex of timestamps, at beginning of period.

**Parameters**

- `freq` [str, default frequency of PeriodIndex] Desired frequency.
- `how` [{‘s’, ‘e’, ‘start’, ‘end’}] Convention for converting period to timestamp; start of period vs. end.
- `axis` [0 or ‘index’, 1 or ‘columns’], default 0] The axis to convert (the index by default).
- `copy` [bool, default True] If False then underlying input data is not copied.

**Returns**

DataFrame with DatetimeIndex

#### pandas.DataFrame.to_xarray

DataFrame.to_xarray()

Return an xarray object from the pandas object.

**Returns**

xarray.DataArray or xarray.Dataset Data in the pandas structure converted to Dataset if the object is a DataFrame, or a DataArray if the object is a Series.

**See also:**

- **DataFrame.to_hdf** Write DataFrame to an HDF5 file.
- **DataFrame.to_parquet** Write a DataFrame to the binary parquet format.
Notes

See the `xarray` docs

Examples

```python
>>> df = pd.DataFrame([('falcon', 'bird', 389.0, 2),
...                    ('parrot', 'bird', 24.0, 2),
...                    ('lion', 'mammal', 80.5, 4),
...                    ('monkey', 'mammal', np.nan, 4)],
...                    columns=['name', 'class', 'max_speed', 'num_legs'])
```
```
name  class  max_speed  num_legs
0  falcon  bird      389.0     2
1  parrot  bird      24.0     2
2  lion    mammal    80.5     4
3  monkey  mammal    NaN     4
```

```python
>>> df.to_xarray()
<xarray.Dataset
  Dimensions:    (index: 4)
  Coordinates:
    * index (index) int64 0 1 2 3
  Data variables:
    name (index) object 'falcon' 'parrot' 'lion' 'monkey'
    class (index) object 'bird' 'bird' 'mammal' 'mammal'
    max_speed (index) float64 389.0 24.0 80.5 nan
    num_legs (index) int64 2 2 4 4
```

```python
>>> df['max_speed'].to_xarray()
<xarray.DataArray 'max_speed' (index: 4)>
array([389., 24., 80.5, nan])
Coordinates:
    * index (index) int64 0 1 2 3
```

```python
dates = pd.to_datetime(['2018-01-01', '2018-01-01',
                        '2018-01-02', '2018-01-02'])
```
```
>>> df_multiindex = pd.DataFrame({'date': dates,
                                 'animal': ['falcon', 'parrot', 'falcon', 'parrot'],
                                 'speed': [350, 18, 361, 15]})
```
```
>>> df_multiindex = df_multiindex.set_index(['date', 'animal'])
```
```
>>> df_multiindex
date  animal  speed
2018-01-01  falcon  350
2018-01-01  parrot  18
2018-01-02  falcon  361
2018-01-02  parrot  15
```
```
>>> df_multiindex.to_xarray()
<xarray.Dataset
  Dimensions:    (index: 4)
  Coordinates:
    * index (index) int64 0 1 2 3
  Data variables:
    speed (index) float64 350 18 361 15
```
```
(continues on next page)
Dimensions: (animal: 2, date: 2)
Coordinates:
* date (date) datetime64[ns] 2018-01-01 2018-01-02
* animal (animal) object 'falcon' 'parrot'
Data variables:
  speed (date, animal) int64 350 18 361 15

pandas.DataFrame.transform

DataFrame.transform(func, axis=0, *args, **kwargs)
Call func on self producing a DataFrame with transformed values.
Produced DataFrame will have same axis length as self.

Parameters

  func [function, str, list or dict] Function to use for transforming the data. If a function,
  must either work when passed a DataFrame or when passed to DataFrame.apply.
  Accepted combinations are:
  • function
  • string function name
  • list of functions and/or function names, e.g. [np.exp, 'sqrt']
  • dict of axis labels -> functions, function names or list of such.

  axis [{0 or 'index', 1 or 'columns'}, default 0] If 0 or ‘index’: apply function to each
  column. If 1 or ‘columns’: apply function to each row.

  *args Positional arguments to pass to func.

  **kwargs Keyword arguments to pass to func.

Returns

  DataFrame A DataFrame that must have the same length as self.

 Raises

  ValueError [If the returned DataFrame has a different length than self.]

See also:

  DataFrame.agg Only perform aggregating type operations.
  DataFrame.apply Invoke function on a DataFrame.
Examples

```python
>>> df = pd.DataFrame({'A': range(3), 'B': range(1, 4)})
>>> df
      A  B
0      0  1
1      1  2
2      2  3
>>> df.transform(lambda x: x + 1)
      A  B
0      1  2
1      2  3
2      3  4
```

Even though the resulting DataFrame must have the same length as the input DataFrame, it is possible to provide several input functions:

```python
>>> s = pd.Series(range(3))
>>> s
0 0
1 1
2 2
dtype: int64
>>> s.transform([np.sqrt, np.exp])
     sqrt     exp
0 0.000000 1.000000
1 1.000000 2.718282
2 1.414214 7.389056
```

**pandas.DataFrame.transpose**

DataFrame.transpose(*args, copy=False)

Transpose index and columns.

Reflect the DataFrame over its main diagonal by writing rows as columns and vice-versa. The property $T$ is an accessor to the method `transpose()`.

**Parameters**

*args [tuple, optional] Accepted for compatibility with NumPy.

**copy** [bool, default False] Whether to copy the data after transposing, even for DataFrames with a single dtype.

Note that a copy is always required for mixed dtype DataFrames, or for DataFrames with any extension types.

**Returns**

DataFrame The transposed DataFrame.

**See also:**

numpy.transpose Permutes the dimensions of a given array.
Notes

Transposing a DataFrame with mixed dtypes will result in a homogeneous DataFrame with the object dtype. In such a case, a copy of the data is always made.

Examples

Square DataFrame with homogeneous dtype

```python
>>> d1 = {'col1': [1, 2], 'col2': [3, 4]}
>>> df1 = pd.DataFrame(data=d1)
>>> df1
   col1  col2
0    1    3
1    2    4

>>> df1_transposed = df1.T # or df1.transpose()
>>> df1_transposed
   0  1
  col1  1  2
  col2  3  4
```

When the dtype is homogeneous in the original DataFrame, we get a transposed DataFrame with the same dtype:

```python
>>> df1.dtypes
col1    int64
col2    int64
dtype: object
>>> df1_transposed.dtypes
0    int64
1    int64
dtype: object
```

Non-square DataFrame with mixed dtypes

```python
>>> d2 = {'name': ['Alice', 'Bob'],
...       'score': [9.5, 8],
...       'employed': [False, True],
...       'kids': [0, 0]}
>>> df2 = pd.DataFrame(data=d2)
>>> df2
   name  score  employed  kids
0  Alice   9.5       False   0
1     Bob   8.0        True   0

>>> df2_transposed = df2.T # or df2.transpose()
>>> df2_transposed
   0  1
  name  Alice  Bob
  score   9.5   8
  employed  False  True
  kids      0      0
```

When the DataFrame has mixed dtypes, we get a transposed DataFrame with the object dtype:
pandas: powerful Python data analysis toolkit, Release 1.1.1

```python
>>> df2.dtypes
name    object
score  float64
employed  bool
kids    int64
dtype: object

>>> df2_transposed.dtypes
0    object
1    object
dtype: object
```

**pandas.DataFrame.truediv**

Dataframe.truediv(other, axis='columns', level=None, fill_value=None)

Get floating division of dataframe and other, element-wise (binary operator truediv).

Equivalent to dataframe / other, but with support to substitute a fill_value for missing data in one of the inputs. With reverse version, rtruediv.

Among flexible wrappers (add, sub, mul, div, mod, pow) to arithmetic operators: +, -, *, /, //, %, **.

**Parameters**

other [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

axis [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.

level [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

fill_value [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

**Returns**

DataFrame Result of the arithmetic operation.

See also:

DataFrame.add Add DataFrames.

DataFrame.sub Subtract DataFrames.

DataFrame.mul Multiply DataFrames.

DataFrame.div Divide DataFrames (float division).

DataFrame.truediv Divide DataFrames (float division).

DataFrame.floordiv Divide DataFrames (integer division).

DataFrame.mod Calculate modulo (remainder after division).

DataFrame.pow Calculate exponential power.
Notes

Mismatched indices will be unioned together.

Examples

```python
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                    'degrees': [360, 180, 360],
...                    index=['circle', 'triangle', 'rectangle'])
>>> df
    angles  degrees
  circle    0      360
   triangle  3      180
  rectangle  4      360

Add a scalar with operator version which return the same results.

```python
>>> df + 1
    angles  degrees
  circle    1      361
   triangle  4      181
  rectangle  5      361
``` 

```python
>>> df.add(1)
    angles  degrees
  circle    1      361
   triangle  4      181
  rectangle  5      361
```

Divide by constant with reverse version.

```python
>>> df.div(10)
    angles  degrees
  circle    0.0     36.0
   triangle  0.3     18.0
  rectangle  0.4     36.0
```

```python
>>> df.rdiv(10)
    angles  degrees
  circle    inf     0.027778
   triangle  3.333333  0.055556
  rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```python
>>> df - [1, 2]
    angles  degrees
  circle    -1      358
   triangle   2      178
  rectangle   3      358
```

```python
>>> df.sub([1, 2], axis='columns')
    angles  degrees
  circle    -1      358
   triangle   2      178
  rectangle   3      358
```
Multiply a DataFrame of different shape with operator version.

```python
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
                        index=['circle', 'triangle', 'rectangle'])
>>> other
angles
circle 0
triangle 3
rectangle 4

>>> df * other
angles degrees
circle 0 NaN
triangle 9 NaN
rectangle 16 NaN

>>> df.mul(other, fill_value=0)
angles degrees
circle 0.0
triangle 0.0
rectangle 0.0
```

Divide by a MultiIndex by level.

```python
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
                               'degrees': [360, 180, 360, 360, 540, 720]},
                              index=['A', 'A', 'A', 'B', 'B', 'B'],
                              columns=['circle', 'triangle', 'rectangle', 'square', 'pentagon', 'hexagon'])
>>> df_multindex
angles degrees
A circle 0 360
triangle 3 180
rectangle 4 360
B square 4 360
pentagon 5 540
hexagon 6 720

>>> df.div(df_multindex, level=0, fill_value=0)
angles degrees
A circle NaN 1.0
triangle 1.0 1.0
rectangle 1.0 1.0
B square 0.0 0.0
pentagon 0.0 0.0
hexagon 0.0 0.0
```
pandas.DataFrame.truncate

DataFrame.truncate(before=None, after=None, axis=None, copy=True)
Truncate a Series or DataFrame before and after some index value.

This is a useful shorthand for boolean indexing based on index values above or below certain thresholds.

Parameters

- **before** [date, str, int] Truncate all rows before this index value.
- **after** [date, str, int] Truncate all rows after this index value.
- **axis** [{0 or ‘index’, 1 or ‘columns’}, optional] Axis to truncate. Truncates the index (rows) by default.
- **copy** [bool, default is True.] Return a copy of the truncated section.

Returns

- type of caller The truncated Series or DataFrame.

See also:

- **DataFrame.loc** Select a subset of a DataFrame by label.
- **DataFrame.iloc** Select a subset of a DataFrame by position.

Notes

If the index being truncated contains only datetime values, before and after may be specified as strings instead of Timestamps.

Examples

```python
>>> df = pd.DataFrame({'A': ['a', 'b', 'c', 'd', 'e'],
                    'B': ['f', 'g', 'h', 'i', 'j'],
                    'C': ['k', 'l', 'm', 'n', 'o']},
                    index=[1, 2, 3, 4, 5])
>>> df
   A  B  C
1  a  f  k
2  b  g  l
3  c  h  m
4  d  i  n
5  e  j  o
```

```python
>>> df.truncate(before=2, after=4)
   A  B  C
2  b  g  l
3  c  h  m
4  d  i  n
```

The columns of a DataFrame can be truncated.
For Series, only rows can be truncated.

```
>>> df['A'].truncate(before=2, after=4)  
2   b  
3   c  
4   d  
Name: A, dtype: object
```

The index values in `truncate` can be datetimes or string dates.

```
>>> dates = pd.date_range('2016-01-01', '2016-02-01', freq='s')
>>> df = pd.DataFrame(index=dates, data={'A': 1})
>>> df.tail()  
      A
2016-01-31 23:59:56 1
2016-01-31 23:59:57 1
2016-01-31 23:59:58 1
2016-01-31 23:59:59 1
2016-02-01 00:00:00 1
```

```
>>> df.truncate(before=pd.Timestamp('2016-01-05'),
...             after=pd.Timestamp('2016-01-10')).tail()  
      A
2016-01-09 23:59:56 1
2016-01-09 23:59:57 1
2016-01-09 23:59:58 1
2016-01-09 23:59:59 1
2016-01-10 00:00:00 1
```

Because the index is a DatetimeIndex containing only dates, we can specify `before` and `after` as strings. They will be coerced to Timestamps before truncation.

```
>>> df.truncate('2016-01-05', '2016-01-10').tail()  
      A
2016-01-09 23:59:56 1
2016-01-09 23:59:57 1
2016-01-09 23:59:58 1
2016-01-09 23:59:59 1
2016-01-10 00:00:00 1
```

Note that `truncate` assumes a 0 value for any unspecified time component (midnight). This differs from partial string slicing, which returns any partially matching dates.

```
>>> df.loc['2016-01-05':'2016-01-10', :].tail()  
      A
2016-01-10 23:59:55 1
2016-01-10 23:59:56 1
2016-01-10 23:59:57 1
(continues on next page)
pandas.DataFrame.tshift

DataFrame.tshift (periods=1, freq=None, axis=0)
Shift the time index, using the index’s frequency if available.
Deprecated since version 1.1.0: Use shift instead.

Parameters

periods [int] Number of periods to move, can be positive or negative.

freq [DateOffset, timedelta, or str, default None] Increment to use from the tseries module or time rule expressed as a string (e.g. ‘EOM’).

axis [[0 or ‘index’, 1 or ‘columns’, None], default 0] Corresponds to the axis that contains the Index.

Returns

shifted [Series/DataFrame]

Notes

If freq is not specified then tries to use the freq or inferred_freq attributes of the index. If neither of those attributes exist, a ValueError is thrown

pandas.DataFrame.tz_convert

DataFrame.tz_convert (tz, axis=0, level=None, copy=True)
Convert tz-aware axis to target time zone.

Parameters

tz [str or tzinfo object]
axis [the axis to convert]
level [int, str, default None] If axis is a MultiIndex, convert a specific level. Otherwise must be None.

copy [bool, default True] Also make a copy of the underlying data.

Returns

{klass} Object with time zone converted axis.

Raises

TypeError If the axis is tz-naive.
pandas.DataFrame.tz_localize

```python
DataFrame.tz_localize(tz, axis=0, level=None, copy=True, ambiguous='raise', nonexistent='raise')
```

Localize tz-naive index of a Series or DataFrame to target time zone.

This operation localizes the Index. To localize the values in a timezone-naive Series, use `Series.dt.tz_localize()`.

**Parameters**

- `tz` [str or tzinfo]
- `axis` [the axis to localize]
- `level` [int, str, default None] If axis ia a MultiIndex, localize a specific level. Otherwise must be None.
- `copy` [bool, default True] Also make a copy of the underlying data.
- `ambiguous` ['infer', bool-ndarray, `NaT`, default 'raise'] When clocks moved backward due to DST, ambiguous times may arise. For example in Central European Time (UTC+01), when going from 03:00 DST to 02:00 non-DST, 02:30:00 local time occurs both at 00:30:00 UTC and at 01:30:00 UTC. In such a situation, the `ambiguous` parameter dictates how ambiguous times should be handled.
  - ‘infer’ will attempt to infer fall dst-transition hours based on order
  - bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
  - ‘NaT’ will return NaT where there are ambiguous times
  - ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.
- `nonexistent` [str, default 'raise'] A nonexistent time does not exist in a particular time-zone where clocks moved forward due to DST. Valid values are:
  - ‘shift_forward’ will shift the nonexistent time forward to the closest existing time
  - ‘shift_backward’ will shift the nonexistent time backward to the closest existing time
  - ‘NaT’ will return NaT where there are nonexistent times
  - timedelta objects will shift nonexistent times by the timedelta
  - ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

**Returns**

- Series or DataFrame Same type as the input.

**Raises**

- TypeError If the TimeSeries is tz-aware and tz is not None.
Examples

Localize local times:

```python
>>> s = pd.Series([1],
                 index=pd.DatetimeIndex(['2018-09-15 01:30:00']))
>>> s.tz_localize('CET')
2018-09-15 01:30:00+02:00 1
dtype: int64
```

Be careful with DST changes. When there is sequential data, pandas can infer the DST time:

```python
>>> s = pd.Series(range(7),
                 index=pd.DatetimeIndex(['2018-10-28 01:30:00',
                                         '2018-10-28 02:00:00',
                                         '2018-10-28 02:30:00',
                                         '2018-10-28 02:00:00',
                                         '2018-10-28 02:30:00',
                                         '2018-10-28 03:00:00',
                                         '2018-10-28 03:30:00']))
>>> s.tz_localize('CET', ambiguous='infer')
2018-10-28 01:30:00+02:00 0
2018-10-28 02:00:00+02:00 1
2018-10-28 02:30:00+02:00 2
2018-10-28 02:00:00+01:00 3
2018-10-28 02:30:00+01:00 4
2018-10-28 03:00:00+01:00 5
2018-10-28 03:30:00+01:00 6
dtype: int64
```

In some cases, inferring the DST is impossible. In such cases, you can pass an ndarray to the ambiguous parameter to set the DST explicitly

```python
>>> s = pd.Series(range(3),
                 index=pd.DatetimeIndex(['2018-10-28 01:20:00',
                                         '2018-10-28 02:36:00',
                                         '2018-10-28 03:46:00']))
>>> s.tz_localize('CET', ambiguous=np.array([True, True, False]))
```

If the DST transition causes nonexistent times, you can shift these dates forward or backward with a timedelta object or ‘shift_forward’ or ‘shift_backward’.

```python
>>> s = pd.Series(range(2),
                 index=pd.DatetimeIndex(['2015-03-29 02:30:00',
                                         '2015-03-29 03:30:00']))
>>> s.tz_localize('Europe/Warsaw', nonexistent='shift_forward')
>>> s.tz_localize('Europe/Warsaw', nonexistent='shift_backward')
>>> s.tz_localize('Europe/Warsaw', nonexistent=pd.Timedelta('1H'))
```

(continues on next page)
pandas.DataFrame.unstack

DataFrame.unstack(level=-1, fill_value=None)

Pivot a level of the (necessarily hierarchical) index labels.

Returns a DataFrame having a new level of column labels whose inner-most level consists of the pivoted index labels.

If the index is not a MultiIndex, the output will be a Series (the analogue of stack when the columns are not a MultiIndex).

Parameters

level [int, str, or list of these, default -1 (last level)] Level(s) of index to unstack, can pass level name.

fill_value [int, str or dict] Replace NaN with this value if the unstack produces missing values.

Returns

Series or DataFrame

See also:

DataFrame.pivot  Pivot a table based on column values.

DataFrame.stack  Pivot a level of the column labels (inverse operation from unstack).

Examples

```python
>>> index = pd.MultiIndex.from_tuples([("one", 'a'), ('one', 'b'), ...
        ('two', 'a'), ('two', 'b')])
>>> s = pd.Series(np.arange(1.0, 5.0), index=index)
>>> s
one a 1.0
   b 2.0
two a 3.0
   b 4.0
dtype: float64

>>> s.unstack(level=-1)
a  b
one 1.0 2.0
two 3.0 4.0

>>> s.unstack(level=0)
one two
a 1.0 3.0
   b 2.0 4.0
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

```python
>>> df = s.unstack(level=0)
>>> df.unstack()
one  a  1.0
   b  2.0
two  a  3.0
   b  4.0
dtype: float64
```

**pandas.DataFrame.update**

DataFrame.update(other, join='left', overwrite=True, filter_func=None, errors='ignore')

Modify in place using non-NA values from another DataFrame.

Aligns on indices. There is no return value.

**Parameters**

- **other** [DataFrame, or object coercible into a DataFrame] Should have at least one matching index/column label with the original DataFrame. If a Series is passed, its name attribute must be set, and that will be used as the column name to align with the original DataFrame.

- **join** [‘left’] Only left join is implemented, keeping the index and columns of the original object.

- **overwrite** [bool, default True] How to handle non-NA values for overlapping keys:
  - True: overwrite original DataFrame’s values with values from other.
  - False: only update values that are NA in the original DataFrame.

- **filter_func** [callable(1d-array) -> bool 1d-array, optional] Can choose to replace values other than NA. Return True for values that should be updated.

- **errors** [‘raise’, ‘ignore’] If ‘raise’, will raise a ValueError if the DataFrame and other both contain non-NA data in the same place.

  Changed in version 0.24.0: Changed from raise_conflict=False|True to errors='ignore'|’raise’.

**Returns**

None [method directly changes calling object]

**Raises**

- **ValueError**
  - When errors=’raise’ and there’s overlapping non-NA data.
  - When errors is not either ‘ignore’ or ‘raise’

- **NotImplementedError**
  - If join != ‘left’

**See also:**

dict.update Similar method for dictionaries.

DataFrame.merge For column(s)-on-columns(s) operations.
Examples

```python
>>> df = pd.DataFrame({'A': [1, 2, 3],
... 'B': [400, 500, 600]})
>>> new_df = pd.DataFrame({'B': [4, 5, 6],
... 'C': [7, 8, 9]})
>>> df.update(new_df)
```

```
  A  B
0  1  4
1  2  5
2  3  6
```

The DataFrame’s length does not increase as a result of the update, only values at matching index/column labels are updated.

```python
>>> df = pd.DataFrame({'A': ['a', 'b', 'c'],
... 'B': ['x', 'y', 'z']})
>>> new_df = pd.DataFrame({'B': ['d', 'e', 'f', 'g', 'h', 'i']})
>>> df.update(new_df)
```

```
  A  B
0 a  d
1 b  e
2 c  f
```

For Series, it’s name attribute must be set.

```python
>>> df = pd.DataFrame({'A': ['a', 'b', 'c'],
... 'B': ['x', 'y', 'z']})
>>> new_column = pd.Series(['d', 'e'], name='B', index=[0, 2])
>>> df.update(new_column)
```

```
  A  B
0 a  d
1 b  y
2 c  e
```

If other contains NaNs the corresponding values are not updated in the original dataframe.

```python
>>> df = pd.DataFrame({'A': [1, 2, 3],
... 'B': [400, 500, 600]})
>>> new_df = pd.DataFrame({'B': [4, np.nan, 6]})
>>> df.update(new_df)
```

```
  A  B
0 1  4.0
1 2 500.0
2 3 6.0
```
pandas.DataFrame.value_counts

DataFrame.value_counts (subset=None, normalize=False, sort=True, ascending=False)

Return a Series containing counts of unique rows in the DataFrame.

New in version 1.1.0.

Parameters

- **subset** [list-like, optional] Columns to use when counting unique combinations.
- **normalize** [bool, default False] Return proportions rather than frequencies.
- **sort** [bool, default True] Sort by frequencies.
- **ascending** [bool, default False] Sort in ascending order.

Returns

Series

See also:

Series.value_counts Equivalent method on Series.

Notes

The returned Series will have a MultiIndex with one level per input column. By default, rows that contain any NA values are omitted from the result. By default, the resulting Series will be in descending order so that the first element is the most frequently-occurring row.

Examples

```python
>>> df = pd.DataFrame({'num_legs': [2, 4, 4, 6],
... 'num_wings': [2, 0, 0, 0]},
... index=['falcon', 'dog', 'cat', 'ant'])
>>> df
  num_legs num_wings  
falcon    2        2  
dog       4        0  
cat       4        0  
ant       6        0

>>> df.value_counts()
  num_legs num_wings
4        0        2
6        0        1
2        2        1
dtype: int64

>>> df.value_counts(sort=False)
  num_legs num_wings
2        2        1
4        0        2
6        0        1
dtype: int64
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

```python
>>> df.value_counts(ascending=True)
num_legs  num_wings
2         2
6         1
4         0
4         2
dtype: int64

>>> df.value_counts(normalize=True)
num_legs  num_wings
4         0  0.50
6         0  0.25
2         2  0.25
dtype: float64
```

**pandas.DataFrame.var**

DataFrame.var (axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)

Return unbiased variance over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

**Parameters**

- **axis** [{index (0), columns (1)}]
- **skipna** [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.
- **level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.
- **ddof** [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.
- **numeric_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**Returns**

Series or DataFrame (if level specified)

**pandas.DataFrame.where**

DataFrame.where (cond, other=nan, inplace=False, axis=None, level=None, errors='raise', try_cast=False)

Replace values where the condition is False.

**Parameters**

- **cond** [bool Series/DataFrame, array-like, or callable] Where cond is True, keep the original value. Where False, replace with corresponding value from other. If cond is callable, it is computed on the Series/DataFrame and should return boolean Series/DataFrame or array. The callable must not change input Series/DataFrame (though pandas doesn’t check it).
- **other** [scalar, Series/DataFrame, or callable] Entries where cond is False are replaced with corresponding value from other. If other is callable, it is computed on the
Series/DataFrame and should return scalar or Series/DataFrame. The callable must not change input Series/DataFrame (though pandas doesn’t check it).

**inplace** [bool, default False] Whether to perform the operation in place on the data.

**axis** [int, default None] Alignment axis if needed.

**level** [int, default None] Alignment level if needed.

**errors** [str, {'raise', ‘ignore’}, default ‘raise’] Note that currently this parameter won’t affect the results and will always coerce to a suitable dtype.

- ‘raise’: allow exceptions to be raised.
- ‘ignore’: suppress exceptions. On error return original object.

**try_cast** [bool, default False] Try to cast the result back to the input type (if possible).

Returns

Same type as caller

See also:

*DataFrame.mask()* Return an object of same shape as self.

Notes

The where method is an application of the if-then idiom. For each element in the calling DataFrame, if *cond* is True the element is used; otherwise the corresponding element from the DataFrame *other* is used.

The signature for *DataFrame.where()* differs from *numpy.where()*.

Roughly *df1.where(m, df2)* is equivalent to *np.where(m, df1, df2)*.

For further details and examples see the *where* documentation in *indexing*.

Examples

```python
>>> s = pd.Series(range(5))
>>> s.where(s > 0)
0    NaN
1    1.0
2    2.0
3    3.0
4    4.0
dtype: float64

>>> s.mask(s > 0)
0    0.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64
```
```python
>>> s.where(s > 1, 10)
0    10
1    10
2     2
3     3
4     4
dtype: int64
```

```python
>>> df = pd.DataFrame(np.arange(10).reshape(-1, 2), columns=['A', 'B'])
```

```python
>>> df.where(m, -df) == df.mask(~m, -df)
```

```python
pandas.DataFrame.xs
```

DataFrame.xs (key, axis=0, level=None, drop_level=True)

Return cross-section from the Series/DataFrame.

This method takes a `key` argument to select data at a particular level of a MultiIndex.

**Parameters**

- **key** [label or tuple of label] Label contained in the index, or partially in a MultiIndex.
- **axis** [{0 or 'index', 1 or 'columns'}, default 0] Axis to retrieve cross-section on.
- **level** [object, defaults to first n levels (n=1 or len(key))] In case of a key partially contained in a MultiIndex, indicate which levels are used. Levels can be referred by label or position.
- **drop_level** [bool, default True] If False, returns object with same levels as self.
Returns

Series or DataFrame: Cross-section from the original Series or DataFrame corresponding to the selected index levels.

See also:

DataFrame.loc: Access a group of rows and columns by label(s) or a boolean array.

DataFrame.iloc: Purely integer-location based indexing for selection by position.

Notes

xs can not be used to set values.

MultiIndex Slicers is a generic way to get/set values on any level or levels. It is a superset of xs functionality, see MultiIndex Slicers.

Examples

```python
>>> d = {'num_legs': [4, 4, 2, 2],
...       'num_wings': [0, 0, 2, 2],
...       'class': ['mammal', 'mammal', 'mammal', 'bird'],
...       'animal': ['cat', 'dog', 'bat', 'penguin'],
...       'locomotion': ['walks', 'walks', 'flies', 'walks']}
>>> df = pd.DataFrame(data=d)
>>> df = df.set_index(['class', 'animal', 'locomotion'])
>>> df
   num_legs  num_wings
animal locomotion
mammal  cat walks  4  0
        dog walks  4  0
        bat flies  2  2
bird    penguin walks  2  2

Get values at specified index

```python
>>> df.xs('mammal')
   num_legs  num_wings
animal locomotion
cat   walks  4  0
dog   walks  4  0
bat   flies  2  2

Get values at several indexes

```python
>>> df.xs(('mammal', 'dog'))
   locomotion
num_legs  num_wings
walks  4  0

Get values at specified index and level

```python
>>> df.xs('cat', level=1)
   num_legs  num_wings
class locomotion
mammal  walks  4  0
```
Get values at several indexes and levels

```python
>>> df.xs(('bird', 'walks'),
...       level=[0, 'locomotion'])
     num_legs num_wings
animal    2         2
penguin    2         2
```

Get values at specified column and axis

```python
>>> df.xs('num_wings', axis=1)
   class       animal  locomotion
  mammal       cat    walks  0
      dog    walks  0
      bat    flies  2
  bird  penguin   walks  2
Name: num_wings, dtype: int64
```

### 3.4.2 Attributes and underlying data

#### Axes

- **DataFrame.index**: The index (row labels) of the DataFrame.
- **DataFrame.columns**: The column labels of the DataFrame.

- **DataFrame.dtypes**: Return the dtypes in the DataFrame.
- **DataFrame.info([verbose, buf, max_cols,...])**: Print a concise summary of a DataFrame.
- **DataFrame.select_dtypes([include, exclude])**: Return a subset of the DataFrame's columns based on the column dtypes.
- **DataFrame.values**: Return a Numpy representation of the DataFrame.
- **DataFrame.axes**: Return a list representing the axes of the DataFrame.
- **DataFrame.ndim**: Return an int representing the number of axes / array dimensions.
- **DataFrame.size**: Return an int representing the number of elements in this object.
- **DataFrame.shape**: Return a tuple representing the dimensionality of the DataFrame.
- **DataFrame.memory_usage([index, deep])**: Return the memory usage of each column in bytes.
- **DataFrame.empty**: Indicator whether DataFrame is empty.

### 3.4.3 Conversion

- **DataFrame.astype(dtype[, copy, errors])**: Cast a pandas object to a specified dtype `dtype`.
- **DataFrame.convert_dtypes([infer_objects, ...])**: Convert columns to best possible dtypes using dtypes supporting `pd.NA`.
- **DataFrame.infer_objects()**: Attempt to infer better dtypes for object columns.
- **DataFrame.copy([deep])**: Make a copy of this object's indices and data.
- **DataFrame.bool()**: Return the bool of a single element Series or DataFrame.
3.4.4 Indexing, iteration

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataFrame.head</td>
<td>Return the first ( n ) rows.</td>
</tr>
<tr>
<td>DataFrame.at</td>
<td>Access a single value for a row/column label pair.</td>
</tr>
<tr>
<td>DataFrame.iat</td>
<td>Access a single value for a row/column pair by integer position.</td>
</tr>
<tr>
<td>DataFrame.loc</td>
<td>Access a group of rows and columns by label(s) or a boolean array.</td>
</tr>
<tr>
<td>DataFrame.iloc</td>
<td>Purely integer-location based indexing for selection by position.</td>
</tr>
<tr>
<td>DataFrame.insert</td>
<td>Insert column into DataFrame at specified location.</td>
</tr>
<tr>
<td>DataFrame.<strong>iter</strong></td>
<td>Iterate over info axis.</td>
</tr>
<tr>
<td>DataFrame.items</td>
<td>Iterate over (column name, Series) pairs.</td>
</tr>
<tr>
<td>DataFrame.iteritems</td>
<td>Iterate over (column name, Series) pairs.</td>
</tr>
<tr>
<td>DataFrame.keys</td>
<td>Get the “info axis” (see Indexing for more).</td>
</tr>
<tr>
<td>DataFrame.iterrows</td>
<td>Iterate over DataFrame rows as (index, Series) pairs.</td>
</tr>
<tr>
<td>DataFrame.iteritems</td>
<td>Iterate over DataFrame rows as namedtuples.</td>
</tr>
<tr>
<td>DataFrame.lookup</td>
<td>Label-based “fancy indexing” function for DataFrame.</td>
</tr>
<tr>
<td>DataFrame.pop</td>
<td>Return item and drop from frame.</td>
</tr>
<tr>
<td>DataFrame.tail</td>
<td>Return the last ( n ) rows.</td>
</tr>
<tr>
<td>DataFrame.xs</td>
<td>Return cross-section from the Series/DataFrame.</td>
</tr>
<tr>
<td>DataFrame.get</td>
<td>Get item from object for given key (ex: DataFrame column).</td>
</tr>
<tr>
<td>DataFrame.isin</td>
<td>Whether each element in the DataFrame is contained in values.</td>
</tr>
<tr>
<td>DataFrame.where</td>
<td>Replace values where the condition is False.</td>
</tr>
<tr>
<td>DataFrame.mask</td>
<td>Replace values where the condition is True.</td>
</tr>
<tr>
<td>DataFrame.query</td>
<td>Query the columns of a DataFrame with a boolean expression.</td>
</tr>
</tbody>
</table>

pandas.DataFrame.__iter__

DataFrame.__iter__()

Iterate over info axis.

Returns

iterator  Info axis as iterator.

For more information on .at, .iat, .loc, and .iloc, see the indexing documentation.

3.4.5 Binary operator functions

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataFrame.add</td>
<td>Get Addition of dataframe and other, element-wise (binary operator add).</td>
</tr>
<tr>
<td>DataFrame.sub</td>
<td>Get Subtraction of dataframe and other, element-wise (binary operator sub).</td>
</tr>
<tr>
<td>DataFrame.mul</td>
<td>Get Multiplication of dataframe and other, element-wise (binary operator mul).</td>
</tr>
<tr>
<td>DataFrame.div</td>
<td>Get Floating division of dataframe and other, element-wise (binary operator truediv).</td>
</tr>
</tbody>
</table>
**Table 64 – continued from previous page**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>DataFrame.truediv(other[, axis, level, ...])</code></td>
<td>Get Floating division of dataframe and other, element-wise (binary operator <code>truediv</code>).</td>
</tr>
<tr>
<td><code>DataFrame.floordiv(other[, axis, level, ...])</code></td>
<td>Get Integer division of dataframe and other, element-wise (binary operator <code>floordiv</code>).</td>
</tr>
<tr>
<td><code>DataFrame.mod(other[, axis, level, fill_value])</code></td>
<td>Get Modulo of dataframe and other, element-wise (binary operator <code>mod</code>).</td>
</tr>
<tr>
<td><code>DataFrame.pow(other[, axis, level, fill_value])</code></td>
<td>Get Exponential power of dataframe and other, element-wise (binary operator <code>pow</code>).</td>
</tr>
<tr>
<td><code>DataFrame.dot(other)</code></td>
<td>Compute the matrix multiplication between the DataFrame and other.</td>
</tr>
<tr>
<td><code>DataFrame.radd(other[, axis, level, fill_value])</code></td>
<td>Get Addition of dataframe and other, element-wise (binary operator <code>radd</code>).</td>
</tr>
<tr>
<td><code>DataFrame.rsub(other[, axis, level, fill_value])</code></td>
<td>Get Subtraction of dataframe and other, element-wise (binary operator <code>rsub</code>).</td>
</tr>
<tr>
<td><code>DataFrame.rmul(other[, axis, level, fill_value])</code></td>
<td>Get Multiplication of dataframe and other, element-wise (binary operator <code>rmul</code>).</td>
</tr>
<tr>
<td><code>DataFrame.rdiv(other[, axis, level, fill_value])</code></td>
<td>Get Floating division of dataframe and other, element-wise (binary operator <code>rtruediv</code>).</td>
</tr>
<tr>
<td><code>DataFrame.rtruediv(other[, axis, level, ...])</code></td>
<td>Get Floating division of dataframe and other, element-wise (binary operator <code>rtruediv</code>).</td>
</tr>
<tr>
<td><code>DataFrame.rfloordiv(other[, axis, level, ...])</code></td>
<td>Get Integer division of dataframe and other, element-wise (binary operator <code>rfloordiv</code>).</td>
</tr>
<tr>
<td><code>DataFrame.rmod(other[, axis, level, fill_value])</code></td>
<td>Get Modulo of dataframe and other, element-wise (binary operator <code>rmod</code>).</td>
</tr>
<tr>
<td><code>DataFrame.rpow(other[, axis, level, fill_value])</code></td>
<td>Get Exponential power of dataframe and other, element-wise (binary operator <code>rpow</code>).</td>
</tr>
<tr>
<td><code>DataFrame.lt(other[, axis, level])</code></td>
<td>Get Less than of dataframe and other, element-wise (binary operator <code>lt</code>).</td>
</tr>
<tr>
<td><code>DataFrame.gt(other[, axis, level])</code></td>
<td>Get Greater than of dataframe and other, element-wise (binary operator <code>gt</code>).</td>
</tr>
<tr>
<td><code>DataFrame.le(other[, axis, level])</code></td>
<td>Get Less than or equal to of dataframe and other, element-wise (binary operator <code>le</code>).</td>
</tr>
<tr>
<td><code>DataFrame.ge(other[, axis, level])</code></td>
<td>Get Greater than or equal to of dataframe and other, element-wise (binary operator <code>ge</code>).</td>
</tr>
<tr>
<td><code>DataFrame.ne(other[, axis, level])</code></td>
<td>Get Not equal to of dataframe and other, element-wise (binary operator <code>ne</code>).</td>
</tr>
<tr>
<td><code>DataFrame.eq(other[, axis, level])</code></td>
<td>Get Equal to of dataframe and other, element-wise (binary operator <code>eq</code>).</td>
</tr>
<tr>
<td><code>DataFrame.combine(other, func[, fill_value, ...])</code></td>
<td>Perform column-wise combine with another DataFrame.</td>
</tr>
<tr>
<td><code>DataFrame.combine_first(other)</code></td>
<td>Update null elements with value in the same location in <code>other</code>.</td>
</tr>
</tbody>
</table>
3.4.6 Function application, GroupBy & window

- **DataFrame.apply**(func[, axis, raw, ...]) Apply a function along an axis of the DataFrame.
- **DataFrame.applymap**(func) Apply a function to a Dataframe elementwise.
- **DataFrame.pipe**(func, *args, **kwargs) Apply func(self, *args, **kwargs).
- **DataFrame.agg**(func[, axis]) Aggregate using one or more operations over the specified axis.
- **DataFrame.aggregate**(func[, axis]) Aggregate using one or more operations over the specified axis.
- **DataFrame.transform**(func[, axis]) Call func on self producing a DataFrame with transformed values.
- **DataFrame.groupby**(by[, axis, level, ...]) Group DataFrame using a mapper or by a Series of columns.
- **DataFrame.rolling**(window[, min_periods, ...]) Provide rolling window calculations.
- **DataFrame.expanding**(min_periods[, center, axis]) Provide expanding transformations.
- **DataFrame.ewm**(com, span, halflife, alpha[, ...]) Provide exponential weighted (EW) functions.

3.4.7 Computations / descriptive stats

- **DataFrame.abs**() Return a Series/DataFrame with absolute numeric value of each element.
- **DataFrame.all**(axis, bool_only, skipna, level) Return whether all elements are True, potentially over an axis.
- **DataFrame.any**(axis, bool_only, skipna, level) Return whether any element is True, potentially over an axis.
- **DataFrame.clip**(lower, upper, axis, inplace) Trim values at input threshold(s).
- **DataFrame.corr**(method, min_periods) Compute pairwise correlation of columns, excluding NA/null values.
- **DataFrame.corrwith**(other[, axis, drop, method]) Compute pairwise correlation.
- **DataFrame.count**(axis, level, numeric_only) Count non-NA cells for each column or row.
- **DataFrame.cov**(min_periods, ddof) Compute pairwise covariance of columns, excluding NA/null values.
- **DataFrame.cummax**(axis, skipna) Return cumulative maximum over a DataFrame or Series axis.
- **DataFrame.cummin**(axis, skipna) Return cumulative minimum over a DataFrame or Series axis.
- **DataFrame.cumprod**(axis, skipna) Return cumulative product over a DataFrame or Series axis.
- **DataFrame.cumsum**(axis, skipna) Return cumulative sum over a DataFrame or Series axis.
- **DataFrame.describe**(percentiles, include, ...) Generate descriptive statistics.
- **DataFrame.diff**(periods, axis) First discrete difference of element.
- **DataFrame.eval**(expr[, inplace]) Evaluate a string describing operations on DataFrame columns.
- **DataFrame.kurt**(axis, skipna, level, ...) Return unbiased kurtosis over requested axis.
- **DataFrame.kurtosis**(axis, skipna, level, ...) Return unbiased kurtosis over requested axis.
- **DataFrame.mad**(axis, skipna, level) Return the mean absolute deviation of the values for the requested axis.

continues on next page
Table 66 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataFrame.max</td>
<td>Return the maximum of the values for the requested axis.</td>
</tr>
<tr>
<td>DataFrame.mean</td>
<td>Return the mean of the values for the requested axis.</td>
</tr>
<tr>
<td>DataFrame.median</td>
<td>Return the median of the values for the requested axis.</td>
</tr>
<tr>
<td>DataFrame.min</td>
<td>Return the minimum of the values for the requested axis.</td>
</tr>
<tr>
<td>DataFrame.mode</td>
<td>Get the mode(s) of each element along the selected axis.</td>
</tr>
<tr>
<td>DataFrame.pct_change</td>
<td>Percentage change between the current and a prior element.</td>
</tr>
<tr>
<td>DataFrame.prod</td>
<td>Return the product of the values for the requested axis.</td>
</tr>
<tr>
<td>DataFrame.product</td>
<td>Return the product of the values for the requested axis.</td>
</tr>
<tr>
<td>DataFrame.quantile</td>
<td>Return values at the given quantile over requested axis.</td>
</tr>
<tr>
<td>DataFrame.rank</td>
<td>Compute numerical data ranks (1 through n) along axis.</td>
</tr>
<tr>
<td>DataFrame.round</td>
<td>Round a DataFrame to a variable number of decimal places.</td>
</tr>
<tr>
<td>DataFrame.sem</td>
<td>Return unbiased standard error of the mean over requested axis.</td>
</tr>
<tr>
<td>DataFrame.skew</td>
<td>Return unbiased skew over requested axis.</td>
</tr>
<tr>
<td>DataFrame.sum</td>
<td>Return the sum of the values for the requested axis.</td>
</tr>
<tr>
<td>DataFrame.std</td>
<td>Return sample standard deviation over requested axis.</td>
</tr>
<tr>
<td>DataFrame.var</td>
<td>Return unbiased variance over requested axis.</td>
</tr>
<tr>
<td>DataFrame.nunique</td>
<td>Count distinct observations over requested axis.</td>
</tr>
<tr>
<td>DataFrame.value_counts</td>
<td>Return a Series containing counts of unique rows in the DataFrame.</td>
</tr>
</tbody>
</table>

3.4.8 Reindexing / selection / label manipulation

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataFrame.add_prefix</td>
<td>Prefix labels with string ( prefix ).</td>
</tr>
<tr>
<td>DataFrame.add_suffix</td>
<td>Suffix labels with string ( suffix ).</td>
</tr>
<tr>
<td>DataFrame.align</td>
<td>Align two objects on their axes with the specified join method.</td>
</tr>
<tr>
<td>DataFrame.at_time</td>
<td>Select values at particular time of day (e.g., 9:30AM).</td>
</tr>
<tr>
<td>DataFrame.between_time</td>
<td>Select values between particular times of the day (e.g., 9:00-9:30 AM).</td>
</tr>
<tr>
<td>DataFrame.drop</td>
<td>Drop specified labels from rows or columns.</td>
</tr>
<tr>
<td>DataFrame.drop_duplicates</td>
<td>Return DataFrame with duplicate rows removed.</td>
</tr>
<tr>
<td>DataFrame.duplicated</td>
<td>Return boolean Series denoting duplicate rows.</td>
</tr>
<tr>
<td>DataFrame.equals</td>
<td>Test whether two objects contain the same elements.</td>
</tr>
<tr>
<td>DataFrame.filter</td>
<td>Subset the dataframe rows or columns according to the specified index labels.</td>
</tr>
<tr>
<td>DataFrame.first</td>
<td>Select initial periods of time series data based on a date offset.</td>
</tr>
<tr>
<td>DataFrame.head</td>
<td>Return the first ( n ) rows.</td>
</tr>
<tr>
<td>DataFrame.idxmax</td>
<td>Return index of first occurrence of maximum over requested axis.</td>
</tr>
<tr>
<td>DataFrame.idxmin</td>
<td>Return index of first occurrence of minimum over requested axis.</td>
</tr>
</tbody>
</table>
**DataFrame.last**(offset) Select final periods of time series data based on a date offset.

**DataFrame.reindex**(**kwargs) Conform Series/DataFrame to new index with optional filling logic.

**DataFrame.reindex_like**(other[, method, ...]) Return an object with matching indices as other object.

**DataFrame.rename**(**kwargs) Alter axes labels.

**DataFrame.rename_axis**(**kwargs) Set the name of the axis for the index or columns.

**DataFrame.reset_index**(level, drop, ...) Reset the index, or a level of it.

**DataFrame.sample**(n, frac, replace, ...) Return a random sample of items from an axis of object.

**DataFrame.set_axis**(labels[, axis, inplace]) Assign desired index to given axis.

**DataFrame.set_index**(keys[, drop, append, ...]) Set the DataFrame index using existing columns.

**DataFrame.tail**(n) Return the last n rows.

**DataFrame.take**(indices[, axis, is_copy]) Return the elements in the given positional indices along an axis.

**DataFrame.truncate**(before, after, axis, copy) Truncate a Series or DataFrame before and after some index value.

### 3.4.9 Missing data handling

**DataFrame.backfill**(axis, inplace, limit, ...) Synonym for **DataFrame.fillna()** with method='bfill'.

**DataFrame.bfill**(axis, inplace, limit, downcast) Synonym for **DataFrame.fillna()** with method='bfill'.

**DataFrame.dropna**(axis, how, thresh, ...) Remove missing values.

**DataFrame.ffill**(axis, inplace, limit, downcast) Synonym for **DataFrame.fillna()** with method='ffill'.

**DataFrame.fillna**(value, method, axis, ...) Fill NA/NaN values using the specified method.

**DataFrame.isna()** Detect missing values.

**DataFrame.isnull()** Detect missing values.

**DataFrame.notna()** Detect existing (non-missing) values.

**DataFrame.notnull()** Detect existing (non-missing) values.

**DataFrame.pad**(axis, inplace, limit, downcast) Synonym for **DataFrame.fillna()** with method='ffill'.

**DataFrame.replace**(to_replace, value) Replace values given in to_replace with value.

### 3.4.10 Reshaping, sorting, transposing

**DataFrame.droplevel**(level[, axis]) Return DataFrame with requested index / column level(s) removed.

**DataFrame.pivot**(index, columns, values) Return reshaped DataFrame organized by given index / column values.

**DataFrame.pivot_table**(values, index, ...) Create a spreadsheet-style pivot table as a DataFrame.

**DataFrame.reorder_levels**(order[, ...]) Rearrange index levels using input order.

**DataFrame.sort_values**(by[, axis, ascending, ...]) Sort by the values along either axis.

continues on next page
Table 69 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>DataFrame.sort_index((axis, level, ...))</code></td>
<td>Sort object by labels (along an axis).</td>
</tr>
<tr>
<td><code>DataFrame.nlargest(n, columns[, keep])</code></td>
<td>Return the first <code>n</code> rows ordered by <code>columns</code> in descending order.</td>
</tr>
<tr>
<td><code>DataFrame.nsmallest(n, columns[, keep])</code></td>
<td>Return the first <code>n</code> rows ordered by <code>columns</code> in ascending order.</td>
</tr>
<tr>
<td><code>DataFrame.swaplevel([i, j, axis])</code></td>
<td>Swap levels i and j in a MultiIndex on a particular axis.</td>
</tr>
<tr>
<td><code>DataFrame.stack([level, dropna])</code></td>
<td>Stack the prescribed level(s) from columns to index.</td>
</tr>
<tr>
<td><code>DataFrame.unstack([level, fill_value])</code></td>
<td>Pivot a level of the (necessarily hierarchical) index labels.</td>
</tr>
<tr>
<td><code>DataFrame.swapaxes(axis1, axis2[, copy])</code></td>
<td>Interchange axes and swap values axes appropriately.</td>
</tr>
<tr>
<td><code>DataFrame.melt([id_vars, value_vars, ...])</code></td>
<td>Unpivot a DataFrame from wide to long format, optionally leaving identifiers set.</td>
</tr>
<tr>
<td><code>DataFrame.explode(column[, ignore_index])</code></td>
<td>Transform each element of a list-like to a row, replicating index values.</td>
</tr>
<tr>
<td><code>DataFrame.squeeze([axis])</code></td>
<td>Squeeze 1 dimensional axis objects into scalars.</td>
</tr>
<tr>
<td><code>DataFrame.to_xarray()</code></td>
<td>Return an xarray object from the pandas object.</td>
</tr>
<tr>
<td><code>DataFrame.T</code></td>
<td>Transpose index and columns.</td>
</tr>
</tbody>
</table>

**property** `DataFrame.T`

### 3.4.11 Combining / comparing / joining / merging

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>DataFrame.append(other[, ignore_index, ...])</code></td>
<td>Append rows of <code>other</code> to the end of caller, returning a new object.</td>
</tr>
<tr>
<td><code>DataFrame.assign(**kwargs)</code></td>
<td>Assign new columns to a DataFrame.</td>
</tr>
<tr>
<td><code>DataFrame.compare(other[, align_axis, ...])</code></td>
<td>Compare to another DataFrame and show the differences.</td>
</tr>
<tr>
<td><code>DataFrame.join(other[, on, how, lsuffix, ...])</code></td>
<td>Join columns of another DataFrame.</td>
</tr>
<tr>
<td><code>DataFrame.merge(right[, how, on, left_on, ...])</code></td>
<td>Merge DataFrame or named Series objects with a database-style join.</td>
</tr>
<tr>
<td><code>DataFrame.update(other[, join, overwrite, ...])</code></td>
<td>Modify in place using non-NA values from another DataFrame.</td>
</tr>
</tbody>
</table>

### 3.4.12 Time Series-related

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>DataFrame.asfreq(freq[, method, how, ...])</code></td>
<td>Convert TimeSeries to specified frequency.</td>
</tr>
<tr>
<td><code>DataFrame.asof(where[, subset])</code></td>
<td>Return the last row(s) without any NaNs before <code>where</code>.</td>
</tr>
<tr>
<td><code>DataFrame.shift([periods, freq, axis, ...])</code></td>
<td>Shift index by desired number of periods with an optional time <code>freq</code>.</td>
</tr>
<tr>
<td><code>DataFrame.slice_shift([periods, axis])</code></td>
<td>Equivalent to <code>shift</code> without copying data.</td>
</tr>
<tr>
<td><code>DataFrame.tshift([periods, freq, axis])</code></td>
<td>(DEPRECATED) Shift the time index, using the index’s frequency if available.</td>
</tr>
<tr>
<td><code>DataFrame.first_valid_index()</code></td>
<td>Return index for first non-NA/null value.</td>
</tr>
<tr>
<td><code>DataFrame.last_valid_index()</code></td>
<td>Return index for last non-NA/null value.</td>
</tr>
</tbody>
</table>

continues on next page
DataFrame.resample(rule[, axis, closed, ...])  Resample time-series data.
DataFrame.to_period([freq, axis, copy])  Convert DataFrame from DatetimeIndex to PeriodIndex.
DataFrame.to_timestamp([freq, how, axis, copy])  Cast to DatetimeIndex of timestamps, at beginning of period.
DataFrame.tz_convert([tz[, axis, level, copy]])  Convert tz-aware axis to target time zone.
DataFrame.tz_localize([tz[, axis, level, ...]])  Localize tz-naive index of a Series or DataFrame to target time zone.

3.4.13 Metadata

DataFrame.attrs is a dictionary for storing global metadata for this DataFrame.

Warning: DataFrame.attrs is considered experimental and may change without warning.

DataFrame.attrs  Dictionary of global attributes on this object.

3.4.14 Plotting

DataFrame.plot is both a callable method and a namespace attribute for specific plotting methods of the form DataFrame.plot.<kind>.

DataFrame.plot([x, y, kind, ax, ...])  DataFrame plotting accessor and method

DataFrame.plot.area([x, y])  Draw a stacked area plot.
DataFrame.plot.bar([x, y])  Vertical bar plot.
DataFrame.plot.barh([x, y])  Make a horizontal bar plot.
DataFrame.plot.box([by])  Make a box plot of the DataFrame columns.
DataFrame.plot.density([bw_method, ind])  Generate Kernel Density Estimate plot using Gaussian kernels.
DataFrame.plot.hexbin(x, y[, C, ...])  Generate a hexagonal binning plot.
DataFrame.plot.hist([by, bins])  Draw one histogram of the DataFrame’s columns.
DataFrame.plot.kde([bw_method, ind])  Generate Kernel Density Estimate plot using Gaussian kernels.
DataFrame.plot.line([x, y])  Plot Series or DataFrame as lines.
DataFrame.plot.pie(**kwargs)  Generate a pie plot.
DataFrame.plot.scatter(x, y[, s, c])  Create a scatter plot with varying marker point size and color.
pandas.DataFrame.plot.area

DataFrame.plot.area(x=None, y=None, **kwargs)

Draw a stacked area plot.

An area plot displays quantitative data visually. This function wraps the matplotlib area function.

Parameters

- x [label or position, optional] Coordinates for the X axis. By default uses the index.
- y [label or position, optional] Column to plot. By default uses all columns.
- stacked [bool, default True] Area plots are stacked by default. Set to False to create a unstacked plot.
- **kwargs Additional keyword arguments are documented in DataFrame.plot().

Returns

- matplotlib.axes.Axes or numpy.ndarray Area plot, or array of area plots if subplots is True.

See also:

- DataFrame.plot Make plots of DataFrame using matplotlib / pylab.

Examples

Draw an area plot based on basic business metrics:

```python
>>> df = pd.DataFrame({
...     'sales': [3, 2, 3, 9, 10, 6],
...     'signups': [5, 5, 6, 12, 14, 13],
...     'visits': [20, 42, 28, 62, 81, 50],
... }, index=pd.date_range(start='2018/01/01', end='2018/07/01',
...     freq='M'))
>>> ax = df.plot.area()
```

Area plots are stacked by default. To produce an unstacked plot, pass stacked=False:

```python
>>> ax = df.plot.area(stacked=False)
```

Draw an area plot for a single column:

```python
>>> ax = df.plot.area(y='sales')
```

Draw with a different x:

```python
>>> df = pd.DataFrame({
...     'sales': [3, 2, 3],
...     'visits': [20, 42, 28],
...     'day': [1, 2, 3],
... })
>>> ax = df.plot.area(x='day')
```
3.4. DataFrame
3.4. DataFrame
**pandas.DataFrame.plot.bar**

`DataFrame.plot.bar(x=None, y=None, **kwargs)`

Vertical bar plot.

A bar plot is a plot that presents categorical data with rectangular bars with lengths proportional to the values that they represent. A bar plot shows comparisons among discrete categories. One axis of the plot shows the specific categories being compared, and the other axis represents a measured value.

**Parameters**

- **x** [label or position, optional] Allows plotting of one column versus another. If not specified, the index of the DataFrame is used.
- **y** [label or position, optional] Allows plotting of one column versus another. If not specified, all numerical columns are used.
- **color** [str, array_like, or dict, optional] The color for each of the DataFrame's columns. Possible values are:
  - A single color string referred to by name, RGB or RGBA code, for instance 'red' or '#a98d19'.
  - A sequence of color strings referred to by name, RGB or RGBA code, which will be used for each column recursively. For instance ['green', 'yellow'] each column's bar will be filled in green or yellow, alternatively.
  - A dict of the form {column name: color}, so that each column will be colored accordingly. For example, if your columns are called `a` and `b`, then passing `{a: 'green', b: 'red'}` will color bars for column `a` in green and bars for column `b` in red.

New in version 1.1.0.

- **kwargs** Additional keyword arguments are documented in `DataFrame.plot()`.

**Returns**

- `matplotlib.axes.Axes` or `np.ndarray` of them An ndarray is returned with one `matplotlib.axes.Axes` per column when `subplots=True`.

**See also:**

- `DataFrame.plot.barh` Horizontal bar plot.
- `DataFrame.plot` Make plots of a DataFrame.
- `matplotlib.pyplot.bar` Make a bar plot with matplotlib.

**Examples**

Basic plot.

```python
>>> df = pd.DataFrame({'lab': ['A', 'B', 'C'], 'val': [10, 30, 20]})
>>> ax = df.plot.bar(x='lab', y='val', rot=0)
```

Plot a whole dataframe to a bar plot. Each column is assigned a distinct color, and each row is nested in a group along the horizontal axis.

```python
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]
>>> index = ['snail', 'pig', 'elephant',
>>>           'rabbit', 'giraffe', 'coyote', 'horse']
```
>>> df = pd.DataFrame({'speed': speed,...
                        'lifespan': lifespan}, index=index)
>>> ax = df.plot.bar(rot=0)

Plot stacked bar charts for the DataFrame

```python
>>> ax = df.plot.bar(stacked=True)
```

Instead of nesting, the figure can be split by column with `subplots=True`. In this case, a `numpy.ndarray` of `matplotlib.axes.Axes` are returned.

```python
>>> axes = df.plot.bar(rot=0, subplots=True)
```  
If you don’t like the default colours, you can specify how you’d like each column to be colored.

```python
>>> axes = df.plot.bar(...
               rot=0, subplots=True, color={"speed": "red", "lifespan": "green"}
...
) >>> axes[1].legend(loc=2)
```

Plot a single column.

3.4. DataFrame
Chapter 3. API reference
Plot only selected categories for the DataFrame.

```python
>>> ax = df.plot.bar(x='lifespan', rot=0)
```

### pandas.DataFrame.plot.barh

DataFrame.plot.barh ($x$=None, $y$=None, **kwargs)

Make a horizontal bar plot.

A horizontal bar plot is a plot that presents quantitative data with rectangular bars with lengths proportional to the values that they represent. A bar plot shows comparisons among discrete categories. One axis of the plot shows the specific categories being compared, and the other axis represents a measured value.

**Parameters**

- **x** [label or position, optional] Allows plotting of one column versus another. If not specified, the index of the DataFrame is used.
- **y** [label or position, optional] Allows plotting of one column versus another. If not specified, all numerical columns are used.
- **color** [str, array_like, or dict, optional] The color for each of the DataFrame’s columns. Possible values are:
• A single color string referred to by name, RGB or RGBA code, for instance ‘red’ or ‘#a98d19’.

• A sequence of color strings referred to by name, RGB or RGBA code, which will be used for each column recursively. For instance ['green', 'yellow'] each column’s bar will be filled in green or yellow, alternatively.

• A dict of the form {column name: color}, so that each column will be colored accordingly. For example, if your columns are called a and b, then passing {'a': 'green', 'b': 'red'} will color bars for column a in green and bars for column b in red.

New in version 1.1.0.

**kwargs Additional keyword arguments are documented in DataFrame.plot().

Returns

matplotlib.axes.Axes or np.ndarray of them An ndarray is returned with one matplotlib.axes.Axes per column when subplots=True.

See also:

DataFrame.plot.bar Vertical bar plot.
DataFrame.plot Make plots of DataFrame using matplotlib.
matplotlib.axes.Axes.bar Plot a vertical bar plot using matplotlib.

Examples

Basic example

>>> df = pd.DataFrame({"lab": ['A', 'B', 'C'], 'val': [10, 30, 20]})
>>> ax = df.plot.barh(x='lab', y='val')

Plot a whole DataFrame to a horizontal bar plot

>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]
>>> index = ['snail', 'pig', 'elephant', ...
            'rabbit', 'giraffe', 'coyote', 'horse']
>>> df = pd.DataFrame({"speed": speed,
                      ...
                      'lifespan': lifespan}, index=index)
>>> ax = df.plot.barh()
3.4. DataFrame
... 'lifespan': lifespan}, index=index)
>>> ax = df.plot.barh(y='speed')

Plot DataFrame versus the desired column

```python
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]
>>> index = ['snail', 'pig', 'elephant', 'rabbit', 'giraffe', 'coyote', 'horse']
>>> df = pd.DataFrame({'speed': speed,
...                    'lifespan': lifespan}, index=index)
>>> ax = df.plot.barh(x='lifespan')
```
3.4. DataFrame
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.DataFrame.plot.box

DataFrame.plot.box(by=None, **kwargs)
Make a box plot of the DataFrame columns.

A box plot is a method for graphically depicting groups of numerical data through their quartiles. The box extends from the Q1 to Q3 quartile values of the data, with a line at the median (Q2). The whiskers extend from the edges of box to show the range of the data. The position of the whiskers is set by default to 1.5*IQR (IQR = Q3 - Q1) from the edges of the box. Outlier points are those past the end of the whiskers.

For further details see Wikipedia’s entry for boxplot.

A consideration when using this chart is that the box and the whiskers can overlap, which is very common when plotting small sets of data.

Parameters
   
   by [str or sequence] Column in the DataFrame to group by.

   **kwargs Additional keywords are documented in DataFrame.plot().

Returns

matplotlib.axes.Axes or numpy.ndarray of them

See also:

DataFrame.boxplot Another method to draw a box plot.
Series.plot.box Draw a box plot from a Series object.
matplotlib.pyplot.boxplot Draw a box plot in matplotlib.

Examples

Draw a box plot from a DataFrame with four columns of randomly generated data.

```python
>>> data = np.random.randn(25, 4)
>>> df = pd.DataFrame(data, columns=list('ABCD'))
>>> ax = df.plot.box()
```

pandas.DataFrame.plot.density

DataFrame.plot.density(bw_method=None, ind=None, **kwargs)
Generate Kernel Density Estimate plot using Gaussian kernels.

In statistics, kernel density estimation (KDE) is a non-parametric way to estimate the probability density function (PDF) of a random variable. This function uses Gaussian kernels and includes automatic bandwidth determination.

Parameters

   bw_method [str, scalar or callable, optional] The method used to calculate the estimator bandwidth. This can be 'scott', 'silverman', a scalar constant or a callable. If None (default), 'scott' is used. See scipy.stats.gaussian_kde for more information.

   ind [NumPy array or int, optional] Evaluation points for the estimated PDF. If None (default), 1000 equally spaced points are used. If ind is a NumPy array, the KDE is evaluated at the points passed. If ind is an integer, ind number of equally spaced points are used.

   **kwargs Additional keyword arguments are documented in pandas.%(this-datatype)s.plot().

1778 Chapter 3. API reference
Returns

matplotlib.axes.Axes or numpy.ndarray of them

See also:

scipy.stats.gaussian_kde  Representation of a kernel-density estimate using Gaussian kernels. This is the function used internally to estimate the PDF.

Examples

Given a Series of points randomly sampled from an unknown distribution, estimate its PDF using KDE with automatic bandwidth determination and plot the results, evaluating them at 1000 equally spaced points (default):

```python
>>> s = pd.Series([1, 2, 2.5, 3, 3.5, 4, 5])
>>> ax = s.plot.kde()
```

![Graph showing a kernel density estimation with default bandwidth](image)

A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

```python
>>> ax = s.plot.kde(bw_method=0.3)
```

```python
>>> ax = s.plot.kde(bw_method=3)
```

Finally, the `ind` parameter determines the evaluation points for the plot of the estimated PDF:
3.4. DataFrame
For DataFrame, it works in the same way:

```python
>>> df = pd.DataFrame({
...     'x': [1, 2, 2.5, 3, 3.5, 4, 5],
...     'y': [4, 4, 4.5, 5, 5.5, 6, 6],
... })
>>> ax = df.plot.kde()
```

A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

```python
>>> ax = df.plot.kde(bw_method=0.3)

>>> ax = df.plot.kde(bw_method=3)
```

Finally, the `ind` parameter determines the evaluation points for the plot of the estimated PDF:

```python
>>> ax = df.plot.kde(ind=[1, 2, 3, 4, 5])
```
pandas.DataFrame.plot.hexbin

DataFrame.plot.hexbin(x, y, C=None, reduce_C_function=None, gridsize=None, **kwargs)

Generate a hexagonal binning plot.

Generate a hexagonal binning plot of \( x \) versus \( y \). If \( C \) is None (the default), this is a histogram of the number of occurrences of the observations at \( (x[i], y[i]) \).

If \( C \) is specified, specifies values at given coordinates \( (x[i], y[i]) \). These values are accumulated for each hexagonal bin and then reduced according to reduce_C_function, having as default the NumPy’s mean function (numpy.mean()). (If \( C \) is specified, it must also be a 1-D sequence of the same length as \( x \) and \( y \), or a column label.)

**Parameters**

- \( x \) [int or str] The column label or position for \( x \) points.
- \( y \) [int or str] The column label or position for \( y \) points.
- \( C \) [int or str, optional] The column label or position for the value of \( (x, y) \) point.
- reduce_C_function [callable, default np.mean] Function of one argument that reduces all the values in a bin to a single number (e.g. np.mean, np.max, np.sum, np.std).
- gridsize [int or tuple of (int, int), default 100] The number of hexagons in the x-direction. The corresponding number of hexagons in the y-direction is chosen in a way that the hexagons are approximately regular. Alternatively, gridsize can be a tuple with two elements specifying the number of hexagons in the x-direction and the y-direction.
- **kwargs Additional keyword arguments are documented in DataFrame.plot().

**Returns**

matplotlib.AxesSubplot The matplotlib Axes on which the hexbin is plotted.

See also:

- DataFrame.plot Make plots of a DataFrame.
- matplotlib.pyplot.hexbin Hexagonal binning plot using matplotlib, the matplotlib function that is used under the hood.

**Examples**

The following examples are generated with random data from a normal distribution.

```python
>>> n = 10000
>>> df = pd.DataFrame({'x': np.random.randn(n),
...                    'y': np.random.randn(n)})
>>> ax = df.plot.hexbin(x='x', y='y', gridsize=20)
```

The next example uses \( C \) and np.sum as reduce_C_function. Note that ‘observations’ values ranges from 1 to 5 but the result plot shows values up to more than 25. This is because of the reduce_C_function.

```python
>>> n = 500
>>> df = pd.DataFrame(
...                   {'coord_x': np.random.uniform(-3, 3, size=n),
...                    'coord_y': np.random.uniform(30, 50, size=n),
...                    'observations': np.random.randint(1,5, size=n)}
...                   )
>>> ax = df.plot.hexbin(x='coord_x',
...                      y='coord_y',
...                      c='observations',
...                      gridsize=20,
...                      reduce_C_function=np.mean)
```
`pandas.DataFrame.plot.hist`

`DataFrame.plot.hist(by=None, bins=10, **kwargs)`

Draw one histogram of the DataFrame's columns.

A histogram is a representation of the distribution of data. This function groups the values of all given Series in the DataFrame into bins and draws all bins in one `matplotlib.axes.Axes`. This is useful when the DataFrame's Series are in a similar scale.

**Parameters**

- **by** [str or sequence, optional] Column in the DataFrame to group by.
- **bins** [int, default 10] Number of histogram bins to be used.
- ****kwargs Additional keyword arguments are documented in `DataFrame.plot()`.

**Returns**

- **class:matplotlib.AxesSubplot** Return a histogram plot.
See also:

**DataFrame.hist** Draw histograms per DataFrame’s Series.

**Series.hist** Draw a histogram with Series’ data.

Examples

When we draw a dice 6000 times, we expect to get each value around 1000 times. But when we draw two dices and sum the result, the distribution is going to be quite different. A histogram illustrates those distributions.

```python
def = pd.DataFrame(
    np.random.randint(1, 7, 6000),
    columns=['one'])
def['two'] = df['one'] + np.random.randint(1, 7, 6000)
ax = df.plot.hist(bins=12, alpha=0.5)
```
DataFrame.plot.kde

Generate Kernel Density Estimate plot using Gaussian kernels.

In statistics, kernel density estimation (KDE) is a non-parametric way to estimate the probability density function (PDF) of a random variable. This function uses Gaussian kernels and includes automatic bandwidth determination.

**Parameters**

- **bw_method** [str, scalar or callable, optional] The method used to calculate the estimator bandwidth. This can be ‘scott’, ‘silverman’, a scalar constant or a callable. If None (default), ‘scott’ is used. See scipy.stats.gaussian_kde for more information.

- **ind** [NumPy array or int, optional] Evaluation points for the estimated PDF. If None (default), 1000 equally spaced points are used. If ind is a NumPy array, the KDE is evaluated at the points passed. If ind is an integer, ind number of equally spaced points are used.

- **kwargs** Additional keyword arguments are documented in pandas.

**Returns**

matplotlib.axes.Axes or numpy.ndarray of them

See also:

- scipy.stats.gaussian_kde Representation of a kernel-density estimate using Gaussian kernels. This is the function used internally to estimate the PDF.

**Examples**

Given a Series of points randomly sampled from an unknown distribution, estimate its PDF using KDE with automatic bandwidth determination and plot the results, evaluating them at 1000 equally spaced points (default):

```python
>>> s = pd.Series([1, 2, 2.5, 3, 3.5, 4, 5])
>>> ax = s.plot.kde()
```

A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

```python
>>> ax = s.plot.kde(bw_method=0.3)

>>> ax = s.plot.kde(bw_method=3)
```

Finally, the **ind** parameter determines the evaluation points for the plot of the estimated PDF:

```python
>>> ax = s.plot.kde(ind=[1, 2, 3, 4, 5])
```

For DataFrame, it works in the same way:

```python
>>> df = pd.DataFrame(
...   {'x': [1, 2, 2.5, 3, 3.5, 4, 5],
...    'y': [4, 4, 4.5, 5, 5.5, 6, 6]},
... )
>>> ax = df.plot.kde()
```
Density

-1  0  1  2  3  4  5  6  7
3.4. DataFrame
A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

```python
>>> ax = df.plot.kde(bw_method=0.3)
```

Finally, the `ind` parameter determines the evaluation points for the plot of the estimated PDF:

```python
>>> ax = df.plot.kde(ind=[1, 2, 3, 4, 5, 6])
```

**pandas.DataFrame.plot.line**

`DataFrame.plot.line(x=None, y=None, **kwargs)`

Plot Series or DataFrame as lines.

This function is useful to plot lines using DataFrame’s values as coordinates.

**Parameters**

- **x** [label or position, optional] Allows plotting of one column versus another. If not specified, the index of the DataFrame is used.
- **y** [label or position, optional] Allows plotting of one column versus another. If not specified, all numerical columns are used.
**color** [str, array_like, or dict, optional] The color for each of the DataFrame's columns. Possible values are:

- **A single color string referred to by name, RGB or RGBA code**, for instance 'red' or '#a98d19'.
- **A sequence of color strings referred to by name, RGB or RGBA code**, which will be used for each column recursively. For instance ['green', 'yellow'] each column's line will be filled in green or yellow, alternatively.
- **A dict of the form {column name: color}**, so that each column will be colored accordingly. For example, if your columns are called a and b, then passing {'a': 'green', 'b': 'red'} will color lines for column a in green and lines for column b in red.

New in version 1.1.0.

**kwargs Additional keyword arguments are documented in DataFrame.plot().**

Returns

- matplotlib.axes.Axes or np.ndarray of them An ndarray is returned with one matplotlib.axes.Axes per column when subplots=True.

See also:

- matplotlib.pyplot.plot Plot y versus x as lines and/or markers.

Examples

```python
>>> s = pd.Series([1, 3, 2])
>>> s.plot.line()

The following example shows the populations for some animals over the years.

```python
>>> df = pd.DataFrame({
...     'pig': [20, 18, 489, 675, 1776],
...     'horse': [4, 25, 281, 600, 1900],
```

```python
>>> lines = df.plot.line()
```

An example with subplots, so an array of axes is returned.

```python
>>> axes = df.plot.line(subplots=True)
>>> type(axes)
<class 'numpy.ndarray'>
```

Let's repeat the same example, but specifying colors for each column (in this case, for each animal).

```python
>>> axes = df.plot.line(subplots=True, color={'pig': 'pink', 'horse': '#742802'})
```

The following example shows the relationship between both populations.

```python
>>> lines = df.plot.line(x='pig', y='horse')
```
3.4. DataFrame
pandas.DataFrame.plot.pie

DataFrame.plot.pie(**kwargs)
Generate a pie plot.
A pie plot is a proportional representation of the numerical data in a column. This function wraps matplotlib.pyplot.pie() for the specified column. If no column reference is passed and subplots=True a pie plot is drawn for each numerical column independently.

Parameters

- y [int or label, optional] Label or position of the column to plot. If not provided, subplots=True argument must be passed.

- **kwargs Keyword arguments to pass on to DataFrame.plot().

Returns

matplotlib.axes.Axes or np.ndarray of them A NumPy array is returned when subplots is True.

See also:

- Series.plot.pie Generate a pie plot for a Series.
- DataFrame.plot Make plots of a DataFrame.

Examples

In the example below we have a DataFrame with the information about planet’s mass and radius. We pass the ‘mass’ column to the pie function to get a pie plot.

```python
>>> df = pd.DataFrame({'mass': [0.330, 4.87 , 5.97],
... 'radius': [2439.7, 6051.8, 6378.1]},
... index=['Mercury', 'Venus', 'Earth'])
>>> plot = df.plot.pie(y='mass', figsize=(5, 5))
>>> plot = df.plot.pie(subplots=True, figsize=(11, 6))
```

pandas.DataFrame.plot.scatter

DataFrame.plot.scatter(x, y, s=None, c=None, **kwargs)
Create a scatter plot with varying marker point size and color.
The coordinates of each point are defined by two dataframe columns and filled circles are used to represent each point. This kind of plot is useful to see complex correlations between two variables. Points could be for instance natural 2D coordinates like longitude and latitude in a map or, in general, any pair of metrics that can be plotted against each other.

Parameters

- x [int or str] The column name or column position to be used as horizontal coordinates for each point.
- y [int or str] The column name or column position to be used as vertical coordinates for each point.
- s [str, scalar or array_like, optional] The size of each point. Possible values are:
  - A string with the name of the column to be used for marker’s size.
  - A single scalar so all points have the same size.
pandas: powerful Python data analysis toolkit, Release 1.1.1

- A sequence of scalars, which will be used for each point’s size recursively. For instance, when passing [2,14] all points size will be either 2 or 14, alternatively.

Changed in version 1.1.0.

**c** [str, int or array_like, optional] The color of each point. Possible values are:

- A single color string referred to by name, RGB or RGBA code, for instance ‘red’ or ‘#a98d19’.
- A sequence of color strings referred to by name, RGB or RGBA code, which will be used for each point’s color recursively. For instance ['green', 'yellow'] all points will be filled in green or yellow, alternatively.
- A column name or position whose values will be used to color the marker points according to a colormap.

**kwargs** Keyword arguments to pass on to DataFrame.plot().

Returns

- matplotlib.axes.Axes or numpy.ndarray of them

See also:

- matplotlib.pyplot.scatter Scatter plot using multiple input data formats.

Examples

Let’s see how to draw a scatter plot using coordinates from the values in a DataFrame’s columns.

```python
>>> df = pd.DataFrame([[5.1, 3.5, 0], [4.9, 3.0, 0], [7.0, 3.2, 1],
...                     [6.4, 3.2, 1], [5.9, 3.0, 2]],
...                     columns=['length', 'width', 'species'])
>>> ax1 = df.plot.scatter(x='length',
...                        y='width',
...                        c='DarkBlue')
```

And now with the color determined by a column as well.

```python
>>> ax2 = df.plot.scatter(x='length',
...                        y='width',
...                        c='species',
...                        colormap='viridis')
```

DataFrame.boxplot([column, by, ax, . . .]) Make a box plot from DataFrame columns.

DataFrame.hist([column, by, grid, . . .]) Make a histogram of the DataFrame’s.

### 3.4.15 Sparse accessor

Sparse-dtype specific methods and attributes are provided under the DataFrame.sparse accessor.

- DataFrame.sparse.density Ratio of non-sparse points to total (dense) data points.
pandas.DataFrame.sparse.density

DataFrame.sparse.density
Ratio of non-sparse points to total (dense) data points.

DataFrame.sparse.from_spmatrix(data[, ...])
Create a new DataFrame from a scipy sparse matrix.

DataFrame.sparse.to_coo()
Return the contents of the frame as a sparse SciPy COO matrix.

DataFrame.sparse.to_dense()
Convert a DataFrame with sparse values to dense.

pandas.DataFrame.sparse.from_spmatrix

classmethod DataFrame.sparse.from_spmatrix(data, index=None, columns=None)
Create a new DataFrame from a scipy sparse matrix.

New in version 0.25.0.

Parameters

- **data** [scipy.sparse.spmatrix] Must be convertible to csc format.
- **index, columns** [Index, optional] Row and column labels to use for the resulting DataFrame. Defaults to a RangeIndex.

Returns

DataFrame Each column of the DataFrame is stored as a arrays.SparseArray.

Examples

```python
>>> import scipy.sparse

>>> mat = scipy.sparse.eye(3)

>>> pd.DataFrame.sparse.from_spmatrix(mat)
   0  1  2
0  1.0 0.0 0.0
1  0.0 1.0 0.0
2  0.0 0.0 1.0
```

pandas.DataFrame.sparse.to_coo

DataFrame.sparse.to_coo()
Return the contents of the frame as a sparse SciPy COO matrix.

New in version 0.25.0.

Returns

coo_matrix [scipy.sparse.spmatrix] If the caller is heterogeneous and contains booleans or objects, the result will be of dtype=object. See Notes.
Notes

The dtype will be the lowest-common-denominator type (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. By numpy.find_common_type convention, mixing int64 and uint64 will result in a float64 dtype.

pandas.DataFrame.sparse.to_dense

Convert a DataFrame with sparse values to dense.

New in version 0.25.0.

Returns

DataFrame A DataFrame with the same values stored as dense arrays.

Examples

```python
>>> df = pd.DataFrame({"A": pd.arrays.SparseArray([0, 1, 0])})
>>> df.sparse.to_dense()
A
  0 0
  1 1
  2 0
```

3.4.16 Serialization / IO / conversion

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataFrame.from_dict(data[, orient, dtype, ...])</td>
<td>Construct DataFrame from dict of array-like or dicts.</td>
</tr>
<tr>
<td>DataFrame.from_records(data[, index, ...])</td>
<td>Convert structured or record ndarray to DataFrame.</td>
</tr>
<tr>
<td>DataFrame.to_parquet(**kwargs)</td>
<td>Write a DataFrame to the binary parquet format.</td>
</tr>
<tr>
<td>DataFrame.to_pickle(path[, compression, ...])</td>
<td>Pickle (serialize) object to file.</td>
</tr>
<tr>
<td>DataFrame.to_csv([path_or_buf, sep, na_rep, ...])</td>
<td>Write object to a comma-separated values (csv) file.</td>
</tr>
<tr>
<td>DataFrame.to_hdf(path_or_buf, key[, mode, ...])</td>
<td>Write the contained data to an HDF5 file using HDFStore.</td>
</tr>
<tr>
<td>DataFrame.to_sql(name, con[, schema, ...])</td>
<td>Write records stored in a DataFrame to a SQL database.</td>
</tr>
<tr>
<td>DataFrame.to_dict(orient, into)</td>
<td>Convert the DataFrame to a dictionary.</td>
</tr>
<tr>
<td>DataFrame.to_excel(excel_writer[, ...])</td>
<td>Write object to an Excel sheet.</td>
</tr>
<tr>
<td>DataFrame.to_json([path_or_buf, orient, ...])</td>
<td>Convert the object to a JSON string.</td>
</tr>
<tr>
<td>DataFrame.to_html([buf, columns, col_space, ...])</td>
<td>Render a DataFrame as an HTML table.</td>
</tr>
<tr>
<td>DataFrame.to_feather(**kwargs)</td>
<td>Write a DataFrame to the binary Feather format.</td>
</tr>
<tr>
<td>DataFrame.to_latex([buf, columns, ...])</td>
<td>Render object to a LaTeX tabular, longtable, or nested table/tabular.</td>
</tr>
<tr>
<td>DataFrame.to_stata(**kwargs)</td>
<td>Export DataFrame object to Stata dta format.</td>
</tr>
<tr>
<td>DataFrame.to_gbq(destination_table[, ...])</td>
<td>Write a DataFrame to a Google BigQuery table.</td>
</tr>
<tr>
<td>DataFrame.to_records([index, column_dtypes, ...])</td>
<td>Convert DataFrame to a NumPy record array.</td>
</tr>
</tbody>
</table>
Table 78 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>DataFrame.to_string([buf, columns, ...])</code></td>
<td>Render a DataFrame to a console-friendly tabular output.</td>
</tr>
<tr>
<td><code>DataFrame.to_clipboard([excel, sep])</code></td>
<td>Copy object to the system clipboard.</td>
</tr>
<tr>
<td><code>DataFrame.to_markdown([buf, mode, index])</code></td>
<td>Print DataFrame in Markdown-friendly format.</td>
</tr>
<tr>
<td><code>DataFrame.style</code></td>
<td>Returns a Styler object.</td>
</tr>
</tbody>
</table>

### 3.5 pandas arrays

For most data types, pandas uses NumPy arrays as the concrete objects contained within a `Index`, `Series`, or `DataFrame`.

For some data types, pandas extends NumPy’s type system. String aliases for these types can be found at `dtypes`.

<table>
<thead>
<tr>
<th>Kind of Data</th>
<th>Pandas Data Type</th>
<th>Scalar</th>
<th>Array</th>
</tr>
</thead>
<tbody>
<tr>
<td>TZ-aware datetime</td>
<td><code>DatetimeTZDtype</code></td>
<td><code>Timestamp</code></td>
<td><code>Datetime data</code></td>
</tr>
<tr>
<td>Timedeltas</td>
<td>(none)</td>
<td><code>Timedelta</code></td>
<td><code>Timedelta data</code></td>
</tr>
<tr>
<td>Period (time spans)</td>
<td><code>PeriodDtype</code></td>
<td><code>Period</code></td>
<td><code>Timespan data</code></td>
</tr>
<tr>
<td>Intervals</td>
<td><code>IntervalDtype</code></td>
<td><code>Interval</code></td>
<td><code>Interval data</code></td>
</tr>
<tr>
<td>Nullable Integer</td>
<td><code>Int64Dtype,...</code></td>
<td>(none)</td>
<td><code>Nullable integer</code></td>
</tr>
<tr>
<td>Categorical</td>
<td><code>CategoricalDtype</code></td>
<td>(none)</td>
<td><code>Categorical data</code></td>
</tr>
<tr>
<td>Sparse</td>
<td><code>SparseDtype</code></td>
<td>(none)</td>
<td><code>Sparse data</code></td>
</tr>
<tr>
<td>Strings</td>
<td><code>StringDtype</code></td>
<td><code>str</code></td>
<td><code>Text data</code></td>
</tr>
<tr>
<td>Boolean (with NA)</td>
<td><code>BooleanDtype</code></td>
<td><code>bool</code></td>
<td><code>Boolean data with missing values</code></td>
</tr>
</tbody>
</table>

Pandas and third-party libraries can extend NumPy’s type system (see `Extension types`). The top-level `array()` method can be used to create a new array, which may be stored in a `Series`, `Index`, or as a column in a `DataFrame`.

```python
array(data[, dtype, copy])
```

Create an array.

### 3.5.1 pandas.array

```python
pandas.array (data, dtype=None, copy=True)
```

Create an array.

New in version 0.24.0.

**Parameters**

- **data** [Sequence of objects] The scalars inside `data` should be instances of the scalar type for `dtype`. It’s expected that `data` represents a 1-dimensional array of data.

  When `data` is an Index or Series, the underlying array will be extracted from `data`.

- **dtype** [str, np.dtype, or ExtensionDtype, optional] The dtype to use for the array. This may be a NumPy dtype or an extension type registered with pandas using `pandas.api.extensions.register_extension_dtype()`.

  If not specified, there are two possibilities:

  1. When `data` is a `Series`, `Index`, or `ExtensionArray`, the `dtype` will be taken from the data.

  2. Otherwise, pandas will attempt to infer the `dtype` from the data.
Note that when `data` is a NumPy array, `data.dtype` is *not* used for inferring the array type. This is because NumPy cannot represent all the types of data that can be held in extension arrays.

Currently, pandas will infer an extension dtype for sequences of

<table>
<thead>
<tr>
<th>Scalar Type</th>
<th>Array Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>pandas.Interval</td>
<td>pandas.arrays.IntervalArray</td>
</tr>
<tr>
<td>pandas.Period</td>
<td>pandas.arrays.PeriodArray</td>
</tr>
<tr>
<td>datetime.datetime</td>
<td>pandas.arrays.DatetimeArray</td>
</tr>
<tr>
<td>datetime.timedelta</td>
<td>pandas.arrays.TimedeltaArray</td>
</tr>
<tr>
<td>int</td>
<td>pandas.arrays.IntegerArray</td>
</tr>
<tr>
<td>str</td>
<td>pandas.arrays.StringArray</td>
</tr>
<tr>
<td>bool</td>
<td>pandas.arrays.BooleanArray</td>
</tr>
</tbody>
</table>

For all other cases, NumPy’s usual inference rules will be used.

Changed in version 1.0.0: Pandas infers nullable-integer dtype for integer data, string dtype for string data, and nullable-boolean dtype for boolean data.

`copy` [bool, default True] Whether to copy the data, even if not necessary. Depending on the type of `data`, creating the new array may require copying data, even if `copy=False`.

Returns

**ExtensionArray** The newly created array.

Raises

**ValueError** When `data` is not 1-dimensional.

See also:

- `numpy.array` Construct a NumPy array.
- `Series` Construct a pandas Series.
- `Index` Construct a pandas Index.
- `arrays.PandasArray` ExtensionArray wrapping a NumPy array.
- `Series.array` Extract the array stored within a Series.

Notes

Omitting the `dtype` argument means pandas will attempt to infer the best array type from the values in the data. As new array types are added by pandas and 3rd party libraries, the “best” array type may change. We recommend specifying `dtype` to ensure that

1. the correct array type for the data is returned
2. the returned array type doesn’t change as new extension types are added by pandas and third-party libraries

Additionally, if the underlying memory representation of the returned array matters, we recommend specifying the `dtype` as a concrete object rather than a string alias or allowing it to be inferred. For example, a future version of pandas or a 3rd-party library may include a dedicated ExtensionArray for string data. In this event, the following would no longer return a `arrays.PandasArray` backed by a NumPy array.

```python
>>> pd.array(['a', 'b'], dtype=str)
<PandasArray>
['a', 'b']
Length: 2, dtype: str32
```

This would instead return the new ExtensionArray dedicated for string data. If you really need the new array to be backed by a NumPy array, specify that in the `dtype`.
Finally, Pandas has arrays that mostly overlap with NumPy

- **arrays.DatetimeArray**
- **arrays.TimedeltaArray**

When data with a `datetime64[ns]` or `timedelta64[ns]` dtype is passed, pandas will always return a `DatetimeArray` or `TimedeltaArray` rather than a `PandasArray`. This is for symmetry with the case of timezone-aware data, which NumPy does not natively support.

```python
>>> pd.array(['2015', '2016'], dtype='datetime64[ns]')
<DatetimeArray>
['2015-01-01 00:00:00', '2016-01-01 00:00:00']
Length: 2, dtype: datetime64[ns]

>>> pd.array(['1H', '2H'], dtype='timedelta64[ns]')
<TimedeltaArray>
['0 days 01:00:00', '0 days 02:00:00']
Length: 2, dtype: timedelta64[ns]
```

### Examples

If a dtype is not specified, pandas will infer the best dtype from the values. See the description of `dtype` for the types pandas infers for.

```python
>>> pd.array([1, 2])
<IntegerArray>
[1, 2]
Length: 2, dtype: Int64

>>> pd.array([1, 2, np.nan])
<IntegerArray>
[1, 2, <NA>]
Length: 3, dtype: Int64

>>> pd.array(['a', None, 'c'])
<StringArray>
['a', <NA>, 'c']
Length: 3, dtype: string

<PeriodArray>
['2000-01-01', '2000-01-01']
Length: 2, dtype: period[D]
```

You can use the string alias for `dtype`

```python
>>> pd.array(['a', 'b', 'a'], dtype='category')
['a', 'b', 'a']
Categories (2, object): ['a', 'b']
```

Or specify the actual dtype
pandas: powerful Python data analysis toolkit, Release 1.1.1

>>> pd.array(['a', 'b', 'a'],
    dtype=pd.CategoricalDtype(['a', 'b', 'c'], ordered=True))
['a', 'b', 'a']
Categories (3, object): ['a' < 'b' < 'c']

If pandas does not infer a dedicated extension type a arrays.PandasArray is returned.

>>> pd.array([1.1, 2.2])
<PandasArray>
[1.1, 2.2]
Length: 2, dtype: float64

As mentioned in the “Notes” section, new extension types may be added in the future (by pandas or 3rd party libraries), causing the return value to no longer be a arrays.PandasArray. Specify the dtype as a NumPy dtype if you need to ensure there’s no future change in behavior.

>>> pd.array([1, 2], dtype=np.dtype("int32"))
<PandasArray>
[1, 2]
Length: 2, dtype: int32

data must be 1-dimensional. A ValueError is raised when the input has the wrong dimensionality.

>>> pd.array(1)
Traceback (most recent call last):
...
ValueError: Cannot pass scalar '1' to 'pandas.array'.

3.5.2 Datetime data

NumPy cannot natively represent timezone-aware datetimes. Pandas supports this with the arrays. DatetimeArray extension array, which can hold timezone-naive or timezone-aware values. 

Timestamp, a subclass of datetime.datetime, is pandas’ scalar type for timezone-naive or timezone-aware datetime data.

pandas.Timestamp

class pandas.Timestamp(ts_input=<object object>, freq=None, tz=None, unit=None, year=None, month=None, day=None, hour=None, minute=None, second=None, microsecond=None, nanosecond=None, tzinfo=None, *, fold=None)

Pandas replacement for python datetime.datetime object.

Timestamp is the pandas equivalent of python’s Datetime and is interchangeable with it in most cases. It’s the type used for the entries that make up a DatetimeIndex, and other timeseries oriented data structures in pandas.

Parameters

- ts_input [datetime-like, str, int, float] Value to be converted to Timestamp.
- freq [str, DateOffset] Offset which Timestamp will have.
- tz [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone for time which Timestamp will
have.

**unit** [str] Unit used for conversion if `ts_input` is of type int or float. The valid values are `'D'`, `'h'`, `'m'`, `'s'`, `'ms'`, `'us'`, and `'ns'`. For example, `'s'` means seconds and `'ms'` means milliseconds.

**year, month, day** [int]

**hour, minute, second, microsecond** [int, optional, default 0]

**nanosecond** [int, optional, default 0] New in version 0.23.0.

**tzinfo** [datetime.tzinfo, optional, default None]

**fold** [{0, 1}, default None, keyword-only] Due to daylight saving time, one wall clock time can occur twice when shifting from summer to winter time; fold describes whether the datetime-like corresponds to the first (0) or the second time (1) the wall clock hits the ambiguous time

New in version 1.1.0.

**Notes**

There are essentially three calling conventions for the constructor. The primary form accepts four parameters. They can be passed by position or keyword.

The other two forms mimic the parameters from `datetime.datetime`. They can be passed by either position or keyword, but not both mixed together.

**Examples**

Using the primary calling convention:

This converts a datetime-like string

```python
>>> pd.Timestamp('2017-01-01T12')
Timestamp('2017-01-01 12:00:00')
```

This converts a float representing a Unix epoch in units of seconds

```python
>>> pd.Timestamp(1513393355.5, unit='s')
Timestamp('2017-12-16 03:02:35.500000')
```

This converts an int representing a Unix-epoch in units of seconds and for a particular timezone

```python
>>> pd.Timestamp(1513393355, unit='s', tz='US/Pacific')
Timestamp('2017-12-15 19:02:35-0800', tz='US/Pacific')
```

Using the other two forms that mimic the API for `datetime.datetime`:

```python
>>> pd.Timestamp(2017, 1, 1, 12)
Timestamp('2017-01-01 12:00:00')
```

```python
>>> pd.Timestamp(year=2017, month=1, day=1, hour=12)
Timestamp('2017-01-01 12:00:00')
```
## Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>asm8</code></td>
<td>Return numpy datetime64 format in nanoseconds.</td>
</tr>
<tr>
<td><code>dayofweek</code></td>
<td>Return day of the week.</td>
</tr>
<tr>
<td><code>dayofyear</code></td>
<td>Return the day of the year.</td>
</tr>
<tr>
<td><code>days_in_month</code></td>
<td>Return the number of days in the month.</td>
</tr>
<tr>
<td><code>daysinmonth</code></td>
<td>Return the number of days in the month.</td>
</tr>
<tr>
<td><code>freqstr</code></td>
<td>Return the total number of days in the month.</td>
</tr>
<tr>
<td><code>is_leap_year</code></td>
<td>Return True if year is a leap year.</td>
</tr>
<tr>
<td><code>is_month_end</code></td>
<td>Return True if date is last day of month.</td>
</tr>
<tr>
<td><code>is_month_start</code></td>
<td>Return True if date is first day of month.</td>
</tr>
<tr>
<td><code>is_quarter_end</code></td>
<td>Return True if date is last day of the quarter.</td>
</tr>
<tr>
<td><code>is_quarter_start</code></td>
<td>Return True if date is first day of the quarter.</td>
</tr>
<tr>
<td><code>is_year_end</code></td>
<td>Return True if date is last day of the year.</td>
</tr>
<tr>
<td><code>is_year_start</code></td>
<td>Return True if date is first day of the year.</td>
</tr>
<tr>
<td><code>quarter</code></td>
<td>Return the quarter of the year.</td>
</tr>
<tr>
<td><code>tz</code></td>
<td>Alias for tzinfo.</td>
</tr>
<tr>
<td><code>week</code></td>
<td>Return the week number of the year.</td>
</tr>
<tr>
<td><code>weekofyear</code></td>
<td>Return the week number of the year.</td>
</tr>
</tbody>
</table>

### `pandas.Timestamp.asm8`  
`Timestamp.asm8`  
Return numpy datetime64 format in nanoseconds.

### `pandas.Timestamp.dayofweek`  
`Timestamp.dayofweek`  
Return day of the week.

### `pandas.Timestamp.dayofyear`  
`Timestamp.dayofyear`  
Return the day of the year.

### `pandas.Timestamp.days_in_month`  
`Timestamp.days_in_month`  
Return the number of days in the month.
pandas.Timestamp.daysinmonth

```
Timestamp.daysinmonth
```

Return the number of days in the month.

pandas.Timestamp.freqstr

```
property Timestamp.freqstr
```

Return the total number of days in the month.

pandas.Timestamp.is_leap_year

```
Timestamp.is_leap_year
```

Return True if year is a leap year.

pandas.Timestamp.is_month_end

```
Timestamp.is_month_end
```

Return True if date is last day of month.

pandas.Timestamp.is_month_start

```
Timestamp.is_month_start
```

Return True if date is first day of month.

pandas.Timestamp.is_quarter_end

```
Timestamp.is_quarter_end
```

Return True if date is last day of the quarter.

pandas.Timestamp.is_quarter_start

```
Timestamp.is_quarter_start
```

Return True if date is first day of the quarter.

pandas.Timestamp.is_year_end

```
Timestamp.is_year_end
```

Return True if date is last day of the year.
pandas.Timestamp.is_year_start

Timestamp.is_year_start
Return True if date is first day of the year.

pandas.Timestamp.quarter

Timestamp.quarter
Return the quarter of the year.

pandas.Timestamp.tz

property Timestamp.tz
Alias for tzinfo.

pandas.Timestamp.week

Timestamp.week
Return the week number of the year.

pandas.Timestamp.weekofyear

Timestamp.weekofyear
Return the week number of the year.

<table>
<thead>
<tr>
<th>day</th>
<th>fold</th>
<th>freq</th>
<th>hour</th>
<th>microsecond</th>
<th>minute</th>
<th>month</th>
<th>nanosecond</th>
<th>second</th>
<th>tzinfo</th>
<th>value</th>
<th>year</th>
</tr>
</thead>
</table>

Methods

astimezone(tz) Convert tz-aware Timestamp to another time zone.

ceil(freq [, ambiguous, nonexistent]) return a new Timestamp ceiled to this resolution.

combine(date, time) date, time -> datetime with same date and time fields.

cTIME
Return ctime() style string.

date
Return date object with same year, month and day.

continues on next page
Table 82 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>day_name</code></td>
<td>Return the day name of the Timestamp with specified locale.</td>
</tr>
<tr>
<td><code>dst</code></td>
<td>Return self.tzinfo.dst(self).</td>
</tr>
<tr>
<td><code>floor(freq[, ambiguous, nonexistent])</code></td>
<td>Return a new Timestamp floored to this resolution.</td>
</tr>
<tr>
<td><code>fromisocalendar</code></td>
<td>int, int, int -&gt; Construct a date from the ISO year, week number and weekday.</td>
</tr>
<tr>
<td><code>fromisoformat</code></td>
<td>string -&gt; datetime from datetime.isoformat() output</td>
</tr>
<tr>
<td><code>fromordinal</code></td>
<td>passed an ordinal, translate and convert to a ts.</td>
</tr>
<tr>
<td><code>fromtimestamp</code></td>
<td>timestamp[, tz] -&gt; tz’s local time from POSIX timestamp.</td>
</tr>
<tr>
<td><code>isocalendar</code></td>
<td>Return a 3-tuple containing ISO year, week number, and weekday.</td>
</tr>
<tr>
<td><code>isoweekday</code></td>
<td>Return the day of the week represented by the date.</td>
</tr>
<tr>
<td><code>month_name</code></td>
<td>Return the month name of the Timestamp with specified locale.</td>
</tr>
<tr>
<td><code>normalize</code></td>
<td>Normalize Timestamp to midnight, preserving tz information.</td>
</tr>
<tr>
<td><code>now([tz])</code></td>
<td>Return new Timestamp object representing current time local to tz.</td>
</tr>
<tr>
<td><code>replace([year, month, day, hour, minute, ...])</code></td>
<td>implements datetime.replace, handles nanoseconds.</td>
</tr>
<tr>
<td><code>round(freq[, ambiguous, nonexistent])</code></td>
<td>Round the Timestamp to the specified resolution.</td>
</tr>
<tr>
<td><code>strftime</code></td>
<td>format -&gt; strftime() style string.</td>
</tr>
<tr>
<td><code>strptime</code></td>
<td>Function is not implemented.</td>
</tr>
<tr>
<td><code>time</code></td>
<td>Return time object with same time but with tz-info=None.</td>
</tr>
<tr>
<td><code>timestamp</code></td>
<td>Return POSIX timestamp as float.</td>
</tr>
<tr>
<td><code>timetz</code></td>
<td>Return time tuple, compatible with time.localtime().</td>
</tr>
<tr>
<td><code>to_datetime64</code></td>
<td>Return a numpy.datetime64 object with ‘ns’ precision.</td>
</tr>
<tr>
<td><code>to_julian_date()</code></td>
<td>Convert TimeStamp to a Julian Date.</td>
</tr>
<tr>
<td><code>to_numeric</code></td>
<td>Convert the Timestamp to a NumPy datetime64.</td>
</tr>
<tr>
<td><code>to_period</code></td>
<td>Return an period of which this timestamp is an observation.</td>
</tr>
<tr>
<td><code>to_pydatetime</code></td>
<td>Convert a Timestamp object to a native Python datetime object.</td>
</tr>
<tr>
<td><code>today(cls[, tz])</code></td>
<td>Return the current time in the local timezone.</td>
</tr>
<tr>
<td><code>toordinal</code></td>
<td>Return proleptic Gregorian ordinal.</td>
</tr>
<tr>
<td><code>tz_convert(tz)</code></td>
<td>Convert tz-aware Timestamp to another time zone.</td>
</tr>
<tr>
<td><code>tz_localize(tz[, ambiguous, nonexistent])</code></td>
<td>Convert naive Timestamp to local time zone, or remove timezone from tz-aware Timestamp.</td>
</tr>
<tr>
<td><code>tzname</code></td>
<td>Return self.tzinfo.tzname(self).</td>
</tr>
<tr>
<td><code>utcfromtimestamp(ts)</code></td>
<td>Construct a naive UTC datetime from a POSIX timestamp.</td>
</tr>
<tr>
<td><code>utcnow()</code></td>
<td>Return a new Timestamp representing UTC day and time.</td>
</tr>
<tr>
<td><code>utcoffset</code></td>
<td>Return self.tzinfo.utcoffset(self).</td>
</tr>
<tr>
<td><code>utctimetuple</code></td>
<td>Return UTC time tuple, compatible with time.localtime().</td>
</tr>
</tbody>
</table>

continues on next page
pandas.Timestamp.astimezone

Timestamp.astimezone(tz)
Convert tz-aware Timestamp to another time zone.

Parameters

tz [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone for time which Timestamp
will be converted to. None will remove timezone holding UTC time.

Returns

converted [Timestamp]

Raises

TypeError If Timestamp is tz-naive.

pandas.Timestamp.ceil

Timestamp.ceil(freq, ambiguous='raise', nonexistent='raise')
return a new Timestamp ceiled to this resolution.

Parameters

freq [str] Frequency string indicating the ceiling resolution.

ambiguous [bool or {‘raise’, ‘NaT’}, default ‘raise’] The behavior is as follows:
• bool contains flags to determine if time is dst or not (note that this flag is only
  applicable for ambiguous fall dst dates).
• ‘NaT’ will return NaT for an ambiguous time.
• ‘raise’ will raise an AmbiguousTimeError for an ambiguous time.

New in version 0.24.0.

nonexistent [{‘raise’, ‘shift_forward’, ‘shift_backward’, ‘NaT’, timedelta}, default
‘raise’] A nonexistent time does not exist in a particular timezone where clocks
moved forward due to DST.
• ‘shift_forward’ will shift the nonexistent time forward to the closest existing
time.
• ‘shift_backward’ will shift the nonexistent time backward to the closest exist-
ing time.
• ‘NaT’ will return NaT where there are nonexistent times.
• timedelta objects will shift nonexistent times by the timedelta.
• ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Raises

ValueError if the freq cannot be converted.
pandas: powerful Python data analysis toolkit, Release 1.1.1

**pandas.Timestamp.combine**

```python
classmethod Timestamp.combine(date, time)
date, time -> datetime with same date and time fields.
```

**pandas.Timestamp.ctime**

```python
Timestamp.ctime()
Return ctime() style string.
```

**pandas.Timestamp.date**

```python
Timestamp.date()
Return date object with same year, month and day.
```

**pandas.Timestamp.day_name**

```python
Timestamp.day_name()
Return the day name of the Timestamp with specified locale.

Parameters
locale [str, default None (English locale)] Locale determining the language in which to return the day name.

Returns
day_name [string]
New in version 0.23.0: ..
```

**pandas.Timestamp.dst**

```python
Timestamp.dst()
Return self.tzinfo.dst(self).
```

**pandas.Timestamp.floor**

```python
Timestamp.floor(freq, ambiguous='raise', nonexistent='raise')
return a new Timestamp floored to this resolution.

Parameters
freq [str] Frequency string indicating the flooring resolution.
ambiguous [bool or {'raise', 'NaT'}, default 'raise'] The behavior is as follows:
  • bool contains flags to determine if time is dst or not (note that this flag is only applicable for ambiguous fall dst dates).
  • ‘NaT’ will return NaT for an ambiguous time.
  • ‘raise’ will raise an AmbiguousTimeError for an ambiguous time.
New in version 0.24.0.
```
nonexistent [{‘raise’, ‘shift_forward’, ‘shift_backward’, ‘NaT’, timedelta}, default ‘raise’} A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- ‘shift_forward’ will shift the nonexistent time forward to the closest existing time.
- ‘shift_backward’ will shift the nonexistent time backward to the closest existing time.
- ‘NaT’ will return NaT where there are nonexistent times.
- timedelta objects will shift nonexistent times by the timedelta.
- ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

 Raises

 ValueError if the freq cannot be converted.

 pandas.Timestamp.fromisocalendar

 `Timestamp.fromisocalendar()`

 int, int, int -> Construct a date from the ISO year, week number and weekday.

 This is the inverse of the date.isocalendar() function

 pandas.Timestamp.fromisoformat

 `Timestamp.fromisoformat()`

 string -> datetime from datetime.isoformat() output

 pandas.Timestamp.fromordinal

classmethod `Timestamp.fromordinal` (ordinal, freq=None, tz=None)

 Passed an ordinal, translate and convert to a ts. Note: by definition there cannot be any tz info on the ordinal itself.

 Parameters

 ordinal [int] Date corresponding to a proleptic Gregorian ordinal.
 freq [str, DateOffset] Offset to apply to the Timestamp.
 tz [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone for the Timestamp.
pandas.Timestamp.fromtimestamp

classmethod Timestamp.fromtimestamp(ts)
    timestamp[, tz] -> tz’s local time from POSIX timestamp.

pandas.Timestamp.isocalendar

Timestamp.isocalendar()
    Return a 3-tuple containing ISO year, week number, and weekday.

pandas.Timestamp.isoformat

Timestamp.isoformat()
    [sep] -> string in ISO 8601 format, YYYY-MM-DDT[HH[:MM[:SS[.mmm[uuu]]]]][+HH:MM]. sep is
    used to separate the year from the time, and defaults to ‘T’. timespec specifies what components of the time
    to include (allowed values are ‘auto’, ‘hours’, ‘minutes’, ‘seconds’, ‘milliseconds’, and ‘microseconds’).

pandas.Timestamp.isoweekday

Timestamp.isoweekday()
    Return the day of the week represented by the date. Monday == 1 . . . Sunday == 7

pandas.Timestamp.month_name

Timestamp.month_name()
    Return the month name of the Timestamp with specified locale.

    Parameters
        locale [str, default None (English locale)] Locale determining the language in which to
        return the month name.

    Returns
        month_name [string]
            New in version 0.23.0: ..

pandas.Timestamp.normalize

Timestamp.normalize()
    Normalize Timestamp to midnight, preserving tz information.
**pandas.Timestamp.now**

**classmethod** `Timestamp.now(tz=None)`

Return new Timestamp object representing current time local to tz.

**Parameters**

- **tz** [str or timezone object, default None] Timezone to localize to.

**pandas.Timestamp.replace**

`Timestamp.replace(year=None, month=None, day=None, hour=None, minute=None, second=None, microsecond=None, nanosecond=None, tzinfo=<class 'object'>, fold=0)`

Implements datetime.replace, handles nanoseconds.

**Parameters**

- **year** [int, optional]
- **month** [int, optional]
- **day** [int, optional]
- **hour** [int, optional]
- **minute** [int, optional]
- **second** [int, optional]
- **microsecond** [int, optional]
- **nanosecond** [int, optional]
- **tzinfo** [tz-convertible, optional]
- **fold** [int, optional, default is 0]

**Returns**

Timestamp with fields replaced

**pandas.Timestamp.round**

`Timestamp.round(freq, ambiguous='raise', nonexistent='raise')`

Round the Timestamp to the specified resolution.

**Parameters**

- **freq** [str] Frequency string indicating the rounding resolution.
- **ambiguous** [bool or {‘raise’, ‘NaT’}, default ‘raise’] The behavior is as follows:
  - bool contains flags to determine if time is dst or not (note that this flag is only applicable for ambiguous fall dst dates).
  - ‘NaT’ will return NaT for an ambiguous time.
  - ‘raise’ will raise an AmbiguousTimeError for an ambiguous time.

New in version 0.24.0.
nonexistent [{‘raise’, ‘shift_forward’, ‘shift_backward’, ‘NaT’, timedelta}, default ‘raise’] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- ‘shift_forward’ will shift the nonexistent time forward to the closest existing time.
- ‘shift_backward’ will shift the nonexistent time backward to the closest existing time.
- ‘NaT’ will return NaT where there are nonexistent times.
- timedelta objects will shift nonexistent times by the timedelta.
- ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

a new Timestamp rounded to the given resolution of freq

Raises

ValueError if the freq cannot be converted

pandas.Timestamp.strptime

Timestamp.strptime(format -> strftime() style string.

pandas.Timestamp.strptime

classmethod Timestamp.strptime(string, format)

Function is not implemented. Use pd.to_datetime().

pandas.Timestamp.time

Timestamp.time()

Return time object with same time but with tzinfo=None.

pandas.Timestamp.timestamp

Timestamp.timestamp()

Return POSIX timestamp as float.
pandas.Timestamp.timetuple

Timestamp.timetuple()
Return time tuple, compatible with time.localtime().

pandas.Timestamp.timetz

Timestamp.timetz()
Return time object with same time and tzinfo.

pandas.Timestamp.to_datetime64

Timestamp.to_datetime64()
Return a numpy.datetime64 object with ‘ns’ precision.

pandas.Timestamp.to_julian_date

Timestamp.to_julian_date()
Convert TimeStamp to a Julian Date. 0 Julian date is noon January 1, 4713 BC.

pandas.Timestamp.to_numpy

Timestamp.to_numpy()
Convert the Timestamp to a NumPy datetime64.
New in version 0.25.0.
This is an alias method for Timestamp.to_datetime64(). The dtype and copy parameters are available here only for compatibility. Their values will not affect the return value.

Returns
numpy.datetime64

See also:

DatetimeIndex.to_numpy  Similar method for DatetimeIndex.

pandas.Timestamp.to_period

Timestamp.to_period()
Return an period of which this timestamp is an observation.
pandas.Timestamp.to_pydatetime

Timestamp.to_pydatetime()
Convert a Timestamp object to a native Python datetime object.
If warn=True, issue a warning if nanoseconds is nonzero.

pandas.Timestamp.today

classmethod Timestamp.today(cls, tz=None)
Return the current time in the local timezone. This differs from datetime.today() in that it can be localized to a passed timezone.

Parameters

tz [str or timezone object, default None] Timezone to localize to.

pandas.Timestamp.toordinal

Timestamp.toordinal()
Return proleptic Gregorian ordinal. January 1 of year 1 is day 1.

pandas.Timestamp.tz_convert

Timestamp.tz_convert(tz)
Convert tz-aware Timestamp to another time zone.

Parameters

tz [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone for time which Timestamp will be converted to. None will remove timezone holding UTC time.

Returns

converted [Timestamp]

Raises

TypeError If Timestamp is tz-naive.

pandas.Timestamp.tz_localize

Timestamp.tz_localize(tz, ambiguous='raise', nonexistent='raise')
Convert naive Timestamp to local time zone, or remove timezone from tz-aware Timestamp.

Parameters

tz [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone for time which Timestamp will be converted to. None will remove timezone holding local time.

ambiguous [bool, ‘NaT’, default ‘raise’] When clocks moved backward due to DST, ambiguous times may arise. For example in Central European Time (UTC+01), when going from 03:00 DST to 02:00 non-DST, 02:30:00 local time occurs both at 00:30:00 UTC and at 01:30:00 UTC. In such a situation, the ambiguous parameter dictates how ambiguous times should be handled.
The behavior is as follows:

- `bool` contains flags to determine if time is dst or not (note that this flag is only applicable for ambiguous fall dst dates).
- ‘NaT’ will return NaT for an ambiguous time.
- ‘raise’ will raise an AmbiguousTimeError for an ambiguous time.

**nonexistent** ['shift_forward', 'shift_backward', 'NaT', timedelta, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

The behavior is as follows:

- ‘shift_forward’ will shift the nonexistent time forward to the closest existing time.
- ‘shift_backward’ will shift the nonexistent time backward to the closest existing time.
- ‘NaT’ will return NaT where there are nonexistent times.
- timedelta objects will shift nonexistent times by the timedelta.
- ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

**Returns**

- **localized** [Timestamp]

**Raises**

- **TypeError** If the Timestamp is tz-aware and tz is not None.

**pandas.Timestamp.tzname**

```
Timestamp.tzname()
Return self.tzinfo.tzname(self).
```

**pandas.Timestamp.utcfromtimestamp**

```
classmethod Timestamp.utcfromtimestamp(ts)
Construct a naive UTC datetime from a POSIX timestamp.
```

**pandas.Timestamp.utcnow**

```
classmethod Timestamp.utcnow()
Return a new Timestamp representing UTC day and time.
```
pandas.Timestamp.utcoffset

```
Timestamp.utcoffset()
    Return self.tzinfo.utcoffset(self).
```

pandas.Timestamp.utctimetuple

```
Timestamp.utctimetuple()
    Return UTC time tuple, compatible with time.localtime().
```

pandas.Timestamp.weekday

```
Timestamp.weekday()
    Return the day of the week represented by the date. Monday == 0 ... Sunday == 6
```

Properties

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Timestamp.asm8</td>
<td>Return numpy datetime64 format in nanoseconds.</td>
</tr>
<tr>
<td>Timestamp.day</td>
<td>Return day of the week.</td>
</tr>
<tr>
<td>Timestamp.dayofweek</td>
<td>Return day of the week.</td>
</tr>
<tr>
<td>Timestamp.dayofyear</td>
<td>Return the day of the year.</td>
</tr>
<tr>
<td>Timestamp.days_in_month</td>
<td>Return the number of days in the month.</td>
</tr>
<tr>
<td>Timestamp.daysinmonth</td>
<td>Return the number of days in the month.</td>
</tr>
<tr>
<td>Timestamp.fold</td>
<td></td>
</tr>
<tr>
<td>Timestamp.is_leap_year</td>
<td>Return True if year is a leap year.</td>
</tr>
<tr>
<td>Timestamp.is_month_end</td>
<td>Return True if date is last day of month.</td>
</tr>
<tr>
<td>Timestamp.is_month_start</td>
<td>Return True if date is first day of month.</td>
</tr>
<tr>
<td>Timestamp.is_quarter_end</td>
<td>Return True if date is last day of the quarter.</td>
</tr>
<tr>
<td>Timestamp.is_quarter_start</td>
<td>Return True if date is first day of the quarter.</td>
</tr>
<tr>
<td>Timestamp.is_year_end</td>
<td>Return True if date is last day of the year.</td>
</tr>
<tr>
<td>Timestamp.is_year_start</td>
<td>Return True if date is first day of the year.</td>
</tr>
<tr>
<td>Timestamp.max</td>
<td></td>
</tr>
<tr>
<td>Timestamp.microsecond</td>
<td></td>
</tr>
<tr>
<td>Timestamp.min</td>
<td></td>
</tr>
<tr>
<td>Timestamp.month</td>
<td></td>
</tr>
<tr>
<td>Timestamp.nanosecond</td>
<td></td>
</tr>
<tr>
<td>Timestamp.quarter</td>
<td>Return the quarter of the year.</td>
</tr>
<tr>
<td>Timestamp.resolution</td>
<td></td>
</tr>
<tr>
<td>Timestamp.second</td>
<td></td>
</tr>
<tr>
<td>Timestamp.tz</td>
<td>Alias for tzinfo.</td>
</tr>
<tr>
<td>Timestamp.tzinfo</td>
<td></td>
</tr>
<tr>
<td>Timestamp.value</td>
<td></td>
</tr>
<tr>
<td>Timestamp.week</td>
<td>Return the week number of the year.</td>
</tr>
<tr>
<td>Timestamp.weekofyear</td>
<td>Return the week number of the year.</td>
</tr>
<tr>
<td>Timestamp.year</td>
<td></td>
</tr>
</tbody>
</table>
pandas.Timestamp.day

Timestamp.day

pandas.Timestamp.fold

Timestamp.fold

pandas.Timestamp.hour

Timestamp.hour

pandas.Timestamp.max

Timestamp.max = Timestamp('2262-04-11 23:47:16.854775807')

pandas.Timestamp.microsecond

Timestamp.microsecond

pandas.Timestamp.min

Timestamp.min = Timestamp('1677-09-21 00:12:43.145225')

pandas.Timestamp.minute

Timestamp.minute

pandas.Timestamp.month

Timestamp.month

pandas.Timestamp.nanosecond

Timestamp.nanosecond
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.Timestamp.resolution

Timestamp.resolution = Timedelta('0 days 00:00:00.000000001')

pandas.Timestamp.second

Timestamp.second

pandas.Timestamp.tzinfo

Timestamp.tzinfo

pandas.Timestamp.value

Timestamp.value

pandas.Timestamp.year

Timestamp.year

Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Timestamp.astimezone(tz)</td>
<td>Convert tz-aware Timestamp to another time zone.</td>
</tr>
<tr>
<td>Timestamp.ceil(freq[, ambiguous, nonexistent])</td>
<td>return a new Timestamp ceiled to this resolution.</td>
</tr>
<tr>
<td>Timestamp.combine(date, time)</td>
<td>date, time -&gt; datetime with same date and time fields.</td>
</tr>
<tr>
<td>Timestamp.ctime</td>
<td>Return ctime() style string.</td>
</tr>
<tr>
<td>Timestamp.date</td>
<td>Return date object with same year, month and day.</td>
</tr>
<tr>
<td>Timestamp.day_name</td>
<td>Return the day name of the Timestamp with specified locale.</td>
</tr>
<tr>
<td>Timestamp.dst</td>
<td>Return self.tzinfo.dst(self).</td>
</tr>
<tr>
<td>Timestamp.floor(freq[, ambiguous, nonexistent])</td>
<td>return a new Timestamp floored to this resolution.</td>
</tr>
<tr>
<td>Timestamp.freq</td>
<td>Return the total number of days in the month.</td>
</tr>
<tr>
<td>Timestamp.freqstr</td>
<td>Passed an ordinal, translate and convert to a ts.</td>
</tr>
<tr>
<td>Timestamp.fromordinal(ordinal[, freq, tz])</td>
<td>timestamp[, tz] -&gt; tz’s local time from POSIX timestamp.</td>
</tr>
<tr>
<td>Timestamp.fromtimestamp(ts)</td>
<td>return a new Timestamp representing current time local to tz.</td>
</tr>
<tr>
<td>Timestamp.isocalendar</td>
<td>Return a 3-tuple containing ISO year, week number, and weekday.</td>
</tr>
<tr>
<td>Timestamp.isoformat[sep]</td>
<td>string in ISO 8601 format, YYYY-MM-DDT[HH][MM][SS][mmm][uuu]][++HH:MM].</td>
</tr>
<tr>
<td>Timestamp.isoweekday</td>
<td>Return the day of the week represented by the date.</td>
</tr>
<tr>
<td>Timestamp.month_name</td>
<td>Return the month name of the Timestamp with specified locale.</td>
</tr>
<tr>
<td>Timestamp.normalize</td>
<td>Normalize Timestamp to midnight, preserving tz information.</td>
</tr>
<tr>
<td>Timestamp.now([tz])</td>
<td>Return new Timestamp object representing current time local to tz.</td>
</tr>
</tbody>
</table>
Table 84 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Timestamp.replace([year, month, day, hour, ...])</code></td>
<td>Implements <code>datetime.replace</code>, handles nanoseconds.</td>
</tr>
<tr>
<td><code>Timestamp.round(freq[, ambiguous, nonexistent])</code></td>
<td>Round the Timestamp to the specified resolution.</td>
</tr>
<tr>
<td><code>Timestamp.strftime(format[, ambiguous, nonexistent])</code></td>
<td>Function is not implemented.</td>
</tr>
<tr>
<td><code>Timestamp.time</code></td>
<td>Return time object with same time but with tz-info=None.</td>
</tr>
<tr>
<td><code>Timestamp.timestamp</code></td>
<td>Return POSIX timestamp as float.</td>
</tr>
<tr>
<td><code>Timestamp.time</code></td>
<td>Return time object with same time and tzinfo.</td>
</tr>
<tr>
<td><code>Timestamp.to_datetime64</code></td>
<td>Return a numpy.datetime64 object with ‘ns’ precision.</td>
</tr>
<tr>
<td><code>Timestamp.to_numpy</code></td>
<td>Convert the Timestamp to a NumPy datetime64.</td>
</tr>
<tr>
<td><code>Timestamp.to_period</code></td>
<td>Return an period of which this timestamp is an observation.</td>
</tr>
<tr>
<td><code>Timestamp.to_pydatetime</code></td>
<td>Convert a Timestamp object to a native Python datetime object.</td>
</tr>
<tr>
<td><code>Timestamp.today(cls[, tz])</code></td>
<td>Return the current time in the local timezone.</td>
</tr>
<tr>
<td><code>Timestamp.coordinated</code></td>
<td>Return proleptic Gregorian ordinal.</td>
</tr>
<tr>
<td><code>Timestamp.tz_convert(tz)</code></td>
<td>Convert tz-aware Timestamp to another time zone.</td>
</tr>
<tr>
<td><code>Timestamp.tz_localize(tz[, ambiguous, ...])</code></td>
<td>Convert naive Timestamp to local time zone, or remove timezone from tz-aware Timestamp.</td>
</tr>
<tr>
<td><code>Timestamp.tzname</code></td>
<td>Return self.tzinfo.tzname(self).</td>
</tr>
<tr>
<td><code>Timestamp.utcfromtimestamp(ts)</code></td>
<td>Construct a naive UTC datetime from a POSIX timestamp.</td>
</tr>
<tr>
<td><code>Timestamp.utcnow()</code></td>
<td>Return a new Timestamp representing UTC day and time.</td>
</tr>
<tr>
<td><code>Timestamp.utcoffset</code></td>
<td>Return self.tzinfo.utcoffset(self).</td>
</tr>
<tr>
<td><code>Timestamp.utctimetuple</code></td>
<td>Return UTC time tuple, compatible with time.localtime().</td>
</tr>
<tr>
<td><code>Timestamp.weekday</code></td>
<td>Return the day of the week represented by the date.</td>
</tr>
</tbody>
</table>

**pandas.Timestamp.freq**

A collection of timestamps may be stored in a `arrays.DatetimeArray`. For timezone-aware data, the `.dtype` of a DatetimeArray is a `DateTimeTzDtype`. For timezone-naive data, `np.dtype("datetime64[ns]")` is used.

If the data are tz-aware, then every value in the array must have the same timezone.

```python
arrays.DatetimeArray(values[, dtype, freq, copy])
```

Pandas ExtensionArray for tz-naive or tz-aware datetime data.

3.5. pandas arrays
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.arrays.DatetimeArray

class pandas.arrays.DatetimeArray(values, dtype=None, freq=None, copy=False)

Pandas ExtensionArray for tz-naive or tz-aware datetime data.

New in version 0.24.0.

Warning: DatetimeArray is currently experimental, and its API may change without warning. In particular, DatetimeArray.dtype is expected to change to always be an instance of an ExtensionDtype subclass.

Parameters

values [Series, Index, DatetimeArray, ndarray] The datetime data.

For DatetimeArray values (or a Series or Index boxing one), dtype and freq will be extracted from values.

dtype [numpy.dtype or DatetimeTZDtype] Note that the only NumPy dtype allowed is ‘datetime64[ns]’.

dtype [string or Offset, optional] The frequency.

copy [bool, default False] Whether to copy the underlying array of values.

Attributes

None

Methods

None

DatetimeTZDtype([unit, tz]) An ExtensionDtype for timezone-aware datetime data.

pandas.DatetimeTZDtype

class pandas.DatetimeTZDtype(unit='ns', tz=None)

An ExtensionDtype for timezone-aware datetime data.

This is not an actual numpy dtype, but a duck type.

Parameters

unit [str, default “ns”] The precision of the datetime data. Currently limited to "ns".

tz [str, int, or datetime.tzinfo] The timezone.

Raises

pytz.UnknownTimeZoneError When the requested timezone cannot be found.
Examples

```python
>>> pd.DatetimeTZDtype(tz='UTC')
datetime64[ns, UTC]

>>> pd.DatetimeTZDtype(tz='dateutil/US/Central')
datetime64[ns, tzfile('/usr/share/zoneinfo/US/Central')]```

Attributes

- **unit**
  The precision of the datetime data.
- **tz**
  The timezone.

```python
pandas.DatetimeTZDtype.unit

[property] DatetimeTZDtype.unit
The precision of the datetime data.

pandas.DatetimeTZDtype.tz

[property] DatetimeTZDtype.tz
The timezone.
```

Methods

- **None**

3.5.3 Timedelta data

NumPy can natively represent timedeltas. Pandas provides `Timedelta` for symmetry with `Timestamp`.

```python
Timedelta([value, unit])
Represents a duration, the difference between two dates or times.
```

```python
class pandas.Timedelta(value=<object object>, unit=None, **kwargs)
Represents a duration, the difference between two dates or times.

Timedelta is the pandas equivalent of python’s `datetime.timedelta` and is interchangeable with it in most cases.

Parameters

- **value** [Timedelta, timedelta, np.timedelta64, str, or int]
- **unit** [str, default ‘ns’] Denote the unit of the input, if input is an integer.
```
Possible values:

- ‘days’ or ‘day’
- ‘hours’, ‘hour’, ‘hr’, or ‘h’
- ‘minutes’, ‘minute’, ‘min’, or ‘m’
- ‘seconds’, ‘second’, or ‘sec’
- ‘milliseconds’, ‘millisecond’, ‘millis’, or ‘milli’
- ‘microseconds’, ‘microsecond’, ‘micros’, or ‘micro’

**kwargs Available kwargs: {days, seconds, microseconds, milliseconds, minutes, hours, weeks}. Values for construction in compat with datetime.timedelta. Numpy ints and floats will be coerced to python ints and floats.

Notes

The .value attribute is always in ns.

Attributes

<table>
<thead>
<tr>
<th></th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>asm8</td>
<td>Return a numpy timedelta64 array scalar view.</td>
</tr>
<tr>
<td>components</td>
<td>Return a components namedtuple-like.</td>
</tr>
<tr>
<td>days</td>
<td>Number of days.</td>
</tr>
<tr>
<td>delta</td>
<td>Return the timedelta in nanoseconds (ns), for internal compatibility.</td>
</tr>
<tr>
<td>microseconds</td>
<td>Number of microseconds (&gt;= 0 and less than 1 second).</td>
</tr>
<tr>
<td>nanoseconds</td>
<td>Return the number of nanoseconds (n), where 0 &lt;= n &lt; 1 microsecond.</td>
</tr>
<tr>
<td>resolution_string</td>
<td>Return a string representing the lowest timedelta resolution.</td>
</tr>
<tr>
<td>seconds</td>
<td>Number of seconds (&gt;= 0 and less than 1 day).</td>
</tr>
</tbody>
</table>

pandas.Timedelta.asm8

Timedelta.asm8

Return a numpy timedelta64 array scalar view.

Provides access to the array scalar view (i.e. a combination of the value and the units) associated with the numpy.timedelta64().view(), including a 64-bit integer representation of the timedelta in nanoseconds (Python int compatible).

Returns

numpy timedelta64 array scalar view Array scalar view of the timedelta in nanoseconds.
Examples

```python
>>> td = pd.Timedelta('1 days 2 min 3 us 42 ns')
>>> td.asm8
numpy.timedelta64(8652000003042,'ns')

>>> td = pd.Timedelta('2 min 3 s')
>>> td.asm8
numpy.timedelta64(123000000000,'ns')

>>> td = pd.Timedelta('3 ms 5 us')
>>> td.asm8
numpy.timedelta64(3005000,'ns')

>>> td = pd.Timedelta(42, unit='ns')
>>> td.asm8
numpy.timedelta64(42,'ns')
```

pandas.Timedelta.components

```python
class Timedelta.components:
    Return a components namedtuple-like.
```

pandas.Timedelta.days

```python
class Timedelta.days:
    Number of days.
```

pandas.Timedelta.delta

```python
class Timedelta.delta:
    Return the timedelta in nanoseconds (ns), for internal compatibility.
    Returns
    int Timedelta in nanoseconds.
```

Examples

```python
>>> td = pd.Timedelta('1 days 42 ns')
>>> td.delta
8640000000042

>>> td = pd.Timedelta('3 s')
>>> td.delta
300000000

>>> td = pd.Timedelta('3 ms 5 us')
>>> td.delta
3005000
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

```python
>>> td = pd.Timedelta(42, unit='ns')
>>> td.delta
42
```

**pandas.Timedelta.microseconds**

Timedelta.microseconds

Number of microseconds (>= 0 and less than 1 second).

**pandas.Timedelta.nanoseconds**

Timedelta.nanoseconds

Return the number of nanoseconds (n), where 0 <= n < 1 microsecond.

Returns

int Number of nanoseconds.

See also:

*Timedelta.components* Return all attributes with assigned values (i.e. days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds).

**Examples**

**Using string input**

```python
>>> td = pd.Timedelta('1 days 2 min 3 us 42 ns')
```

```python
>>> td.nanoseconds
42
```

**Using integer input**

```python
>>> td = pd.Timedelta(42, unit='ns')
>>> td.nanoseconds
42
```

**pandas.Timedelta.resolution_string**

Timedelta.resolution_string

Return a string representing the lowest timedelta resolution.

Each timedelta has a defined resolution that represents the lowest OR most granular level of precision. Each level of resolution is represented by a short string as defined below:

Resolution: Return value

- Days: ‘D’
- Hours: ‘H’
- Minutes: ‘T’
• Seconds: ‘S’
• Milliseconds: ‘L’
• Microseconds: ‘U’
• Nanoseconds: ‘N’

Returns

str  Timedelta resolution.

Examples

>>> td = pd.Timedelta('1 days 2 min 3 us 42 ns')
>>> td.resolution_string
'N'

>>> td = pd.Timedelta('1 days 2 min 3 us')
>>> td.resolution_string
'U'

>>> td = pd.Timedelta('2 min 3 s')
>>> td.resolution_string
'S'

>>> td = pd.Timedelta(36, unit='us')
>>> td.resolution_string
'U'

pandas.Timedelta.seconds

Timedelta.seconds
Number of seconds (>= 0 and less than 1 day).

<table>
<thead>
<tr>
<th>freq</th>
<th>is_populated</th>
<th>value</th>
</tr>
</thead>
</table>

Methods

ceil(freq)  Return a new Timedelta ceiled to this resolution.
floor(freq)  Return a new Timedelta floored to this resolution.
round(freq)  Round the Timedelta to the specified resolution.
to_numpy  Convert the Timedelta to a NumPy timedelta64.
to_pytimedelta  Convert a pandas Timedelta object into a python timedelta object.

continues on next page
Table 90 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>to_timedelta64</code></td>
<td>Return a numpy.timedelta64 object with ‘ns’ precision.</td>
</tr>
<tr>
<td><code>total_seconds</code></td>
<td>Total seconds in the duration.</td>
</tr>
<tr>
<td><code>view</code></td>
<td>Array view compatibility.</td>
</tr>
</tbody>
</table>

**pandas.Timedelta.ceil**

Timedelta.ceil(freq)

Return a new Timedelta ceiled to this resolution.

**Parameters**

- freq [str] Frequency string indicating the ceiling resolution.

**pandas.Timedelta.floor**

Timedelta.floor(freq)

Return a new Timedelta floored to this resolution.

**Parameters**

- freq [str] Frequency string indicating the flooring resolution.

**pandas.Timedelta.isoformat**

Timedelta.isoformat()


**Returns**

- str

**See also:**

`Timestamp.isoformat`

**Notes**

The longest component is days, whose value may be larger than 365. Every component is always included, even if its value is 0. Pandas uses nanosecond precision, so up to 9 decimal places may be included in the seconds component. Trailing 0’s are removed from the seconds component after the decimal. We do not 0 pad components, so it’s …T5H…, not …T05H…
Examples

```python
td = pd.Timedelta(days=6, minutes=50, seconds=3, milliseconds=10, microseconds=10, nanoseconds=12)
```

```python
>>> td.isoformat()
'P6DT0H50M3.010010012S'
>>> pd.Timedelta(hours=1, seconds=10).isoformat()
'P0DT0H0M10S'
>>> pd.Timedelta(hours=1, seconds=10).isoformat()
'P0DT0H0M10S'
>>> pd.Timedelta(days=500.5).isoformat()
'P500DT12H0MS'
```

**pandas.Timedelta.round**

Timedelta.round(freq)

Round the Timedelta to the specified resolution.

**Parameters**

- `freq` [str]: Frequency string indicating the rounding resolution.

**Returns**

A new Timedelta rounded to the given resolution of `freq`.

**Raises**

ValueError if the freq cannot be converted.

**pandas.Timedelta.to_numpy**

Timedelta.to_numpy()

Convert the Timedelta to a NumPy timedelta64.

New in version 0.25.0.

This is an alias method for Timedelta.to_timedelta64(). The dtype and copy parameters are available here only for compatibility. Their values will not affect the return value.

**Returns**

numpy.timedelta64

See also:

Series.to_numpy Similar method for Series.
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.Timedelta.to_pytimedelta

Timedelta.to_pytimedelta()
Convert a pandas Timedelta object into a python timedelta object.
Timedelta objects are internally saved as numpy datetime64[ns] dtype. Use to_pytimedelta() to convert to
object dtype.

Returns
datetime.timedelta or numpy.array of datetime.timedelta

See also:

to_timedelta Convert argument to Timedelta type.

Notes
Any nanosecond resolution will be lost.

pandas.Timedelta.to_timedelta64

Timedelta.to_timedelta64()
Return a numpy.timedelta64 object with ‘ns’ precision.

pandas.Timedelta.total_seconds

Timedelta.total_seconds()
Total seconds in the duration.

pandas.Timedelta.view

Timedelta.view()
Array view compatibility.

Properties

<table>
<thead>
<tr>
<th>Property</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Timedelta.asm8</td>
<td>Return a numpy timedelta64 array scalar view.</td>
</tr>
<tr>
<td>Timedelta.components</td>
<td>Return a components namedtuple-like.</td>
</tr>
<tr>
<td>Timedelta.days</td>
<td>Number of days.</td>
</tr>
<tr>
<td>Timedelta.delta</td>
<td>Return the timedelta in nanoseconds (ns), for internal compatibility.</td>
</tr>
<tr>
<td>Timedelta.freq</td>
<td></td>
</tr>
<tr>
<td>Timedelta.is_populated</td>
<td></td>
</tr>
<tr>
<td>Timedelta.max</td>
<td></td>
</tr>
<tr>
<td>Timedelta.microseconds</td>
<td>Number of microseconds (&gt;= 0 and less than 1 second).</td>
</tr>
<tr>
<td>Timedelta.min</td>
<td></td>
</tr>
<tr>
<td>Timedelta.nanoseconds</td>
<td>Return the number of nanoseconds (n), where 0 &lt;= n &lt; 1 microsecond.</td>
</tr>
</tbody>
</table>

continues on next page
Table 91 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Timedelta.resolution</td>
<td>Number of seconds (≥ 0 and less than 1 day).</td>
</tr>
<tr>
<td>Timedelta.seconds</td>
<td>Number of seconds (≥ 0 and less than 1 day).</td>
</tr>
<tr>
<td>Timedelta.value</td>
<td>Number of seconds (≥ 0 and less than 1 day).</td>
</tr>
<tr>
<td>Timedelta.view</td>
<td>Array view compatibility.</td>
</tr>
</tbody>
</table>

**pandas.Timedelta.freq**

Timedelta.freq

**pandas.Timedelta.is_populated**

Timedelta.is_populated

**pandas.Timedelta.max**

Timedelta.max = Timedelta('106751 days 23:47:16.854775807')

**pandas.Timedelta.min**

Timedelta.min = Timedelta('-106752 days +00:12:43.145224193')

**pandas.Timedelta.resolution**

Timedelta.resolution = Timedelta('0 days 00:00:00.000000001')

**pandas.Timedelta.value**

Timedelta.value

### Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Timedelta.ceil(freq)</td>
<td>Return a new Timedelta ceiled to this resolution.</td>
</tr>
<tr>
<td>Timedelta.floor(freq)</td>
<td>Return a new Timedelta floored to this resolution.</td>
</tr>
<tr>
<td>Timedelta.round(freq)</td>
<td>Round the Timedelta to the specified resolution.</td>
</tr>
<tr>
<td>Timedelta.to_pytimedelta</td>
<td>Convert a pandas Timedelta into a python timedelta object.</td>
</tr>
<tr>
<td>Timedelta.to_timedelta64</td>
<td>Return a numpy.timedelta64 object with ‘ns’ precision.</td>
</tr>
<tr>
<td>Timedelta.to_numpy</td>
<td>Convert the Timedelta to a NumPy timedelta64.</td>
</tr>
<tr>
<td>Timedelta.total_seconds</td>
<td>Total seconds in the duration.</td>
</tr>
</tbody>
</table>

A collection of timedeltas may be stored in a TimedeltaArray.
The `TimedeltaArray` class is a Pandas ExtensionArray for timedelta data. It was introduced in version 0.24.0.

### Parameters

- **values** [array-like] The timedelta data.
- **dtype** [numpy.dtype] Currently, only `numpy.dtype("timedelta64[ns]")` is accepted.
- **freq** [Offset, optional]
- **copy** [bool, default False] Whether to copy the underlying array of data.

### Attributes

None

### Methods

None

#### 3.5.4 Timespan data

Pandas represents spans of times as `Period` objects.

#### 3.5.5 Period

`Period([value, freq, ordinal, year, month, ...])` Represents a period of time.
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.Period

class pandas.Period(value=None, freq=None, ordinal=None, year=None, month=None, quarter=None, day=None, hour=None, minute=None, second=None)

Represents a period of time.

Parameters

- value [Period or str, default None] The time period represented (e.g., ‘4Q2005’).
- freq [str, default None] One of pandas period strings or corresponding objects.
- ordinal [int, default None] The period offset from the gregorian proleptic epoch.
- year [int, default None] Year value of the period.
- month [int, default 1] Month value of the period.
- quarter [int, default None] Quarter value of the period.
- day [int, default 1] Day value of the period.
- hour [int, default 0] Hour value of the period.
- minute [int, default 0] Minute value of the period.
- second [int, default 0] Second value of the period.

Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>day</td>
<td>Get day of the month that a Period falls on.</td>
</tr>
<tr>
<td>dayofweek</td>
<td>Day of the week the period lies in, with Monday=0 and Sunday=6.</td>
</tr>
<tr>
<td>dayofyear</td>
<td>Return the day of the year.</td>
</tr>
<tr>
<td>days_in_month</td>
<td>Get the total number of days in the month that this period falls on.</td>
</tr>
<tr>
<td>daysinmonth</td>
<td>Get the total number of days of the month that the Period falls in.</td>
</tr>
<tr>
<td>hour</td>
<td>Get the hour of the day component of the Period.</td>
</tr>
<tr>
<td>minute</td>
<td>Get minute of the hour component of the Period.</td>
</tr>
<tr>
<td>qyear</td>
<td>Fiscal year the Period lies in according to its starting-quarter.</td>
</tr>
<tr>
<td>second</td>
<td>Get the second component of the Period.</td>
</tr>
<tr>
<td>start_time</td>
<td>Get the Timestamp for the start of the period.</td>
</tr>
<tr>
<td>week</td>
<td>Get the week of the year on the given Period.</td>
</tr>
<tr>
<td>weekday</td>
<td>Day of the week the period lies in, with Monday=0 and Sunday=6.</td>
</tr>
</tbody>
</table>
pandas.Period.day

Period.day
Get day of the month that a Period falls on.

Returns
int

See also:

Period.dayofweek Get the day of the week.
Period.dayofyear Get the day of the year.

Examples

```python
>>> p = pd.Period("2018-03-11", freq='H')
>>> p.day
11
```

pandas.Period.dayofweek

Period.dayofweek
Day of the week the period lies in, with Monday=0 and Sunday=6.

If the period frequency is lower than daily (e.g. hourly), and the period spans over multiple days, the day at the start of the period is used.

If the frequency is higher than daily (e.g. monthly), the last day of the period is used.

Returns
int  Day of the week.

See also:

Period.dayofweek Day of the week the period lies in.
Period.weekday Alias of Period.dayofweek.
Period.day Day of the month.
Period.dayofyear Day of the year.

Examples

```python
>>> per = pd.Period('2017-12-31 22:00', 'H')
>>> per.dayofweek
6
```

For periods that span over multiple days, the day at the beginning of the period is returned.
```python
>>> per = pd.Period('2017-12-31 22:00', '4H')
>>> per.dayofweek
6
>>> per.start_time.dayofweek
6
```

For periods with a frequency higher than days, the last day of the period is returned.

```python
>>> per = pd.Period('2018-01', 'M')
>>> per.dayofweek
2
>>> per.end_time.dayofweek
2
```

### pandas.Period.dayofyear

`Period.dayofyear` Return the day of the year.

This attribute returns the day of the year on which the particular date occurs. The return value ranges between 1 to 365 for regular years and 1 to 366 for leap years.

**Returns**

- `int` The day of year.

**See also:**

- `Period.day` Return the day of the month.
- `Period.dayofweek` Return the day of week.
- `PeriodIndex.dayofyear` Return the day of year of all indexes.

### Examples

```python
>>> period = pd.Period("2015-10-23", freq='H')
>>> period.dayofyear
296
>>> period = pd.Period("2012-12-31", freq='D')
>>> period.dayofyear
366
>>> period = pd.Period("2013-01-01", freq='D')
>>> period.dayofyear
1
```
pandas.Period.days_in_month

Period.days_in_month
Get the total number of days in the month that this period falls on.

Returns
int

See also:

Period.daysinmonth Gets the number of days in the month.

DatetimeIndex.daysinmonth Gets the number of days in the month.

calendar.monthrange Returns a tuple containing weekday (0-6 ~ Mon-Sun) and number of days (28-31).

Examples

```python
>>> p = pd.Period('2018-2-17')
>>> p.days_in_month
28
```

```python
>>> pd.Period('2018-03-01').days_in_month
31
```
Handles the leap year case as well:

```python
>>> p = pd.Period('2016-2-17')
>>> p.days_in_month
29
```

pandas.Period.daysinmonth

Period.daysinmonth
Get the total number of days of the month that the Period falls in.

Returns
int

See also:

Period.days_in_month Return the days of the month.

Period.dayofyear Return the day of the year.
Examples

```python
>>> p = pd.Period("2018-03-11", freq='H')
>>> p.daysinmonth
31
```

**pandas.Period.hour**

Period.hour
Get the hour of the day component of the Period.

Returns
- `int`: The hour as an integer, between 0 and 23.

See also:
- **Period.second**: Get the second component of the Period.
- **Period.minute**: Get the minute component of the Period.

Examples

```python
>>> p.hour
13
```

Period longer than a day

```python
>>> p = pd.Period("2018-03-11", freq="M")
>>> p.hour
0
```

**pandas.Period.minute**

Period.minute
Get minute of the hour component of the Period.

Returns
- `int`: The minute as an integer, between 0 and 59.

See also:
- **Period.hour**: Get the hour component of the Period.
- **Period.second**: Get the second component of the Period.
Examples

```python
>>> p.minute
3
```

`pandas.Period.qyear`

`Period.qyear`
Fiscal year the Period lies in according to its starting-quarter.

The `year` and the `qyear` of the period will be the same if the fiscal and calendar years are the same. When they are not, the fiscal year can be different from the calendar year of the period.

**Returns**

- `int` The fiscal year of the period.

**See also:**

`Period.year` Return the calendar year of the period.

**Examples**

If the natural and fiscal year are the same, `qyear` and `year` will be the same.

```python
>>> per = pd.Period('2018Q1', freq='Q')
>>> per.qyear
2018
>>> per.year
2018
```

If the fiscal year starts in April (`Q-MAR`), the first quarter of 2018 will start in April 2017. `year` will then be 2018, but `qyear` will be the fiscal year, 2018.

```python
>>> per = pd.Period('2018Q1', freq='Q-MAR')
>>> per.start_time
Timestamp('2017-04-01 00:00:00')
>>> per.qyear
2018
>>> per.year
2017
```

`pandas.Period.second`

`Period.second`
Get the second component of the Period.

**Returns**

- `int` The second of the Period (ranges from 0 to 59).

**See also:**

`Period.hour` Get the hour component of the Period.
**Period.minute** Get the minute component of the Period.

**Examples**

```python
>>> p.second
12
```

**pandas.Period.start_time**

Period.start_time

Get the Timestamp for the start of the period.

Returns

Timestamp

See also:

**Period.end_time** Return the end Timestamp.

**Period.dayofyear** Return the day of year.

**Period.daysinmonth** Return the days in that month.

**Period.dayofweek** Return the day of the week.

**Examples**

```python
>>> period = pd.Period('2012-1-1', freq='D')
>>> period
Period('2012-01-01', 'D')

>>> period.start_time
Timestamp('2012-01-01 00:00:00')

>>> period.end_time
Timestamp('2012-01-01 23:59:59.999999999')
```

**pandas.Period.week**

Period.week

Get the week of the year on the given Period.

Returns

int

See also:

**Period.dayofweek** Get the day component of the Period.

**Period.weekday** Get the day component of the Period.
Examples

```python
cp = pd.Period("2018-03-11", "H")
cp.week
10

cp = pd.Period("2018-02-01", "D")
cp.week
5

cp = pd.Period("2018-01-06", "D")
cp.week
1
```

`pandas.Period.weekday`

`Period.weekday`

Day of the week the period lies in, with Monday=0 and Sunday=6.

If the period frequency is lower than daily (e.g. hourly), and the period spans over multiple days, the day at the start of the period is used.

If the frequency is higher than daily (e.g. monthly), the last day of the period is used.

Returns

```
int  Day of the week.
```

See also:

- `Period.dayofweek`  Day of the week the period lies in.
- `Period.weekday`  Alias of `Period.dayofweek`.
- `Period.day`  Day of the month.
- `Period.dayofyear`  Day of the year.

Examples

```python
cper = pd.Period('2017-12-31 22:00', 'H')
cper.dayofweek
dayofweek
6
```

For periods that span over multiple days, the day at the beginning of the period is returned.

```python
cper = pd.Period('2017-12-31 22:00', '4H')
cper.dayofweek
dayofweek
6
cper.start_time.dayofweek
dayofweek
6
```

For periods with a frequency higher than days, the last day of the period is returned.
>>> per = pd.Period('2018-01', 'M')
>>> per.dayofweek
2
>>> per.end_time.dayofweek
2

<table>
<thead>
<tr>
<th>end_time</th>
<th>freq</th>
<th>freqstr</th>
<th>is_leap_year</th>
<th>month</th>
<th>ordinal</th>
<th>quarter</th>
<th>weekofyear</th>
<th>year</th>
</tr>
</thead>
</table>

Methods

- `asfreq` Convert Period to desired frequency, at the start or end of the interval.
- `strftime` Returns the string representation of the `Period`, depending on the selected `fmt`.
- `to_timestamp` Return the Timestamp representation of the Period.

**pandas.Period.asfreq**

`Period.asfreq()` Convert Period to desired frequency, at the start or end of the interval.

**Parameters**

- `freq` [str] The desired frequency.
- `how` [{‘E’, ‘S’, ‘end’, ‘start’}, default ‘end’] Start or end of the timespan.

**Returns**

- `resampled` [Period]

**pandas.Period.strftime**

`Period.strftime()` Returns the string representation of the `Period`, depending on the selected `fmt`.

`fmt` must be a string containing one or several directives. The method recognizes the same directives as the `time.strftime()` function of the standard Python distribution, as well as the specific additional directives `%f`, `%E`, `%q`. (formatting & docs originally from scikits.timeries).
<table>
<thead>
<tr>
<th>Directive</th>
<th>Meaning</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>%a</td>
<td>Locale’s abbreviated weekday name.</td>
<td></td>
</tr>
<tr>
<td>%A</td>
<td>Locale’s full weekday name.</td>
<td></td>
</tr>
<tr>
<td>%b</td>
<td>Locale’s abbreviated month name.</td>
<td></td>
</tr>
<tr>
<td>%B</td>
<td>Locale’s full month name.</td>
<td></td>
</tr>
<tr>
<td>%c</td>
<td>Locale’s appropriate date and time representation.</td>
<td></td>
</tr>
<tr>
<td>%d</td>
<td>Day of the month as a decimal number [01,31].</td>
<td></td>
</tr>
<tr>
<td>%f</td>
<td>‘Fiscal’ year without a century as a decimal number [00,99]</td>
<td>(1)</td>
</tr>
<tr>
<td>%F</td>
<td>‘Fiscal’ year with a century as a decimal number</td>
<td>(2)</td>
</tr>
<tr>
<td>%H</td>
<td>Hour (24-hour clock) as a decimal number [00,23].</td>
<td></td>
</tr>
<tr>
<td>%I</td>
<td>Hour (12-hour clock) as a decimal number [01,12].</td>
<td></td>
</tr>
<tr>
<td>%j</td>
<td>Day of the year as a decimal number [001,366].</td>
<td></td>
</tr>
<tr>
<td>%m</td>
<td>Month as a decimal number [01,12].</td>
<td></td>
</tr>
<tr>
<td>%M</td>
<td>Minute as a decimal number [00,59].</td>
<td></td>
</tr>
<tr>
<td>%p</td>
<td>Locale’s equivalent of either AM or PM.</td>
<td>(3)</td>
</tr>
<tr>
<td>%q</td>
<td>Quarter as a decimal number [01,04]</td>
<td></td>
</tr>
<tr>
<td>%s</td>
<td>Second as a decimal number [00,61].</td>
<td>(4)</td>
</tr>
<tr>
<td>%U</td>
<td>Week number of the year (Sunday as the first day of the week) as a decimal number [00,53]. All days in a new year preceding the first Sunday are considered to be in week 0.</td>
<td>(5)</td>
</tr>
<tr>
<td>%W</td>
<td>Week number of the year (Monday as the first day of the week) as a decimal number [00,53]. All days in a new year preceding the first Monday are considered to be in week 0.</td>
<td>(5)</td>
</tr>
<tr>
<td>%x</td>
<td>Locale’s appropriate date representation.</td>
<td></td>
</tr>
<tr>
<td>%X</td>
<td>Locale’s appropriate time representation.</td>
<td></td>
</tr>
<tr>
<td>%y</td>
<td>Year without century as a decimal number [00,99].</td>
<td></td>
</tr>
<tr>
<td>%Y</td>
<td>Year with century as a decimal number.</td>
<td></td>
</tr>
<tr>
<td>%z</td>
<td>Time zone name (no characters if no time zone exists).</td>
<td></td>
</tr>
<tr>
<td>%z</td>
<td>A literal ‘%’ character.</td>
<td></td>
</tr>
</tbody>
</table>

**Notes**

1. The `%f` directive is the same as `%y` if the frequency is not quarterly. Otherwise, it corresponds to the ‘fiscal’ year, as defined by the `qyear` attribute.
2. The `%F` directive is the same as `%Y` if the frequency is not quarterly. Otherwise, it corresponds to the ‘fiscal’ year, as defined by the `qyear` attribute.
3. The `%p` directive only affects the output hour field if the `%I` directive is used to parse the hour.
4. The range really is 0 to 61; this accounts for leap seconds and the (very rare) double leap seconds.
5. The `%U` and `%W` directives are only used in calculations when the day of the week and the year are specified.
Examples

```python
>>> a = Period(freq='Q-JUL', year=2006, quarter=1)
>>> a.strftime('%F-Q%q')
'2006-Q1'
>>> # Output the last month in the quarter of this date
>>> a.strftime('%b-%Y')
'Oct-2005'
>>> # Output the last month in the quarter of this date
>>> a.strftime('%b-%Y')
'Oct-2005'

>>> a = Period(freq='D', year=2001, month=1, day=1)
>>> a.strftime('%d-%b-%Y')
'01-Jan-2006'
>>> a.strftime('%b. %d, %Y was a %A')
'Jan. 01, 2001 was a Monday'
```

`pandas.Period.to_timestamp`

Period.to_timestamp() - Return the Timestamp representation of the Period.

Uses the target frequency specified at the part of the period specified by `how`, which is either Start or Finish.

**Parameters**

- `freq` [str or DateOffset] Target frequency. Default is ‘D’ if self.freq is week or longer and ‘S’ otherwise.

**Returns**

- `Timestamp`

**Properties**

<table>
<thead>
<tr>
<th>Property</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period.day</td>
<td>Get day of the month that a Period falls on.</td>
</tr>
<tr>
<td>Period.dayofweek</td>
<td>Day of the week the period lies in, with Monday=0 and Sunday=6.</td>
</tr>
<tr>
<td>Period.dayofyear</td>
<td>Return the day of the year.</td>
</tr>
<tr>
<td>Period.days_in_month</td>
<td>Get the total number of days in the month that this period falls on.</td>
</tr>
<tr>
<td>Period.daysinmonth</td>
<td>Get the total number of days of the month that the Period falls in.</td>
</tr>
<tr>
<td>Period.end_time</td>
<td></td>
</tr>
<tr>
<td>Period.freq</td>
<td>Get the hour of the day component of the Period.</td>
</tr>
<tr>
<td>Period.freqstr</td>
<td></td>
</tr>
<tr>
<td>Period.hour</td>
<td>Get minute of the hour component of the Period.</td>
</tr>
<tr>
<td>Period.is_leap_year</td>
<td></td>
</tr>
<tr>
<td>Period.minute</td>
<td></td>
</tr>
</tbody>
</table>

continues on next page
### Table 97 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Period.month</code></td>
<td>Fiscal year the Period lies in according to its starting-quarter.</td>
</tr>
<tr>
<td><code>Period.ordinal</code></td>
<td>Get the second component of the Period.</td>
</tr>
<tr>
<td><code>Period.quarter</code></td>
<td>Get the Timestamp for the start of the period.</td>
</tr>
<tr>
<td><code>Period.qyear</code></td>
<td>Get the week of the year on the given Period.</td>
</tr>
<tr>
<td><code>Period.second</code></td>
<td>Day of the week the period lies in, with Monday=0 and Sunday=6.</td>
</tr>
</tbody>
</table>

**pandas.Period.end_time**

`Period.end_time`

**pandas.Period.freq**

`Period.freq`

**pandas.Period.freqstr**

`Period.freqstr`

**pandas.Period.is_leap_year**

`Period.is_leap_year`

**pandas.Period.month**

`Period.month`

**pandas.Period.ordinal**

`Period.ordinal`
pandas: powerful Python data analysis toolkit, Release 1.1.1

**pandas.Period.quarter**

Period.quarter

**pandas.Period.weekofyear**

Period.weekofyear

**pandas.Period.year**

Period.year

**Methods**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period.asfreq</td>
<td>Convert Period to desired frequency, at the start or end of the interval.</td>
</tr>
<tr>
<td>Period.now</td>
<td>A collection of timedeltas may be stored in a arrays.PeriodArray. Every period in a PeriodArray must have the same freq.</td>
</tr>
<tr>
<td>Period.strftime</td>
<td>Returns the string representation of the Period, depending on the selected fmt.</td>
</tr>
<tr>
<td>Period.to_timestamp</td>
<td>Return the Timestamp representation of the Period.</td>
</tr>
</tbody>
</table>

**pandas.Period.now**

Period.now()

**arrays.PeriodArray**

class pandas.arrays.PeriodArray(values[, freq, dtype, copy])

Pandas ExtensionArray for storing Period data.

Users should use period_array() to create new instances.

**Parameters**

- **values** [Union[PeriodArray, Series[period], ndarray[int], PeriodIndex]] The data to store. These should be arrays that can be directly converted to ordinals without inference or copy (PeriodArray, ndarray[int64]), or a box around such an array (Series[period], PeriodIndex).

- **freq** [str or DateOffset] The freq to use for the array. Mostly applicable when values is an ndarray of integers, when freq is required. When values is a PeriodArray (or box around), it’s checked that values.freq matches freq.

- **dtype** [PeriodDtype, optional] A PeriodDtype instance from which to extract a freq. If both freq and dtype are specified, then the frequencies must match.
copy [bool, default False] Whether to copy the ordinals before storing.

See also:

period_array Create a new PeriodArray.
PeriodIndex Immutable Index for period data.

Notes

There are two components to a PeriodArray
• ordinals : integer ndarray
• freq : pd.tseries.offsets.Offset

The values are physically stored as a 1-D ndarray of integers. These are called “ordinals” and represent some kind of offset from a base.

The freq indicates the span covered by each element of the array. All elements in the PeriodArray have the same freq.

Attributes

None

Methods

None

PeriodDtype([freq]) An ExtensionDtype for Period data.

pandas.PeriodDtype
class pandas.PeriodDtype(freq=\text{None})
An ExtensionDtype for Period data.

This is not an actual numpy dtype, but a duck type.

Parameters

freq [str or DateOffset] The frequency of this PeriodDtype.

Examples

```python
>>> pd.PeriodDtype(freq='D')
period[D]

>>> pd.PeriodDtype(freq=pd.offsets.MonthEnd())
period[M]
```
Attributes

freq
The frequency object of this PeriodDtype.

pandas.PeriodDtype.freq

property PeriodDtype.freq
The frequency object of this PeriodDtype.

Methods
None

3.5.6 Interval data

Arbitrary intervals can be represented as Interval objects.

Interval
Immutable object implementing an Interval, a bounded slice-like interval.

pandas.Interval

class pandas.Interval
Immutable object implementing an Interval, a bounded slice-like interval.

Parameters
- left [orderable scalar] Left bound for the interval.
- right [orderable scalar] Right bound for the interval.
- closed [‘right’, ‘left’, ‘both’, ‘neither’], default ‘right’ Whether the interval is closed on the left-side, right-side, both or neither. See the Notes for more detailed explanation.

See also:
- IntervalIndex An Index of Interval objects that are all closed on the same side.
- cut Convert continuous data into discrete bins (Categorical of Interval objects).
- qcut Convert continuous data into bins (Categorical of Interval objects) based on quantiles.
- Period Represents a period of time.

Notes

The parameters left and right must be from the same type, you must be able to compare them and they must satisfy left <= right.

A closed interval (in mathematics denoted by square brackets) contains its endpoints, i.e. the closed interval [0, 5] is characterized by the conditions 0 <= x <= 5. This is what closed='both' stands for. An open interval (in mathematics denoted by parentheses) does not contain its endpoints, i.e. the open interval (0, 5) is characterized by the conditions 0 < x < 5. This is what closed='neither' stands for. Intervals can also be half-open or half-closed, i.e. [0, 5) is described by 0 <= x < 5(closed='left') and (0, 5] is described by 0 < x <= 5(closed='right').

3.5. pandas arrays 1861
Examples

It is possible to build Intervals of different types, like numeric ones:

```python
>>> iv = pd.Interval(left=0, right=5)
>>> iv
Interval(0, 5, closed='right')
```

You can check if an element belongs to it

```python
>>> 2.5 in iv
True
```

You can test the bounds (closed='right', so 0 < x <= 5):

```python
>>> 0 in iv
False
>>> 5 in iv
True
>>> 0.0001 in iv
True
```

Calculate its length

```python
>>> iv.length
5
```

You can operate with + and * over an Interval and the operation is applied to each of its bounds, so the result depends on the type of the bound elements

```python
>>> shifted_iv = iv + 3
>>> shifted_iv
Interval(3, 8, closed='right')
>>> extended_iv = iv * 10.0
>>> extended_iv
Interval(0.0, 50.0, closed='right')
```

To create a time interval you can use Timestamps as the bounds

```python
>>> year_2017 = pd.Interval(pd.Timestamp('2017-01-01 00:00:00'),
... pd.Timestamp('2018-01-01 00:00:00'),
... closed='left')
>>> pd.Timestamp('2017-01-01 00:00') in year_2017
True
>>> year_2017.length
Timedelta('365 days 00:00:00')
```

And also you can create string intervals

```python
>>> volume_1 = pd.Interval('Ant', 'Dog', closed='both')
>>> 'Bee' in volume_1
True
```
Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>closed</td>
<td>Whether the interval is closed on the left-side, right-side, both or neither.</td>
</tr>
<tr>
<td>closed_left</td>
<td>Check if the interval is closed on the left side.</td>
</tr>
<tr>
<td>closed_right</td>
<td>Check if the interval is closed on the right side.</td>
</tr>
<tr>
<td>is_empty</td>
<td>Indicates if an interval is empty, meaning it contains no points.</td>
</tr>
<tr>
<td>left</td>
<td>Left bound for the interval.</td>
</tr>
<tr>
<td>length</td>
<td>Return the length of the Interval.</td>
</tr>
<tr>
<td>mid</td>
<td>Return the midpoint of the Interval.</td>
</tr>
<tr>
<td>open_left</td>
<td>Check if the interval is open on the left side.</td>
</tr>
<tr>
<td>open_right</td>
<td>Check if the interval is open on the right side.</td>
</tr>
<tr>
<td>right</td>
<td>Right bound for the interval.</td>
</tr>
</tbody>
</table>

pandas.Interval.closed

Interval.closed
Whether the interval is closed on the left-side, right-side, both or neither.

pandas.Interval.closed_left

Interval.closed_left
Check if the interval is closed on the left side.
For the meaning of closed and open see Interval.
Returns
bool True if the Interval is closed on the left-side.

pandas.Interval.closed_right

Interval.closed_right
Check if the interval is closed on the right side.
For the meaning of closed and open see Interval.
Returns
bool True if the Interval is closed on the left-side.

pandas.Interval.is_empty

Interval.is_empty
Indicates if an interval is empty, meaning it contains no points.
New in version 0.25.0.
Returns
bool or ndarray A boolean indicating if a scalar Interval is empty, or a boolean ndarray positionally indicating if an Interval in an IntervalArray or IntervalIndex is empty.

Examples

An Interval that contains points is not empty:

```python
>>> pd.Interval(0, 1, closed='right').is_empty
False
```

An Interval that does not contain any points is empty:

```python
>>> pd.Interval(0, 0, closed='right').is_empty
True
>>> pd.Interval(0, 0, closed='left').is_empty
True
>>> pd.Interval(0, 0, closed='neither').is_empty
True
```

An Interval that contains a single point is not empty:

```python
>>> pd.Interval(0, 0, closed='both').is_empty
False
```

An IntervalArray or IntervalIndex returns a boolean ndarray positionally indicating if an Interval is empty:

```python
>>> ivs = [pd.Interval(0, 0, closed='neither'), ...
        pd.Interval(1, 2, closed='neither')]
>>> pd.arrays.IntervalArray(ivs).is_empty
array([ True, False])
```

Missing values are not considered empty:

```python
>>> ivs = [pd.Interval(0, 0, closed='neither'), np.nan]
>>> pd.IntervalIndex(ivs).is_empty
array([ True, False])
```

pandas.Interval.left

Interval.left
Left bound for the interval.

pandas.Interval.length

Interval.length
Return the length of the Interval.
pandas.Interval.mid

**Interval.mid**

Return the midpoint of the Interval.

pandas.Interval.open_left

**Interval.open_left**

Check if the interval is open on the left side.

For the meaning of *closed* and *open* see *Interval*.

Returns

**bool** True if the Interval is closed on the left-side.

pandas.Interval.open_right

**Interval.open_right**

Check if the interval is open on the right side.

For the meaning of *closed* and *open* see *Interval*.

Returns

**bool** True if the Interval is closed on the left-side.

pandas.Interval.right

**Interval.right**

Right bound for the interval.

Methods

**overlaps**

Check whether two Interval objects overlap.

pandas.Interval.overlaps

**Interval.overlaps()**

Check whether two Interval objects overlap.

Two intervals overlap if they share a common point, including closed endpoints. Intervals that only have an open endpoint in common do not overlap.

New in version 0.24.0.

**Parameters**

**other** [Interval] Interval to check against for an overlap.

**Returns**

**bool** True if the two intervals overlap.
See also:

**IntervalArray.overlaps** The corresponding method for IntervalArray.

**IntervalIndex.overlaps** The corresponding method for IntervalIndex.

### Examples

```python
>>> i1 = pd.Interval(0, 2)
>>> i2 = pd.Interval(1, 3)
>>> i1.overlaps(i2)
True
>>> i3 = pd.Interval(4, 5)
>>> i1.overlaps(i3)
False
```

Intervals that share closed endpoints overlap:

```python
>>> i4 = pd.Interval(0, 1, closed='both')
>>> i5 = pd.Interval(1, 2, closed='both')
>>> i4.overlaps(i5)
True
```

Intervals that only have an open endpoint in common do not overlap:

```python
>>> i6 = pd.Interval(1, 2, closed='neither')
>>> i4.overlaps(i6)
False
```

### Properties

<table>
<thead>
<tr>
<th>Property</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interval.closed</td>
<td>Whether the interval is closed on the left-side, right-side, both or neither.</td>
</tr>
<tr>
<td>Interval.closed_left</td>
<td>Check if the interval is closed on the left side.</td>
</tr>
<tr>
<td>Interval.closed_right</td>
<td>Check if the interval is closed on the right side.</td>
</tr>
<tr>
<td>Interval.is_empty</td>
<td>Indicates if an interval is empty, meaning it contains no points.</td>
</tr>
<tr>
<td>Interval.left</td>
<td>Left bound for the interval.</td>
</tr>
<tr>
<td>Interval.length</td>
<td>Return the length of the Interval.</td>
</tr>
<tr>
<td>Interval.mid</td>
<td>Return the midpoint of the Interval.</td>
</tr>
<tr>
<td>Interval.open_left</td>
<td>Check if the interval is open on the left side.</td>
</tr>
<tr>
<td>Interval.open_right</td>
<td>Check if the interval is open on the right side.</td>
</tr>
<tr>
<td>Interval.overlaps</td>
<td>Check whether two Interval objects overlap.</td>
</tr>
<tr>
<td>Interval.right</td>
<td>Right bound for the interval.</td>
</tr>
</tbody>
</table>

A collection of intervals may be stored in an `arrays.IntervalArray`.

```python
arrays.IntervalArray(data[, closed, dtype, ...])
```
**pandas.arrays.IntervalArray**

**class pandas.arrays.IntervalArray**(data, closed=None, dtype=None, copy=False, verify_integrity=True)

Pandas array for interval data that are closed on the same side.

New in version 0.24.0.

**Parameters**

- **data** [array-like (1-dimensional)] Array-like containing Interval objects from which to build the IntervalArray.
- **closed** [{'left', 'right', 'both', 'neither'}, default 'right'] Whether the intervals are closed on the left-side, right-side, both or neither.
- **dtype** [dtype or None, default None] If None, dtype will be inferred. New in version 0.23.0.
- **copy** [bool, default False] Copy the input data.
- **verify_integrity** [bool, default True] Verify that the IntervalArray is valid.

**See also:**

- **Index** The base pandas Index type.
- **Interval** A bounded slice-like interval; the elements of an IntervalArray.
- **interval_range** Function to create a fixed frequency IntervalIndex.
- **cut** Bin values into discrete Intervals.
- **qcut** Bin values into equal-sized Intervals based on rank or sample quantiles.

**Notes**

See the [user guide](#) for more.

**Examples**

A new IntervalArray can be constructed directly from an array-like of Interval objects:

```python
>>> pd.arrays.IntervalArray([pd.Interval(0, 1), pd.Interval(1, 5)])
<IntervalArray>
[[0, 1], (1, 5)]
Length: 2, closed: right, dtype: interval[int64]
```

It may also be constructed using one of the constructor methods: `IntervalArray.from_arrays()`, `IntervalArray.from_breaks()`, and `IntervalArray.from_tuples()`.

**Attributes**

- **left**
  - Return the left endpoints of each Interval in the IntervalArray as an Index.
- **right**
  - Return the right endpoints of each Interval in the IntervalArray as an Index.
- **closed**
  - Whether the intervals are closed on the left-side, right-side, both or neither.

continues on next page
Table 107 – continued from previous page

<table>
<thead>
<tr>
<th>Method Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>mid</td>
<td>Return the midpoint of each Interval in the IntervalArray as an Index.</td>
</tr>
<tr>
<td>length</td>
<td>Return an Index with entries denoting the length of each Interval in the IntervalArray.</td>
</tr>
<tr>
<td>is_empty</td>
<td>Indicates if an interval is empty, meaning it contains no points.</td>
</tr>
<tr>
<td>is_non_overlapping_monotonic</td>
<td>Return True if the IntervalArray is non-overlapping (no Intervals share points) and is either monotonic increasing or monotonic decreasing, else False.</td>
</tr>
</tbody>
</table>

`pandas.arrays.IntervalArray.left`

**property** IntervalArray.left

Return the left endpoints of each Interval in the IntervalArray as an Index.

`pandas.arrays.IntervalArray.right`

**property** IntervalArray.right

Return the right endpoints of each Interval in the IntervalArray as an Index.

`pandas.arrays.IntervalArray.closed`

**property** IntervalArray.closed

Whether the intervals are closed on the left-side, right-side, both or neither.

`pandas.arrays.IntervalArray.mid`

**property** IntervalArray.mid

Return the midpoint of each Interval in the IntervalArray as an Index.

`pandas.arrays.IntervalArray.length`

**property** IntervalArray.length

Return an Index with entries denoting the length of each Interval in the IntervalArray.

`pandas.arrays.IntervalArray.is_empty`

**IntervalArray.is_empty**

Indicates if an interval is empty, meaning it contains no points.

New in version 0.25.0.

**Returns**

- bool or ndarray  A boolean indicating if a scalar Interval is empty, or a boolean ndarray positionally indicating if an Interval in an IntervalArray or IntervalIndex is empty.
Examples

An Interval that contains points is not empty:

```python
gp.Interval(0, 1, closed='right').is_empty
False
```

An Interval that does not contain any points is empty:

```python
gp.Interval(0, 0, closed='right').is_empty
True
gp.Interval(0, 0, closed='left').is_empty
True
gp.Interval(0, 0, closed='neither').is_empty
True
```

An Interval that contains a single point is not empty:

```python
gp.Interval(0, 0, closed='both').is_empty
False
```

An IntervalArray or IntervalIndex returns a boolean ndarray positionally indicating if an Interval is empty:

```python
ivs = [gp.Interval(0, 0, closed='neither'),
      ...  gp.Interval(1, 2, closed='neither')]
gp.arrays.IntervalArray(ivs).is_empty
array([ True, False])
```

Missing values are not considered empty:

```python
ivs = [gp.Interval(0, 0, closed='neither'), np.nan]
gp.IntervalIndex(ivs).is_empty
array([ True, False])
```

**pandas.arrays.IntervalArray.is_non_overlapping_monotonic**

**property** IntervalArray.is_non_overlapping_monotonic

Return True if the IntervalArray is non-overlapping (no Intervals share points) and is either monotonic increasing or monotonic decreasing, else False.

**Methods**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>from_arrays(left, right[, closed, copy, dtype])</td>
<td>Construct from two arrays defining the left and right bounds.</td>
</tr>
<tr>
<td>from_tuples(data[, closed, copy, dtype])</td>
<td>Construct an IntervalArray from an array-like of tuples.</td>
</tr>
<tr>
<td>from_breaks(breaks[, closed, copy, dtype])</td>
<td>Construct an IntervalArray from an array of splits.</td>
</tr>
<tr>
<td>contains(other)</td>
<td>Check elementwise if the Intervals contain the value.</td>
</tr>
<tr>
<td>overlaps(other)</td>
<td>Check elementwise if an Interval overlaps the values in the IntervalArray.</td>
</tr>
</tbody>
</table>

continues on next page
**set_closed**

Return an IntervalArray identical to the current one, but closed on the specified side.

**to_tuples**

Return an ndarray of tuples of the form (left, right).

---

**pandas.arrays.IntervalArray.from_arrays**

**classmethod** `IntervalArray.from_arrays(left, right, closed='right', copy=False, dtype=None)`

Construct from two arrays defining the left and right bounds.

**Parameters**

- `left` [array-like (1-dimensional)] Left bounds for each interval.
- `right` [array-like (1-dimensional)] Right bounds for each interval.
- `closed` [{'left', 'right', 'both', 'neither'}, default 'right'] Whether the intervals are closed on the left-side, right-side, both or neither.
- `copy` [bool, default False] Copy the data.
- `dtype` [dtype, optional] If None, dtype will be inferred.

**Returns**

IntervalArray

**Raises**

- **ValueError** When a value is missing in only one of `left` or `right`. When a value in `left` is greater than the corresponding value in `right`.

**See also:**

- `interval_range` Function to create a fixed frequency IntervalIndex.
- `IntervalArray.from_breaks` Construct an IntervalArray from an array of splits.
- `IntervalArray.from_tuples` Construct an IntervalArray from an array-like of tuples.

**Notes**

Each element of `left` must be less than or equal to the `right` element at the same position. If an element is missing, it must be missing in both `left` and `right`. A TypeError is raised when using an unsupported type for `left` or `right`. At the moment, ‘category’, ‘object’, and ‘string’ subtypes are not supported.

```python
>>> pd.arrays.IntervalArray.from_arrays([[0, 1, 2], [1, 2, 3]])
<IntervalArray>
[(0, 1], (1, 2], (2, 3]]
Length: 3, closed: right, dtype: interval[int64]
```
pandas.arrays.IntervalArray.from_tuples

classmethod IntervalArray.from_tuples(data, closed='right', copy=False, dtype=None)
Construct an IntervalArray from an array-like of tuples.

Parameters

- **data** [array-like (1-dimensional)] Array of tuples.
- **closed** [‘left’, ‘right’, ‘both’, ‘neither’], default ‘right’] Whether the intervals are closed on the left-side, right-side, both or neither.
- **copy** [bool, default False] By-default copy the data, this is compat only and ignored.
- **dtype** [dtype or None, default None] If None, dtype will be inferred.

New in version 0.23.0.

Returns

IntervalArray

See also:

- interval_range Function to create a fixed frequency IntervallIndex.
- IntervalArray.from_arrays Construct an IntervalArray from a left and right array.
- IntervalArray.from_breaks Construct an IntervalArray from an array of splits.

Examples

```python
>>> pd.arrays.IntervalArray.from_tuples([(0, 1), (1, 2)])
<IntervalArray>
[(0, 1], (1, 2]]
Length: 2, closed: right, dtype: interval[int64]
```

pandas.arrays.IntervalArray.from_breaks

classmethod IntervalArray.from_breaks(breaks, closed='right', copy=False, dtype=None)
Construct an IntervalArray from an array of splits.

Parameters

- **breaks** [array-like (1-dimensional)] Left and right bounds for each interval.
- **closed** [‘left’, ‘right’, ‘both’, ‘neither’], default ‘right’] Whether the intervals are closed on the left-side, right-side, both or neither.
- **copy** [bool, default False] Copy the data.
- **dtype** [dtype or None, default None] If None, dtype will be inferred.

New in version 0.23.0.

Returns

IntervalArray

See also:
**interval_range**  Function to create a fixed frequency IntervalIndex.

*IntervalArray.from_arrays*  Construct from a left and right array.

*IntervalArray.from_tuples*  Construct from a sequence of tuples.

**Examples**

```python
>>> pd.arrays.IntervalArray.from_breaks([0, 1, 2, 3])
<IntervalArray>
[(0, 1], (1, 2], (2, 3])
Length: 3, closed: right, dtype: interval[int64]
```

**pandas.arrays.IntervalArray.contains**

*IntervalArray.contains*(*other*)

Check elementwise if the Intervals contain the value.

Return a boolean mask whether the value is contained in the Intervals of the IntervalArray.

New in version 0.25.0.

**Parameters**

*other*  [scalar]  The value to check whether it is contained in the Intervals.

**Returns**

*boolean array*

**See also:**

*Interval.contains*  Check whether Interval object contains value.

*IntervalArray.overlaps*  Check if an Interval overlaps the values in the IntervalArray.

**Examples**

```python
>>> intervals = pd.arrays.IntervalArray.from_tuples([(0, 1), (1, 3), (2, 4)])
>>> intervals
<IntervalArray>
[(0, 1], (1, 3], (2, 4])
Length: 3, closed: right, dtype: interval[int64]

>>> intervals.contains(0.5)
array([ True, False, False])
```
pandas.arrays.IntervalArray.overlaps

\texttt{IntervalArray\_overlaps(\textit{other})}

Check elementwise if an Interval overlaps the values in the IntervalArray.

Two intervals overlap if they share a common point, including closed endpoints. Intervals that only have an open endpoint in common do not overlap.

New in version 0.24.0.

\textbf{Parameters}

- \texttt{other} [IntervalArray] Interval to check against for an overlap.

\textbf{Returns}

\texttt{ndarray} Boolean array positionally indicating where an overlap occurs.

\textbf{See also:}

\texttt{Interval\_overlaps} Check whether two Interval objects overlap.

\textbf{Examples}

```
>>> data = [(0, 1), (1, 3), (2, 4)]
>>> intervals = pd.arrays.IntervalArray.from_tuples(data)
>>> intervals
<IntervalArray>
[(0, 1], (1, 3], (2, 4]
Length: 3, closed: right, dtype: interval[int64]
```

```
>>> intervals.overlaps(pd.Interval(0.5, 1.5))
array([ True, True, False])
```

Intervals that share closed endpoints overlap:

```
>>> intervals.overlaps(pd.Interval(1, 3, closed='left'))
array([ True, True, True])
```

Intervals that only have an open endpoint in common do not overlap:

```
>>> intervals.overlaps(pd.Interval(1, 2, closed='right'))
array([False, True, False])
```

pandas.arrays.IntervalArray.set_closed

\texttt{IntervalArray\_set\_closed(\textit{closed})}

Return an IntervalArray identical to the current one, but closed on the specified side.

New in version 0.24.0.

\textbf{Parameters}

- \texttt{closed} [{‘left’, ‘right’, ‘both’, ‘neither’}] Whether the intervals are closed on the left-side, right-side, both or neither.

\textbf{Returns}
new_index  [IntervalArray]

Examples

```python
>>> index = pd.arrays.IntervalArray.from_breaks(range(4))
>>> index
<IntervalArray>
[(0, 1], (1, 2], (2, 3]]
Length: 3, closed: right, dtype: interval[int64]
>>> index.set_closed('both')
<IntervalArray>
[[0, 1], [1, 2], [2, 3]]
Length: 3, closed: both, dtype: interval[int64]
```

pandas.arrays.IntervalArray.to_tuples

IntervalArray.

to_tuples (na_tuple=True)

Return an ndarray of tuples of the form (left, right).

Parameters

na_tuple  [bool, default True] Returns NA as a tuple if True, (nan, nan), or just as the NA value itself if False, nan.

New in version 0.23.0.

Returns

tuples: ndarray

IntervalDtype([subtype])  An ExtensionDtype for Interval data.

pandas.IntervalDtype

class pandas.IntervalDtype (subtype=None)

An ExtensionDtype for Interval data.

This is not an actual numpy dtype, but a duck type.

Parameters


Examples

```python
>>> pd.IntervalDtype(subtype='int64')
interval[int64]
```
Attributes

subtype

The dtype of the Interval bounds.

pandas.IntervalDtypesubtype

property IntervalDtype subtype

The dtype of the Interval bounds.

Methods

None

3.5.7 Nullable integer

numpy.ndarray cannot natively represent integer-data with missing values. Pandas provides this through arrays.IntegerArray.

arrays.IntegerArray(values, mask[, copy]) Array of integer (optional missing) values.

pandas.arrays.IntegerArray

class pandas.arrays.IntegerArray(values, mask, copy=False) Array of integer (optional missing) values.

New in version 0.24.0.

Changed in version 1.0.0: Now uses pandas.NA as the missing value rather than numpy.nan.

Warning: IntegerArray is currently experimental, and its API or internal implementation may change without warning.

We represent an IntegerArray with 2 numpy arrays:

- data: contains a numpy integer array of the appropriate dtype
- mask: a boolean array holding a mask on the data, True is missing

To construct an IntegerArray from generic array-like input, use pandas.array() with one of the integer dtypes (see examples).

See Nullable integer data type for more.

Parameters


copy [bool, default False] Whether to copy the values and mask.

Returns

IntegerArray
Examples

Create an IntegerArray with `pandas.array()`.

```python
>>> int_array = pd.array([1, None, 3], dtype=pd.Int32Dtype())
>>> int_array
<IntegerArray>
[1, <NA>, 3]
Length: 3, dtype: Int32
```

String aliases for the dtypes are also available. They are capitalized.

```python
>>> pd.array([1, None, 3], dtype='Int32')
<IntegerArray>
[1, <NA>, 3]
Length: 3, dtype: Int32
```

```python
>>> pd.array([1, None, 3], dtype='UInt16')
<IntegerArray>
[1, <NA>, 3]
Length: 3, dtype: UInt16
```

Attributes

None

Methods

None

---

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Int8Dtype()</td>
<td>An ExtensionDtype for int8 integer data.</td>
</tr>
<tr>
<td>Int16Dtype()</td>
<td>An ExtensionDtype for int16 integer data.</td>
</tr>
<tr>
<td>Int32Dtype()</td>
<td>An ExtensionDtype for int32 integer data.</td>
</tr>
<tr>
<td>Int64Dtype()</td>
<td>An ExtensionDtype for int64 integer data.</td>
</tr>
<tr>
<td>UInt8Dtype()</td>
<td>An ExtensionDtype for uint8 integer data.</td>
</tr>
<tr>
<td>UInt16Dtype()</td>
<td>An ExtensionDtype for uint16 integer data.</td>
</tr>
<tr>
<td>UInt32Dtype()</td>
<td>An ExtensionDtype for uint32 integer data.</td>
</tr>
<tr>
<td>UInt64Dtype()</td>
<td>An ExtensionDtype for uint64 integer data.</td>
</tr>
</tbody>
</table>
pandas.Int8Dtype

class pandas.Int8Dtype
    An ExtensionDtype for int8 integer data.
    Changed in version 1.0.0: Now uses pandas.NA as its missing value, rather than numpy.nan.

Attributes

None

Methods

None

pandas.Int16Dtype

class pandas.Int16Dtype
    An ExtensionDtype for int16 integer data.
    Changed in version 1.0.0: Now uses pandas.NA as its missing value, rather than numpy.nan.

Attributes

None

Methods

None

pandas.Int32Dtype

class pandas.Int32Dtype
    An ExtensionDtype for int32 integer data.
    Changed in version 1.0.0: Now uses pandas.NA as its missing value, rather than numpy.nan.
pandas: powerful Python data analysis toolkit, Release 1.1.1

Attributes

Methods

pandas.Int64Dtype

class pandas.Int64Dtype
An ExtensionDtype for int64 integer data.
Changed in version 1.0.0: Now uses pandas.NA as its missing value, rather than numpy.nan.

Attributes

Methods

pandas.UInt8Dtype

class pandas.UInt8Dtype
An ExtensionDtype for uint8 integer data.
Changed in version 1.0.0: Now uses pandas.NA as its missing value, rather than numpy.nan.

Attributes

Methods
**pandas.UInt16Dtype**

`class pandas.UInt16Dtype`

An ExtensionDtype for uint16 integer data.

Changed in version 1.0.0: Now uses `pandas.NA` as its missing value, rather than `numpy.nan`.

**Attributes**

None

**Methods**

None

**pandas.UInt32Dtype**

`class pandas.UInt32Dtype`

An ExtensionDtype for uint32 integer data.

Changed in version 1.0.0: Now uses `pandas.NA` as its missing value, rather than `numpy.nan`.

**Attributes**

None

**Methods**

None

**pandas.UInt64Dtype**

`class pandas.UInt64Dtype`

An ExtensionDtype for uint64 integer data.

Changed in version 1.0.0: Now uses `pandas.NA` as its missing value, rather than `numpy.nan`. 
### Attributes

**None**

### Methods

**None**

### 3.5.8 Categorical data

Pandas defines a custom data type for representing data that can take only a limited, fixed set of values. The dtype of a `Categorical` can be described by a `pandas.api.types.CategoricalDtype`.

<table>
<thead>
<tr>
<th>CategoricalDtype(categories, ordered)</th>
<th>Type for categorical data with the categories and orderedness.</th>
</tr>
</thead>
</table>

#### pandas.CategoricalDtype

**class** `pandas.CategoricalDtype(categories=None, ordered=False)`  
Type for categorical data with the categories and orderedness.  

**Parameters**

- **categories** [sequence, optional] Must be unique, and must not contain any nulls. The categories are stored in an Index, and if an index is provided the dtype of that index will be used.

- **ordered** [bool or None, default False] Whether or not this categorical is treated as a ordered categorical. None can be used to maintain the ordered value of existing categoricals when used in operations that combine categoricals, e.g. astype, and will resolve to False if there is no existing ordered to maintain.

**See also:**

- **Categorical** Represent a categorical variable in classic R / S-plus fashion.

**Notes**

This class is useful for specifying the type of a `Categorical` independent of the values. See `CategoricalDtype` for more.

**Examples**

```python
>>> t = pd.CategoricalDtype(categories=['b', 'a'], ordered=True)
>>> pd.Series(['a', 'b', 'a', 'c'], dtype=t)
0   a
1   b
2   a
3  NaN
dtype: category
Categories (2, object): ['b' < 'a']
```
An empty CategoricalDtype with a specific dtype can be created by providing an empty index. As follows,

```python
>>> pd.CategoricalDtype(pd.DatetimeIndex([])).categories.dtype
dtype('<M8[ns]')
```

### Attributes

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>categories</td>
<td>An Index containing the unique categories allowed.</td>
</tr>
<tr>
<td>ordered</td>
<td>Whether the categories have an ordered relationship.</td>
</tr>
</tbody>
</table>

#### pandas.CategoricalDtype.categories

**property** `CategoricalDtype.categories`  
An Index containing the unique categories allowed.

#### pandas.CategoricalDtype.ordered

**property** `CategoricalDtype.ordered`  
Whether the categories have an ordered relationship.

### Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>CategoricalDtype.categories</td>
<td>An Index containing the unique categories allowed.</td>
</tr>
<tr>
<td>CategoricalDtype.ordered</td>
<td>Whether the categories have an ordered relationship.</td>
</tr>
</tbody>
</table>

Categorical data can be stored in a `pandas.Categorical`:

```python
Categorical(values[, categories, ordered, ...])  
Represent a categorical variable in classic R / S-plus fashion.
```

#### pandas.Categorical

**class** `pandas.Categorical`  
Represent a categorical variable in classic R / S-plus fashion.

Categoricals can only take on only a limited, and usually fixed, number of possible values (categories). In contrast to statistical categorical variables, a Categorical might have an order, but numerical operations (additions, divisions, ...) are not possible.

All values of the Categorical are either in categories or np.nan. Assigning values outside of categories will raise a `ValueError`. Order is defined by the order of the categories, not lexical order of the values.

**Parameters**

- `values` [list-like] The values of the categorical. If categories are given, values not in categories will be replaced with NaN.
**categories** [Index-like (unique), optional] The unique categories for this categorical. If not given, the categories are assumed to be the unique values of values (sorted, if possible, otherwise in the order in which they appear).

**ordered** [bool, default False] Whether or not this categorical is treated as an ordered categorical. If True, the resulting categorical will be ordered. An ordered categorical respects, when sorted, the order of its categories attribute (which in turn is the categories argument, if provided).

**dtype** [CategoricalDtype] An instance of CategoricalDtype to use for this categorical.

Raises

- **ValueError** If the categories do not validate.
- **TypeError** If an explicit ordered=True is given but no categories and the values are not sortable.

See also:

- CategoricalDtype Type for categorical data.
- CategoricalIndex An Index with an underlying Categorical.

Notes

See the user guide for more.

Examples

```python
>>> pd.Categorical([1, 2, 3, 1, 2, 3])
[1, 2, 3, 1, 2, 3]
Categories (3, int64): [1, 2, 3]
```

```python
>>> pd.Categorical(['a', 'b', 'c', 'a', 'b', 'c'])
['a', 'b', 'c', 'a', 'b', 'c']
Categories (3, object): ['a', 'b', 'c']
```

Ordered Categoricals can be sorted according to the custom order of the categories and can have a min and max value.

```python
>>> c = pd.Categorical(['a', 'b', 'c', 'a', 'b', 'c'], ordered=True, ...
...                         categories=['c', 'b', 'a'])
>>> c
['a', 'b', 'c', 'a', 'b', 'c']
Categories (3, object): ['c' < 'b' < 'a']
>>> c.min()
'c'
```
Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>categories</td>
<td>The categories of this categorical.</td>
</tr>
<tr>
<td>codes</td>
<td>The category codes of this categorical.</td>
</tr>
<tr>
<td>ordered</td>
<td>Whether the categories have an ordered relationship.</td>
</tr>
<tr>
<td>dtype</td>
<td>The CategoricalDtype for this instance.</td>
</tr>
</tbody>
</table>

**pandas.Categorical.categories**

**property Categorical.categories**
The categories of this categorical.

- Setting assigns new values to each category (effectively a rename of each individual category).
- The assigned value has to be a list-like object. All items must be unique and the number of items in the new categories must be the same as the number of items in the old categories.
- Assigning to categories is a inplace operation!

**Raises**

**ValueError** If the new categories do not validate as categories or if the number of new categories is unequal the number of old categories.

**See also:**

- rename_categories Rename categories.
- reorder_categories Reorder categories.
- add_categories Add new categories.
- remove_categories Remove the specified categories.
- remove_unused_categories Remove categories which are not used.
- set_categories Set the categories to the specified ones.

**pandas.Categorical.codes**

**property Categorical.codes**
The category codes of this categorical.

- Codes are an array of integers which are the positions of the actual values in the categories array.
- There is no setter, use the other categorical methods and the normal item setter to change values in the categorical.

**Returns**

**ndarray[int]** A non-writable view of the codes array.
pandas.Categorical.ordered

**property** Categorical.ordered

Whether the categories have an ordered relationship.

pandas.Categorical.dtype

**property** Categorical.dtype

The CategoricalDtype for this instance.

Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>from_codes</td>
<td>Make a Categorical type from codes and categories or dtype.</td>
</tr>
<tr>
<td><strong>array</strong></td>
<td>The numpy array interface.</td>
</tr>
</tbody>
</table>

pandas.Categorical.from_codes

**classmethod** Categorical.from_codes(codes, categories=None, ordered=None, dtype=None)

Make a Categorical type from codes and categories or dtype.

This constructor is useful if you already have codes and categories/dtype and so do not need the (computation intensive) factorization step, which is usually done on the constructor.

If your data does not follow this convention, please use the normal constructor.

**Parameters**

- **codes** [array-like of int] An integer array, where each integer points to a category in categories or dtype.categories, or else is -1 for NaN.

- **categories** [index-like, optional] The categories for the categorical. Items need to be unique. If the categories are not given here, then they must be provided in dtype.

- **ordered** [bool, optional] Whether or not this categorical is treated as an ordered categorical. If not given here or in dtype, the resulting categorical will be unordered.

- **dtype** [CategoricalDtype or “category”, optional] If CategoricalDtype, cannot be used together with categories or ordered.

  New in version 0.24.0: When dtype is provided, neither categories nor ordered should be provided.

**Returns**

- Categorical
Examples

```python
>>> dtype = pd.CategoricalDtype(['a', 'b'], ordered=True)
>>> pd.Categorical.from_codes(codes=[0, 1, 0, 1], dtype=dtype)
['a', 'b', 'a', 'b']
Categories (2, object): ['a' < 'b']
```

```python
pandas.Categorical.__array__
```

Categorical.__array__(dtype=None)
The numpy array interface.

Returns

numpy.array A numpy array of either the specified dtype or, if dtype==None (default),
the same dtype as categorical.categories.dtype.

The alternative `Categorical.from_codes()` constructor can be used when you have the categories and integer
codes already:

```python
Categorical.from_codes(codes=[], categories, . . .)
```
Make a Categorical type from codes and categories or
dtype.

The dtype information is available on the Categorical

```python
Categorical.dtype
```
The CategoricalDtype for this instance.

```python
Categorical.categories
```
The categories of this categorical.

```python
Categorical.ordered
```
Whether the categories have an ordered relationship.

```python
Categorical.codes
```
The category codes of this categorical.

```python
np.asarray(categorical)
```
works by implementing the array interface. Be aware, that this converts the Cate-
gorical back to a NumPy array, so categories and order information is not preserved!

```python
Categorical.__array__((dtype))
```
The numpy array interface.

A Categorical can be stored in a Series or DataFrame. To create a Series of dtype category, use `cat =

```python
s.astype(dtype) or Series(..., dtype=dtype) where dtype is either
```

• the string 'category'

• an instance of CategoricalDtype.

If the Series is of dtype CategoricalDtype, Series.cat can be used to change the categorical data. See

Categorical accessor for more.

3.5. pandas arrays
3.5.9 Sparse data

Data where a single value is repeated many times (e.g. 0 or NaN) may be stored efficiently as a `arrays.SparseArray`.

```
arrays.SparseArray(data[, sparse_index, ...])  # An ExtensionArray for storing sparse data.
```

`pandas.arrays.SparseArray`

```
class pandas.arrays.SparseArray(data, sparse_index=None, index=None, fill_value=None, kind='integer', dtype=None, copy=False)
```

An ExtensionArray for storing sparse data.

Changed in version 0.24.0: Implements the ExtensionArray interface.

**Parameters**

- `data` [array-like] A dense array of values to store in the SparseArray. This may contain `fill_value`.
- `sparse_index` [SparseIndex, optional]
- `index` [Index]
- `fill_value` [scalar, optional] Elements in `data` that are `fill_value` are not stored in the SparseArray. For memory savings, this should be the most common value in `data`. By default, `fill_value` depends on the dtype of `data`:

<table>
<thead>
<tr>
<th>data.dtype</th>
<th>na_value</th>
</tr>
</thead>
<tbody>
<tr>
<td>float</td>
<td>np.nan</td>
</tr>
<tr>
<td>int</td>
<td>0</td>
</tr>
<tr>
<td>bool</td>
<td>False</td>
</tr>
<tr>
<td>datetime64</td>
<td>pd.NaT</td>
</tr>
<tr>
<td>timedelta64</td>
<td>pd.NaT</td>
</tr>
</tbody>
</table>

The fill value is potentially specified in three ways. In order of precedence, these are

1. The `fill_value` argument
2. `dtype.fill_value` if `fill_value` is None and `dtype` is a SparseDtype
3. `data.dtype.fill_value` if `fill_value` is None and `dtype` is not a SparseDtype and `data` is a SparseArray.

- `kind` [{'integer', 'block'}, default 'integer'] The type of storage for sparse locations.
  - ‘block’: Stores a block and `block_length` for each contiguous span of sparse values. This is best when sparse data tends to be clumped together, with large regions of fill-value values between sparse values.
  - ‘integer’: uses an integer to store the location of each sparse value.

- `dtype` [np.dtype or SparseDtype, optional] The dtype to use for the SparseArray. For numpy dtypes, this determines the dtype of `self.sp_values`. For SparseDtype, this determines `self.sp_values` and `self.fill_value`.

- `copy` [bool, default False] Whether to explicitly copy the incoming `data` array.
Examples

```python
>>> from pandas.arrays import SparseArray
>>> arr = SparseArray([0, 0, 1, 2])
>>> arr
[0, 0, 1, 2]
Fill: 0
IntIndex
Indices: array([2, 3], dtype=int32)
```

Attributes

```
None
```

Methods

```
None
```

```{python}
_SparseDtype([dtype, fill_value])_ Dtype for data stored in SparseArray.
```

**pandas.SparseDtype**

```{python}
class pandas.SparseDtype(dtype=<class 'numpy.float64'>, fill_value=None)
```

Dtype for data stored in SparseArray.

This dtype implements the pandas ExtensionDtype interface.

New in version 0.24.0.

**Parameters**

- **dtype** [str, ExtensionDtype, numpy.dtype, type, default numpy.float64] The dtype of the underlying array storing the non-fill value values.

- **fill_value** [scalar, optional] The scalar value not stored in the SparseArray. By default, this depends on `dtype`.

<table>
<thead>
<tr>
<th>dtype</th>
<th>na_value</th>
</tr>
</thead>
<tbody>
<tr>
<td>float</td>
<td>np.nan</td>
</tr>
<tr>
<td>int</td>
<td>0</td>
</tr>
<tr>
<td>bool</td>
<td>False</td>
</tr>
<tr>
<td>datetime64</td>
<td>pd.NaT</td>
</tr>
<tr>
<td>timedelta64</td>
<td>pd.NaT</td>
</tr>
</tbody>
</table>

The default value may be overridden by specifying a `fill_value`. 
The `Series.sparse` accessor may be used to access sparse-specific attributes and methods if the `Series` contains sparse values. See `Sparse accessor` for more.

### 3.5.10 Text data

When working with text data, where each valid element is a string or missing, we recommend using `StringDtype` (with the alias "string").

```
arrays.StringArray(values[, copy])
```

Extension array for string data.

**pandas.arrays.StringArray**

```
class pandas.arrays.StringArray(values, copy=False)
```

Extension array for string data.

New in version 1.0.0.

**Warning:** `StringArray` is considered experimental. The implementation and parts of the API may change without warning.

**Parameters**

- `values` [array-like] The array of data.

  **Warning:** Currently, this expects an object-dtype ndarray where the elements are Python strings or `pandas.NA`. This may change without warning in the future. Use `pandas.array()` with `dtype="string"` for a stable way of creating a `StringArray` from any sequence.

- `copy` [bool, default False] Whether to copy the array of data.

**See also:**

- `array` The recommended function for creating a `StringArray`.
- `Series.str` The string methods are available on Series backed by a `StringArray`. 


Notes

StringArray returns a BooleanArray for comparison methods.

Examples

```python
>>> pd.array(['This is', 'some text', None, 'data.'], dtype="string")
<StringArray>
['This is', 'some text', <NA>, 'data.]
Length: 4, dtype: string

Unlike arrays instantiated with dtype="object", StringArray will convert the values to strings.

```python
>>> pd.array([1, 1], dtype="object")
<PandasArray>
[1, 1]
Length: 2, dtype: object
>>> pd.array([1, 1], dtype="string")
<StringArray>
[1, 1]
Length: 2, dtype: string

However, instantiating StringArrays directly with non-strings will raise an error.

For comparison methods, StringArray returns a pandas.BooleanArray:

```python
>>> pd.array(['a', None, 'c'], dtype="string") == "a"
<BooleanArray>
[True, <NA>, False]
Length: 3, dtype: boolean
```

Attributes

None

Methods

None

StringDtype()  Extension dtype for string data.
### pandas.StringDtype

**Class** `pandas.StringDtype`  
Extension dtype for string data.

New in version 1.0.0.

**Warning:** StringDtype is considered experimental. The implementation and parts of the API may change without warning.  
In particular, StringDtype.na_value may change to no longer be `numpy.nan`.

**Examples**

```python
>>> pd.StringDtype()
StringDtype
```

**Attributes**

None

**Methods**

None

The `Series.str` accessor is available for `Series` backed by an `arrays.StringArray`. See String handling for more.

#### 3.5.11 Boolean data with missing values

The boolean dtype (with the alias "boolean") provides support for storing boolean data (True, False values) with missing values, which is not possible with a bool `numpy.ndarray`.

```python
arrays.BooleanArray(values, mask[, copy])  
Array of boolean (True/False) data with missing values.
```

**pandas.arrays.BooleanArray**

**Class** `pandas.arrays.BooleanArray(values, mask[, copy=False])`  
Array of boolean (True/False) data with missing values.

This is a pandas Extension array for boolean data, under the hood represented by 2 numpy arrays: a boolean array with the data and a boolean array with the mask (True indicating missing).

BooleanArray implements Kleene logic (sometimes called three-value logic) for logical operations. See Kleene logical operations for more.

To construct an BooleanArray from generic array-like input, use `pandas.array()` specifying `dtype=boolean` (see examples below).
New in version 1.0.0.

**Warning:** BooleanArray is considered experimental. The implementation and parts of the API may change without warning.

**Parameters**

values [numpy.ndarray] A 1-d boolean-dtype array with the data.

mask [numpy.ndarray] A 1-d boolean-dtype array indicating missing values (True indicates missing).

copy [bool, default False] Whether to copy the values and mask arrays.

**Returns**

BooleanArray

**Examples**

Create an BooleanArray with `pandas.array()`:

```python
>>> pd.array([True, False, None], dtype="boolean")
<BooleanArray>
[True, False, <NA>]
Length: 3, dtype: boolean
```

**Attributes**

None

**Methods**

None

---

**BooleanDtype**

Extension dtype for boolean data.

**pandas.BooleanDtype**

class pandas.BooleanDtype

Extension dtype for boolean data.

New in version 1.0.0.

**Warning:** BooleanDtype is considered experimental. The implementation and parts of the API may change without warning.
Examples

```python
>>> pd.BooleanDtype()
BooleanDtype
```

Attributes

| None |

Methods

| None |

3.6 Panel

*Panel* was removed in 0.25.0. For prior documentation, see the 0.24 documentation

3.7 Index objects

3.7.1 Index

Many of these methods or variants thereof are available on the objects that contain an index (Series/DataFrame) and those should most likely be used before calling these methods directly.

| Index([data, dtype, copy, name, tupleize_cols]) | Immutable ndarray implementing an ordered, sliceable set. |

**pandas.Index**

**class pandas.Index** *(data=None, dtype=None, copy=False, name=None, tupleize_cols=True, **kwargs)*

Immutable ndarray implementing an ordered, sliceable set. The basic object storing axis labels for all pandas objects.

**Parameters**

- **data** [array-like (1-dimensional)]
- **dtype** [NumPy dtype (default: object)] If dtype is None, we find the dtype that best fits the data. If an actual dtype is provided, we coerce to that dtype if it’s safe. Otherwise, an error will be raised.
- **copy** [bool] Make a copy of input ndarray.
- **name** [object] Name to be stored in the index.
- **tupleize_cols** [bool (default: True)] When True, attempt to create a MultiIndex if possible.

See also:
**RangeIndex**  Index implementing a monotonic integer range.

**CategoricalIndex**  Index of `Categoricals`.

**MultiIndex**  A multi-level, or hierarchical Index.

**IntervalIndex**  An Index of `Intervals`.

**DatetimeIndex**  Index of datetime64 data.

**TimedeltaIndex**  Index of timedelta64 data.

**PeriodIndex**  Index of Period data.

**Int64Index**  A special case of `Index` with purely integer labels.

**UInt64Index**  A special case of `Index` with purely unsigned integer labels.

**Float64Index**  A special case of `Index` with purely float labels.

### Notes

An Index instance can **only** contain hashable objects

### Examples

```python
>>> pd.Index([1, 2, 3])
Int64Index([1, 2, 3], dtype='int64')

>>> pd.Index(list('abc'))
Index(['a', 'b', 'c'], dtype='object')
```

### Attributes

- **T**  Return the transpose, which is by definition self.
- **array**  The ExtensionArray of the data backing this Series or Index.
- **asi8**  Integer representation of the values.
- **dtype**  Return the dtype object of the underlying data.
- **has_duplicates**  Check if the Index has duplicate values.
- **hasnans**  Return if I have any nans; enables various perf speedups.
- **inferred_type**  Return a string of the type inferred from the values.
- **is_all_dates**  Whether or not the index values only consist of dates.
- **is_monotonic**  Alias for `is_monotonic_increasing`.
- **is_monotonic_decreasing**  Return if the index is monotonic decreasing (only equal or decreasing) values.
- **is_monotonic_increasing**  Return if the index is monotonic increasing (only equal or increasing) values.
- **is_unique**  Return if the index has unique values.
- **name**  Return Index or MultiIndex name.
- **nbytes**  Return the number of bytes in the underlying data.
- **ndim**  Number of dimensions of the underlying data, by definition 1.
- **nlevels**  Number of levels.
- **shape**  Return a tuple of the shape of the underlying data.
- **size**  Return the number of elements in the underlying data.
values

Return an array representing the data in the Index.

*pandas.Index.T*

**property** Index.T

Return the transpose, which is by definition self.

*pandas.Index.array*

Index.array

The ExtensionArray of the data backing this Series or Index.

New in version 0.24.0.

**Returns**

ExtensionArray An ExtensionArray of the values stored within. For extension types, this is the actual array. For NumPy native types, this is a thin (no copy) wrapper around numpy.ndarray.

.array differs .values which may require converting the data to a different form.

See also:

Index.to_numpy Similar method that always returns a NumPy array.

Series.to_numpy Similar method that always returns a NumPy array.

Notes

This table lays out the different array types for each extension dtype within pandas.

<table>
<thead>
<tr>
<th>dtype</th>
<th>array type</th>
</tr>
</thead>
<tbody>
<tr>
<td>category</td>
<td>Categorical</td>
</tr>
<tr>
<td>period</td>
<td>PeriodArray</td>
</tr>
<tr>
<td>interval</td>
<td>IntervalArray</td>
</tr>
<tr>
<td>IntegerNA</td>
<td>IntegerArray</td>
</tr>
<tr>
<td>string</td>
<td>StringArray</td>
</tr>
<tr>
<td>boolean</td>
<td>BooleanArray</td>
</tr>
<tr>
<td>datetime64[ns, tz]</td>
<td>DatetimeArray</td>
</tr>
</tbody>
</table>

For any 3rd-party extension types, the array type will be an ExtensionArray.

For all remaining dtypes .array will be a arrays.NumpyExtensionArray wrapping the actual ndarray stored within. If you absolutely need a NumPy array (possibly with copying / coercing data), then use Series.to_numpy() instead.
Examples

For regular NumPy types like int, and float, a PandasArray is returned.

```python
>>> pd.Series([1, 2, 3]).array
<PandasArray>
[1, 2, 3]
Length: 3, dtype: int64
```

For extension types, like Categorical, the actual ExtensionArray is returned

```python
>>> ser = pd.Series(pd.Categorical(['a', 'b', 'a']))
>>> ser.array
['a', 'b', 'a']
Categories (2, object): ['a', 'b']
```

**pandas.Index.asi8**

**property** Index.asi8

Integer representation of the values.

**Returns**

- ndarray An ndarray with int64 dtype.

**pandas.Index.dtype**

Index.dtype

Return the dtype object of the underlying data.

**pandas.Index.has_duplicates**

**property** Index.has_duplicates

Check if the Index has duplicate values.

**Returns**

- bool Whether or not the Index has duplicate values.

Examples

```python
>>> idx = pd.Index([1, 5, 7, 7])
>>> idx.has_duplicates
True

>>> idx = pd.Index([1, 5, 7])
>>> idx.has_duplicates
False

>>> idx = pd.Index(["Watermelon", "Orange", "Apple",
... "Watermelon"]).astype("category")
>>> idx.has_duplicates
True
```
```python
>>> idx = pd.Index(["Orange", "Apple", "Watermelon"]).astype("category")
>>> idx.has_duplicates
False
```

**pandas.Index.hasnans**

```
Index.hasnans
Return if I have any nans; enables various perf speedups.
```

**pandas.Index.inferred_type**

```
Index.inferred_type
Return a string of the type inferred from the values.
```

**pandas.Index.is_all_dates**

```
Index.is_all_dates
Whether or not the index values only consist of dates.
```

**pandas.Index.is_monotonic**

```
property Index.is_monotonic
Alias for is_monotonic_increasing.
```

**pandas.Index.is_monotonic_decreasing**

```
property Index.is_monotonic_decreasing
Return if the index is monotonic decreasing (only equal or decreasing) values.
```

**Examples**

```python
>>> Index([3, 2, 1]).is_monotonic_decreasing
True
>>> Index([3, 2, 2]).is_monotonic_decreasing
True
>>> Index([3, 1, 2]).is_monotonic_decreasing
False
```
### pandas.Index.is_monotonic_increasing

**property** `Index.is_monotonic_increasing`

Return if the index is monotonic increasing (only equal or increasing) values.

**Examples**

```python
>>> Index([1, 2, 3]).is_monotonic_increasing
True
>>> Index([1, 2, 2]).is_monotonic_increasing
True
>>> Index([1, 3, 2]).is_monotonic_increasing
False
```

### pandas.Index.is_unique

`Index.is_unique`

Return if the index has unique values.

### pandas.Index.name

**property** `Index.name`

Return Index or MultiIndex name.

### pandas.Index.nbytes

**property** `Index.nbytes`

Return the number of bytes in the underlying data.

### pandas.Index.ndim

**property** `Index.ndim`

Number of dimensions of the underlying data, by definition 1.

### pandas.Index.nlevels

**property** `Index.nlevels`

Number of levels.
pandas: powerful Python data analysis toolkit, Release 1.1.1

**pandas.Index.shape**

*property Index.shape*

Return a tuple of the shape of the underlying data.

**pandas.Index.size**

*property Index.size*

Return the number of elements in the underlying data.

**pandas.Index.values**

*property Index.values*

Return an array representing the data in the Index.

**Warning:** We recommend using `Index.array` or `Index.to_numpy()`, depending on whether you need a reference to the underlying data or a NumPy array.

**Returns**

array: numpy.ndarray or ExtensionArray

**See also:**

*Index.array* Reference to the underlying data.

*Index.to_numpy* A NumPy array representing the underlying data.

<table>
<thead>
<tr>
<th>empty</th>
<th>names</th>
</tr>
</thead>
</table>

**Methods**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>all(*args, **kwangs)</code></td>
<td>Return whether all elements are True.</td>
</tr>
<tr>
<td><code>any(*args, **kwangs)</code></td>
<td>Return whether any element is True.</td>
</tr>
<tr>
<td><code>append(other)</code></td>
<td>Append a collection of Index options together.</td>
</tr>
<tr>
<td><code>argmax([axis, skipna])</code></td>
<td>Return int position of the largest value in the Series.</td>
</tr>
<tr>
<td><code>argmin([axis, skipna])</code></td>
<td>Return int position of the smallest value in the Series.</td>
</tr>
<tr>
<td><code>argsort(*args, **kwargs)</code></td>
<td>Return the integer indices that would sort the index.</td>
</tr>
<tr>
<td><code>asof(label)</code></td>
<td>Return the label from the index, or, if not present, the previous one.</td>
</tr>
<tr>
<td><code>asof_locs(where, mask)</code></td>
<td>Return the locations (indices) of labels in the index.</td>
</tr>
<tr>
<td><code>astype(dtype[, copy])</code></td>
<td>Create an Index with values cast to dtypes.</td>
</tr>
<tr>
<td><code>copy([name, deep, dtype, names])</code></td>
<td>Make a copy of this object.</td>
</tr>
<tr>
<td><code>delete(loc)</code></td>
<td>Make new Index with passed location(-s) deleted.</td>
</tr>
<tr>
<td><code>difference(other[, sort])</code></td>
<td>Return a new Index with elements of index not in other.</td>
</tr>
</tbody>
</table>

continues on next page
Table 130 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>drop(labels[, errors])</code></td>
<td>Make new Index with passed list of labels deleted.</td>
</tr>
<tr>
<td><code>drop_duplicates(keep)</code></td>
<td>Return Index with duplicate values removed.</td>
</tr>
<tr>
<td><code>droplevel([level])</code></td>
<td>Return index with requested level(s) removed.</td>
</tr>
<tr>
<td><code>dropna([how])</code></td>
<td>Return Index without NA/NaN values.</td>
</tr>
<tr>
<td><code>duplicated(keep)</code></td>
<td>Indicate duplicate index values.</td>
</tr>
<tr>
<td><code>equals(other)</code></td>
<td>Determine if two Index object are equal.</td>
</tr>
<tr>
<td><code>factorize([sort, na_sentinel])</code></td>
<td>Encode the object as an enumerated type or categorical variable.</td>
</tr>
<tr>
<td><code>fillna([value, downcast])</code></td>
<td>Fill NA/NaN values with the specified value.</td>
</tr>
<tr>
<td><code>format([name, formatter, na_rep])</code></td>
<td>Render a string representation of the Index.</td>
</tr>
<tr>
<td><code>get_indexer(target[, method, limit, tolerance])</code></td>
<td>Compute indexer and mask for new index given the current index.</td>
</tr>
<tr>
<td><code>get_indexer_for(target, **kwargs)</code></td>
<td>Guaranteed return of an indexer even when non-unique.</td>
</tr>
<tr>
<td><code>get_indexer_non_unique(target)</code></td>
<td>Compute indexer and mask for new index given the current index.</td>
</tr>
<tr>
<td><code>get_level_values(level)</code></td>
<td>Return an Index of values for requested level.</td>
</tr>
<tr>
<td><code>get_loc(key[, method, tolerance])</code></td>
<td>Get integer location, slice or boolean mask for requested label.</td>
</tr>
<tr>
<td><code>get_slice_bound(label, side, kind)</code></td>
<td>Calculate slice bound that corresponds to given label.</td>
</tr>
<tr>
<td><code>get_value(series, key)</code></td>
<td>Fast lookup of value from 1-dimensional ndarray.</td>
</tr>
<tr>
<td><code>groupby(values)</code></td>
<td>Group the index labels by a given array of values.</td>
</tr>
<tr>
<td><code>holds_integer()</code></td>
<td>Whether the type is an integer type.</td>
</tr>
<tr>
<td><code>identical(other)</code></td>
<td>Similar to equals, but checks that object attributes and types are also equal.</td>
</tr>
<tr>
<td><code>insert(loc, item)</code></td>
<td>Make new Index inserting new item at location.</td>
</tr>
<tr>
<td><code>intersection(other[, sort])</code></td>
<td>Form the intersection of two Index objects.</td>
</tr>
<tr>
<td><code>is_(other)</code></td>
<td>More flexible, faster check like <code>is</code> but that works through views.</td>
</tr>
<tr>
<td><code>is_boolean()</code></td>
<td>Check if the Index only consists of booleans.</td>
</tr>
<tr>
<td><code>is_categorical()</code></td>
<td>Check if the Index holds categorical data.</td>
</tr>
<tr>
<td><code>is_floating()</code></td>
<td>Check if the Index is a floating type.</td>
</tr>
<tr>
<td><code>is_integer()</code></td>
<td>Check if the Index only consists of integers.</td>
</tr>
<tr>
<td><code>is_interval()</code></td>
<td>Check if the Index holds Interval objects.</td>
</tr>
<tr>
<td><code>is_mixed()</code></td>
<td>Check if the Index holds data with mixed data types.</td>
</tr>
<tr>
<td><code>is_numeric()</code></td>
<td>Check if the Index only consists of numeric data.</td>
</tr>
<tr>
<td><code>is_object()</code></td>
<td>Check if the Index is of the object dtype.</td>
</tr>
<tr>
<td><code>is_type_compatible(kind)</code></td>
<td>Whether the index type is compatible with the provided type.</td>
</tr>
<tr>
<td><code>isin(values[, level])</code></td>
<td>Return a boolean array where the index values are in <code>values</code>.</td>
</tr>
<tr>
<td><code>isna()</code></td>
<td>Detect missing values.</td>
</tr>
<tr>
<td><code>isnull()</code></td>
<td>Detect missing values.</td>
</tr>
<tr>
<td><code>item()</code></td>
<td>Return the first element of the underlying data as a python scalar.</td>
</tr>
<tr>
<td><code>join(other[, how, level, return_indexers, sort])</code></td>
<td>Compute join_index and indexers to conform data structures to the new index.</td>
</tr>
<tr>
<td><code>map(mapper[, na_action])</code></td>
<td>Map values using input correspondence (a dict, Series, or function).</td>
</tr>
<tr>
<td><code>max(laxis, skipna)</code></td>
<td>Return the maximum value of the Index.</td>
</tr>
<tr>
<td><code>memory_usage([deep])</code></td>
<td>Memory usage of the values.</td>
</tr>
</tbody>
</table>

continues on next page
Table 13.0 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>min</code> (axis, skipna)</td>
<td>Return the minimum value of the Index.</td>
</tr>
<tr>
<td><code>notna()</code></td>
<td>Detect existing (non-missing) values.</td>
</tr>
<tr>
<td><code>notnull()</code></td>
<td>Detect existing (non-missing) values.</td>
</tr>
<tr>
<td><code>nunique</code> (dropna)</td>
<td>Return number of unique elements in the object.</td>
</tr>
<tr>
<td><code>putmask</code> (mask, value)</td>
<td>Return a new Index of the values set with the mask.</td>
</tr>
<tr>
<td><code>ravel</code> (order)</td>
<td>Return an ndarray of the flattened values of the underlying data.</td>
</tr>
<tr>
<td><code>reindex</code> (target[, method, level, limit, …])</td>
<td>Create index with target’s values.</td>
</tr>
<tr>
<td><code>rename</code> (name[, inplace])</td>
<td>Alter Index or MultiIndex name.</td>
</tr>
<tr>
<td><code>repeat</code> (repeats[, axis])</td>
<td>Repeat elements of a Index.</td>
</tr>
<tr>
<td><code>searchsorted</code> (value[, side, sorter])</td>
<td>Find indices where elements should be inserted to maintain order.</td>
</tr>
<tr>
<td><code>set_names</code> (names[, level, inplace])</td>
<td>Set Index or MultiIndex name.</td>
</tr>
<tr>
<td><code>set_value</code> (arr, key, value)</td>
<td>(DEPRECATED) Fast lookup of value from 1-dimensional ndarray.</td>
</tr>
<tr>
<td><code>shift</code> (periods, freq)</td>
<td>Shift index by desired number of time frequency increments.</td>
</tr>
<tr>
<td><code>slice_indexer</code> (start, end, step, kind)</td>
<td>Compute the slice indexer for input labels and step.</td>
</tr>
<tr>
<td><code>slice_locs</code> (start, end, step, kind)</td>
<td>Compute slice locations for input labels.</td>
</tr>
<tr>
<td><code>sort_values</code> (return_indexer, ascending, key)</td>
<td>Return a sorted copy of the index.</td>
</tr>
<tr>
<td><code>sortlevel</code> (level, ascending, sort_remaining)</td>
<td>For internal compatibility with with the Index API.</td>
</tr>
<tr>
<td><code>str</code></td>
<td>alias of pandas.core.strings.StringMethods</td>
</tr>
<tr>
<td><code>symmetric_difference</code> (other[, result_name, sort])</td>
<td>Compute the symmetric difference of two Index objects.</td>
</tr>
<tr>
<td><code>take</code> (indices[, axis, allow_fill, fill_value])</td>
<td>Return a new Index of the values selected by the indices.</td>
</tr>
<tr>
<td><code>to_flat_index</code> ()</td>
<td>Identity method.</td>
</tr>
<tr>
<td><code>to_frame</code> (index, name)</td>
<td>Create a DataFrame with a column containing the Index.</td>
</tr>
<tr>
<td><code>tolist()</code></td>
<td>Return a list of the values.</td>
</tr>
<tr>
<td><code>to_native_types</code> ([slicer])</td>
<td>Format specified values of self and return them.</td>
</tr>
<tr>
<td><code>to_numpy</code> (dtype, copy, na_value)</td>
<td>A NumPy ndarray representing the values in this Series or Index.</td>
</tr>
<tr>
<td><code>to_series</code> (index, name)</td>
<td>Create a Series with both index and values equal to the index keys.</td>
</tr>
<tr>
<td><code>tolist()</code></td>
<td>Return a list of the values.</td>
</tr>
<tr>
<td><code>transpose</code> (*args, **kwargs)</td>
<td>Return the transpose, which is by definition self.</td>
</tr>
<tr>
<td><code>union</code> (other[, sort])</td>
<td>Form the union of two Index objects.</td>
</tr>
<tr>
<td><code>unique</code> (level)</td>
<td>Return unique values in the index.</td>
</tr>
<tr>
<td><code>value_counts</code> ([normalize, sort, ascending, …])</td>
<td>Return a Series containing counts of unique values.</td>
</tr>
<tr>
<td><code>where</code> (cond[, other])</td>
<td>Replace values where the condition is False.</td>
</tr>
</tbody>
</table>
pandas.Index.all

Index.all (*args, **kwargs)
Return whether all elements are True.

Parameters

*args  These parameters will be passed to numpy.all.

**kwargs  These parameters will be passed to numpy.all.

Returns

all  [bool or array_like (if axis is specified)] A single element array_like may be converted to bool.

See also:

Index.any  Return whether any element in an Index is True.
Series.any  Return whether any element in a Series is True.
Series.all  Return whether all elements in a Series are True.

Notes

Not a Number (NaN), positive infinity and negative infinity evaluate to True because these are not equal to zero.

Examples

all

True, because nonzero integers are considered True.

```python
>>> pd.Index([1, 2, 3]).all()
True
```

False, because 0 is considered False.

```python
>>> pd.Index([0, 1, 2]).all()
False
```

any

True, because 1 is considered True.

```python
>>> pd.Index([0, 0, 1]).any()
True
```

False, because 0 is considered False.

```python
>>> pd.Index([0, 0, 0]).any()
False
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

**pandas.Index.any**

Index.

*any* (*args, **kwargs)*

Return whether any element is True.

**Parameters**

* *args* These parameters will be passed to numpy.any.

**kwargs** These parameters will be passed to numpy.any.

**Returns**

*any* [bool or array_like (if axis is specified)] A single element array_like may be converted to bool.

**See also:**

* Index.all Return whether all elements are True.

* Series.all Return whether all elements are True.

**Notes**

Not a Number (NaN), positive infinity and negative infinity evaluate to True because these are not equal to zero.

**Examples**

```python
>>> index = pd.Index([0, 1, 2])
>>> index.any()
True
```

```python
>>> index = pd.Index([0, 0, 0])
>>> index.any()
False
```

**pandas.Index.append**

Index.

*append* (*other*)

Append a collection of Index options together.

**Parameters**

*other* [Index or list/tuple of indices]

**Returns**

*appended* [Index]
pandas.Index.argmax

Index.argmax (axis=None, skipna=True, *args, **kwargs)

Return int position of the largest value in the Series.

If the maximum is achieved in multiple locations, the first row position is returned.

Parameters

axis [{None}] Dummy argument for consistency with Series.

skipna [bool, default True] Exclude NA/null values when showing the result.

*args, **kwargs Additional arguments and keywords for compatibility with NumPy.

Returns

int Row position of the maximum value.

See also:

Series.argmax Return position of the maximum value.

Series.argmin Return position of the minimum value.

numpy.ndarray.argmax Equivalent method for numpy arrays.

Series.idxmax Return index label of the maximum values.

Series.idxmin Return index label of the minimum values.

Examples

Consider dataset containing cereal calories

```python
>>> s = pd.Series({'Corn Flakes': 100.0, 'Almond Delight': 110.0,
... 'Cinnamon Toast Crunch': 120.0, 'Cocoa Puff': 110.0})
>>> s
Corn Flakes 100.0
Almond Delight 110.0
Cinnamon Toast Crunch 120.0
Cocoa Puff 110.0
dtype: float64
```

```python
>>> s.argmax()
2
>>> s.argmin()
0
```

The maximum cereal calories is the third element and the minimum cereal calories is the first element, since series is zero-indexed.
pandas.Index.argmin

Index.argmin(axis=None, skipna=True, *args, **kwargs)

Return int position of the smallest value in the Series.

If the minimum is achieved in multiple locations, the first row position is returned.

Parameters

axis [{None}] Dummy argument for consistency with Series.
skipna [bool, default True] Exclude NA/null values when showing the result.
*args, **kwargs Additional arguments and keywords for compatibility with NumPy.

Returns

int Row position of the minimum value.

See also:

Series.argmin Return position of the minimum value.
Series.argmax Return position of the maximum value.
numpy.ndarray.argmin Equivalent method for numpy arrays.
Series.idxmax Return index label of the maximum values.
Series.idxmin Return index label of the minimum values.

Examples

Consider dataset containing cereal calories

```
>>> s = pd.Series({'Corn Flakes': 100.0, 'Almond Delight': 110.0,
...                   'Cinnamon Toast Crunch': 120.0, 'Cocoa Puff': 110.0})
```

```
>>> s
Corn Flakes    100.0
Almond Delight 110.0
Cinnamon Toast Crunch    120.0
Cocoa Puff            110.0
dtype: float64
```

```
>>> s.argmax() 2
>>> s.argmin() 0
```

The maximum cereal calories is the third element and the minimum cereal calories is the first element, since series is zero-indexed.
pandas.Index.argsort

Index.argsort (*args, **kwargs)
Return the integer indices that would sort the index.

Parameters

*args Passed to numpy.ndarray.argsort.
**kwargs Passed to numpy.ndarray.argsort.

Returns

numpy.ndarray Integer indices that would sort the index if used as an indexer.

See also:

numpy.argsort Similar method for NumPy arrays.
Index.sort_values Return sorted copy of Index.

Examples

```python
>>> idx = pd.Index(['b', 'a', 'd', 'c'])
>>> idx
Index(['b', 'a', 'd', 'c'], dtype='object')

>>> order = idx.argsort()
>>> order
array([1, 0, 3, 2])

>>> idx[order]
Index(['a', 'b', 'c', 'd'], dtype='object')
```

pandas.Index.asof

Index.asof (label)
Return the label from the index, or, if not present, the previous one.

Assuming that the index is sorted, return the passed index label if it is in the index, or return the previous index label if the passed one is not in the index.

Parameters

label [object] The label up to which the method returns the latest index label.

Returns

object The passed label if it is in the index. The previous label if the passed label is not in the sorted index or NaN if there is no such label.

See also:

Series.asof Return the latest value in a Series up to the passed index.
merge_asof Perform an asof merge (similar to left join but it matches on nearest key rather than equal key).
Index.get_loc An asof is a thin wrapper around get_loc with method='pad'.
Examples

`Index.asof` returns the latest index label up to the passed label.

```python
>>> idx = pd.Index(['2013-12-31', '2014-01-02', '2014-01-03'])
>>> idx.asof('2014-01-01')
'2013-12-31'
```

If the label is in the index, the method returns the passed label.

```python
>>> idx.asof('2014-01-02')
'2014-01-02'
```

If all of the labels in the index are later than the passed label, NaN is returned.

```python
>>> idx.asof('1999-01-02')
nan
```

If the index is not sorted, an error is raised.

```python
>>> idx_not_sorted = pd.Index(['2013-12-31', '2015-01-02', ...
... '2014-01-03'])
>>> idx_not_sorted.asof('2013-12-31')
Traceback (most recent call last):
  ValueError: index must be monotonic increasing or decreasing
```

`pandas.Index.asof_locs`  

`Index.asof_locs`(where, mask)

Return the locations (indices) of labels in the index.

As in the `asof` function, if the label (a particular entry in where) is not in the index, the latest index label up to the passed label is chosen and its index returned.

If all of the labels in the index are later than a label in `where`, -1 is returned.  
`mask` is used to ignore NA values in the index during calculation.

**Parameters**

- **where** [Index] An Index consisting of an array of timestamps.
- **mask** [array-like] Array of booleans denoting where values in the original data are not NA.

**Returns**

- **numpy.ndarray** An array of locations (indices) of the labels from the Index which correspond to the return values of the `asof` function for every element in `where`. 
**pandas.Index.astype**

`Index.astype(dtype, copy=True)`

Create an Index with values cast to dtypes.

The class of a new Index is determined by dtype. When conversion is impossible, a ValueError exception is raised.

**Parameters**

- **dtype** [numpy dtype or pandas type] Note that any signed integer `dtype` is treated as `int64`, and any unsigned integer `dtype` is treated as `uint64`, regardless of the size.
- **copy** [bool, default True] By default, astype always returns a newly allocated object. If copy is set to False and internal requirements on dtype are satisfied, the original data is used to create a new Index or the original Index is returned.

**Returns**

- **Index** Index with values cast to specified dtype.

**pandas.Index.copy**

`Index.copy(name=None, deep=False, dtype=None, names=None)`

Make a copy of this object.

Name and dtype sets those attributes on the new object.

**Parameters**

- **name** [Label, optional] Set name for new object.
- **deep** [bool, default False]
- **dtype** [numpy dtype or pandas type, optional] Set dtype for new object.
- **names** [list-like, optional] Kept for compatibility with MultiIndex. Should not be used.

**Returns**

- **Index** Index refer to new object which is a copy of this object.

**Notes**

In most cases, there should be no functional difference from using `deep`, but if `deep` is passed it will attempt to deepcopy.

**pandas.Index.delete**

`Index.delete(loc)`

Make new Index with passed location(-s) deleted.

**Parameters**

- **loc** [int or list of int] Location of item(-s) which will be deleted. Use a list of locations to delete more than one value at the same time.

**Returns**

3.7. Index objects
Index New Index with passed location(-s) deleted.

See also:

numpy.delete Delete any rows and column from NumPy array (ndarray).

Examples

```python
define
>>> idx = pd.Index(['a', 'b', 'c'])
>>> idx.delete(1)
Index(['a', 'c'], dtype='object')

>>> idx = pd.Index(['a', 'b', 'c'])
>>> idx.delete([0, 2])
Index(['b'], dtype='object')
```

pandas.Index.difference

Index.difference(other, sort=None)  
Return a new Index with elements of index not in other.  
This is the set difference of two Index objects.

Parameters

- other [Index or array-like]  
- sort [False or None, default None] Whether to sort the resulting index. By default, the values are attempted to be sorted, but any TypeError from incomparable elements is caught by pandas.
  - None : Attempt to sort the result, but catch any TypeErrors from comparing incomparable elements.
  - False : Do not sort the result.

New in version 0.24.0.

Changed in version 0.24.1: Changed the default value from True to None (without change in behaviour).

Returns
difference [Index]

Examples

```python
define
>>> idx1 = pd.Index([2, 1, 3, 4])
>>> idx2 = pd.Index([3, 4, 5, 6])
>>> idx1.difference(idx2)
Int64Index([1, 2], dtype='int64')

>>> idx1.difference(idx2, sort=False)
Int64Index([2, 1], dtype='int64')
```
pandas.Index.drop

Index.drop(labels, errors='raise')
Make new Index with passed list of labels deleted.

Parameters

- labels [array-like]
- errors [{‘ignore’, ‘raise’}, default ‘raise’] If ‘ignore’, suppress error and existing labels are dropped.

Returns

- dropped [Index]

Raises

- KeyError If not all of the labels are found in the selected axis

pandas.Index.drop_duplicates

Index.drop_duplicates(keep='first')
Return Index with duplicate values removed.

Parameters

- keep [{‘first’, ‘last’, False}, default ‘first’]
  - ‘first’ : Drop duplicates except for the first occurrence.
  - ‘last’ : Drop duplicates except for the last occurrence.
  - False : Drop all duplicates.

Returns

- deduplicated [Index]

See also:

- Series.drop_duplicates Equivalent method on Series.
- DataFrame.drop_duplicates Equivalent method on DataFrame.
- Index.duplicated Related method on Index, indicating duplicate Index values.

Examples

Generate an pandas.Index with duplicate values.

```python
>>> idx = pd.Index(['lama', 'cow', 'lama', 'beetle', 'lama', 'hippo'])
```

The keep parameter controls which duplicate values are removed. The value ‘first’ keeps the first occurrence for each set of duplicated entries. The default value of keep is ‘first’.

```python
>>> idx.drop_duplicates(keep='first')
Index(['lama', 'cow', 'beetle', 'hippo'], dtype='object')
```

The value ‘last’ keeps the last occurrence for each set of duplicated entries.
```python
>>> idx.drop_duplicates(keep='last')
Index(['cow', 'beetle', 'lama', 'hippo'], dtype='object')
```

The value `False` discards all sets of duplicated entries.

```python
>>> idx.drop_duplicates(keep=False)
Index(['cow', 'beetle', 'hippo'], dtype='object')
```

**pandas.Index.droplevel**

`Index.droplevel(level=0)`

Return index with requested level(s) removed.

If resulting index has only 1 level left, the result will be of Index type, not MultiIndex.

New in version 0.23.1: (support for non-MultiIndex)

**Parameters**

- `level` [int, str, or list-like, default 0] If a string is given, must be the name of a level. If list-like, elements must be names or indexes of levels.

**Returns**

- `Index` or `MultiIndex`

**pandas.Index.dropna**

`Index.dropna(how='any')`

Return Index without NA/NaN values.

**Parameters**

- `how` [{'any', 'all'}, default 'any'] If the Index is a MultiIndex, drop the value when any or all levels are NaN.

**Returns**

- `Index`

**pandas.Index.duplicated**

`Index.duplicated(keep='first')`

Indicate duplicate index values.

Duplicated values are indicated as `True` values in the resulting array. Either all duplicates, all except the first, or all except the last occurrence of duplicates can be indicated.

**Parameters**

- `keep` [{'first', 'last', False}, default 'first'] The value or values in a set of duplicates to mark as missing.
  - 'first': Mark duplicates as `True` except for the first occurrence.
  - 'last': Mark duplicates as `True` except for the last occurrence.
  - `False`: Mark all duplicates as `True`.

---

1910 Chapter 3. API reference
Returns

- numpy.ndarray

See also:

- `Series.duplicated` Equivalent method on pandas.Series.
- `DataFrame.duplicated` Equivalent method on pandas.DataFrame.
- `Index.drop_duplicates` Remove duplicate values from Index.

Examples

By default, for each set of duplicated values, the first occurrence is set to False and all others to True:

```python
>>> idx = pd.Index(['lama', 'cow', 'lama', 'beetle', 'lama'])
>>> idx.duplicated()
array([False, False, True, False, True])
```

which is equivalent to

```python
>>> idx.duplicated(keep='first')
array([False, False, True, False, True])
```

By using 'last', the last occurrence of each set of duplicated values is set on False and all others on True:

```python
>>> idx.duplicated(keep='last')
array([ True, False, True, False, False])
```

By setting keep on `False`, all duplicates are True:

```python
>>> idx.duplicated(keep=False)
array([ True, False, True, False, True])
```

**pandas.Index.equals**

`Index.equals(other)`

Determine if two Index object are equal.

The things that are being compared are:

- The elements inside the Index object.
- The order of the elements inside the Index object.

**Parameters**

- `other` [Any] The other object to compare against.

**Returns**

- `bool` True if “other” is an Index and it has the same elements and order as the calling index; False otherwise.
Examples

```python
>>> idx1 = pd.Index([1, 2, 3])
>>> idx1
Int64Index([1, 2, 3], dtype='int64')
>>> idx1.equals(pd.Index([1, 2, 3]))
True

The elements inside are compared

```python
>>> idx2 = pd.Index(['1', '2', '3'])
>>> idx2
Index(['1', '2', '3'], dtype='object')
>>> idx1.equals(idx2)
False

The order is compared

```python
>>> ascending_idx = pd.Index([1, 2, 3])
>>> ascending_idx
Int64Index([1, 2, 3], dtype='int64')
>>> descending_idx = pd.Index([3, 2, 1])
>>> descending_idx
Int64Index([3, 2, 1], dtype='int64')
>>> ascending_idx.equals(descending_idx)
False

The dtype is not compared

```python
>>> int64_idx = pd.Int64Index([1, 2, 3])
>>> int64_idx
Int64Index([1, 2, 3], dtype='int64')
>>> uint64_idx = pd.UInt64Index([1, 2, 3])
>>> uint64_idx
UInt64Index([1, 2, 3], dtype='uint64')
>>> int64_idx.equals(uint64_idx)
True
```

`pandas.Index.factorize`

`Index.factorize(sort=False, na_sentinel=-1)`

Encode the object as an enumerated type or categorical variable.

This method is useful for obtaining a numeric representation of an array when all that matters is identifying distinct values. `factorize` is available as both a top-level function `pandas.factorize()`, and as a method `Series.factorize()` and `Index.factorize()`.

Parameters

- `sort` [bool, default False] Sort `uniques` and shuffle `codes` to maintain the relationship.
- `na_sentinel` [int, default -1] Value to mark “not found”.

Returns

- `codes` [ndarray] An integer ndarray that’s an indexer into `uniques`. `uniques.take(codes)` will have the same values as `values`. 

1912 Chapter 3. API reference
uniques [ndarray, Index, or Categorical] The unique valid values. When values is Categorical, uniques is a Categorical. When values is some other pandas object, an Index is returned. Otherwise, a 1-D ndarray is returned.

Note: Even if there’s a missing value in values, uniques will not contain an entry for it.

See also:

cut Discretize continuous-valued array.
unique Find the unique value in an array.

Examples

These examples all show factorize as a top-level method like pd.factorize(values). The results are identical for methods like Series.factorize().

```python
>>> codes, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'])
>>> codes
array([0, 0, 1, 2, 0]...)
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

With sort=True, the uniques will be sorted, and codes will be shuffled so that the relationship is maintained.

```python
>>> codes, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'], sort=True)
>>> codes
array([1, 1, 0, 2, 1]...)
>>> uniques
array(['a', 'b', 'c'], dtype=object)
```

Missing values are indicated in codes with na_sentinel (-1 by default). Note that missing values are never included in uniques.

```python
>>> codes, uniques = pd.factorize(['b', None, 'a', 'c', 'b'])
>>> codes
array([ 0, -1, 1, 2, 0]...)
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

Thus far, we’ve only factorized lists (which are internally coerced to NumPy arrays). When factorizing pandas objects, the type of uniques will differ. For Categoricals, a Categorical is returned.

```python
>>> cat = pd.Categorical(['a', 'a', 'c'], categories=['a', 'b', 'c'])
>>> codes, uniques = pd.factorize(cat)
>>> codes
array([0, 0, 1]...)
>>> uniques
['a', 'c']
Categories (3, object): ['a', 'b', 'c']
```

Notice that 'b' is in uniques.categories, despite not being present in cat.values.

For all other pandas objects, an Index of the appropriate type is returned.
```python
>>> cat = pd.Series(["a", "a", "c"])
>>> codes, uniques = pd.factorize(cat)
>>> codes
array([0, 0, 1]...)
>>> uniques
Index(["a", "c"], dtype='object')
```

### pandas.Index.fillna

**Index.fillna**(value=None, downcast=None)

Fill NA/NaN values with the specified value.

**Parameters**

- **value** [scalar] Scalar value to use to fill holes (e.g. 0). This value cannot be a list-likes.
- **downcast** [dict, default is None] A dict of item->dtype of what to downcast if possible, or the string 'infer' which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible).

**Returns**

Index

**See also:**

- **DataFrame.fillna** Fill NaN values of a DataFrame.
- **Series.fillna** Fill NaN Values of a Series.

### pandas.Index.format

**Index.format**(name=False, formatter=None, na_rep='NaN')

Render a string representation of the Index.

### pandas.Index.get_indexer

**Index.get_indexer**(target, method=None, limit=None, tolerance=None)

Compute indexer and mask for new index given the current index. The indexer should be then used as an input to ndarray.take to align the current data to the new index.

**Parameters**

- **target** [Index]
- **method** [[None, 'pad'/'ffill', 'backfill'/'bfill', 'nearest'], optional]
  - default: exact matches only.
  - pad / ffill: find the PREVIOUS index value if no exact match.
  - backfill / bfill: use NEXT index value if no exact match
  - nearest: use the NEAREST index value if no exact match. Tied distances are broken by preferring the larger index value.
- **limit** [int, optional] Maximum number of consecutive labels in target to match for inexact matches.
tolerance  [optional] Maximum distance between original and new labels for inexact matches. The values of the index at the matching locations most satisfy the equation \( \text{abs}(\text{index}[\text{indexer}] - \text{target}) \leq \text{tolerance} \).

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index’s type.

**Returns**

**indexer**  [ndarray of int] Integers from 0 to n - 1 indicating that the index at these positions matches the corresponding target values. Missing values in the target are marked by -1.

**Examples**

```python
>>> index = pd.Index(['c', 'a', 'b'])
>>> index.get_indexer(['a', 'b', 'x'])
array([ 1, 2, -1])
```

Notice that the return value is an array of locations in `index` and `x` is marked by -1, as it is not in `index`.

**pandas.Index.get_indexer_for**

Index.get_indexer_for(target, **kwargs)

Guaranteed return of an indexer even when non-unique.

This dispatches to get_indexer or get_indexer_non_unique as appropriate.

**Returns**

**numpy.ndarray** List of indices.

**pandas.Index.get_indexer_non_unique**

Index.get_indexer_non_unique(target)

Compute indexer and mask for new index given the current index. The indexer should be then used as an input to ndarray.take to align the current data to the new index.

**Parameters**

**target**  [Index]

**Returns**

**indexer**  [ndarray of int] Integers from 0 to n - 1 indicating that the index at these positions matches the corresponding target values. Missing values in the target are marked by -1.

**missing**  [ndarray of int] An indexer into the target of the values not found. These correspond to the -1 in the indexer array.
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.Index.get_level_values

`Index.get_level_values(level)`

Return an Index of values for requested level.

This is primarily useful to get an individual level of values from a MultiIndex, but is provided on Index as well for compatibility.

**Parameters**

- **level** [int or str] It is either the integer position or the name of the level.

**Returns**

- **Index** Calling object, as there is only one level in the Index.

**See also:**

- `MultiIndex.get_level_values` Get values for a level of a MultiIndex.

**Notes**

For Index, level should be 0, since there are no multiple levels.

**Examples**

```python
>>> idx = pd.Index(list('abc'))
>>> idx
Index(['a', 'b', 'c'], dtype='object')

Get level values by supplying `level` as integer:

```python
>>> idx.get_level_values(0)  
Index(['a', 'b', 'c'], dtype='object')
```

pandas.Index.get_loc

`Index.get_loc(key, method=None, tolerance=None)`

Get integer location, slice or boolean mask for requested label.

**Parameters**

- **key** [label]
- **method** [{None, ‘pad’/’ffill’, ‘backfill’/’bfill’, ‘nearest’}, optional]
  - default: exact matches only.
  - pad / ffill: find the PREVIOUS index value if no exact match.
  - backfill / bfill: use NEXT index value if no exact match
  - nearest: use the NEAREST index value if no exact match. Tied distances are broken by preferring the larger index value.
- **tolerance** [int or float, optional] Maximum distance from index value for inexact matches. The value of the index at the matching location most satisfy the equation `abs(index[loc] - key) <= tolerance`. 
Retons

\texttt{loc}  [int if unique index, slice if monotonic index, else mask]

Examples

\begin{verbatim}
>>> unique_index = pd.Index(list('abc'))
>>> unique_index.get_loc('b')
1

>>> monotonic_index = pd.Index(list('abbc'))
>>> monotonic_index.get_loc('b')
slice(1, 3, None)

>>> non_monotonic_index = pd.Index(list('abcb'))
>>> non_monotonic_index.get_loc('b')
array([False, True, False, True])
\end{verbatim}

\texttt{pandas.Index.get_slice_bound}

\texttt{Index.get_slice_bound(label, side, kind)}

Calculate slice bound that corresponds to given label.

Returns leftmost (one-past-the-rightmost if \texttt{side}=='right') position of given label.

Parameters

\begin{itemize}
  \item \texttt{label}  [object]
  \item \texttt{side}  [[‘left’, ‘right’]]
  \item \texttt{kind}  [[‘loc’, ‘getitem’] or None]
\end{itemize}

Returns

\begin{itemize}
  \item \texttt{int}  Index of label.
\end{itemize}

\texttt{pandas.Index.get_value}

\texttt{Index.get_value(series, key)}

Fast lookup of value from 1-dimensional ndarray.

Only use this if you know what you’re doing.

Returns

\begin{itemize}
  \item \texttt{scalar} or \texttt{Series}
\end{itemize}
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.Index.groupby

Index.groupby(values)
Group the index labels by a given array of values.

Parameters

values [array] Values used to determine the groups.

Returns

dict {group name -> group labels}

pandas.Index.holds_integer

Index.holds_integer()
Whether the type is an integer type.

pandas.Index.identical

Index.identical(other)
Similar to equals, but checks that object attributes and types are also equal.

Returns

bool If two Index objects have equal elements and same type True, otherwise False.

pandas.Index.insert

Index.insert(loc, item)
Make new Index inserting new item at location.
Follows Python list.append semantics for negative values.

Parameters

loc [int]
item [object]

Returns

new_index [Index]

pandas.Index.intersection

Index.intersection(other, sort=False)
Form the intersection of two Index objects.
This returns a new Index with elements common to the index and other.

Parameters

other [Index or array-like]

sort [False or None, default False] Whether to sort the resulting index.
• False : do not sort the result.
• None : sort the result, except when self and other are equal or when the values cannot be compared.

New in version 0.24.0.

Changed in version 0.24.1: Changed the default from True to False, to match the behaviour of 0.23.4 and earlier.

Returns

intersection [Index]

Examples

```python
>>> idx1 = pd.Index([1, 2, 3, 4])
>>> idx2 = pd.Index([3, 4, 5, 6])
>>> idx1.intersection(idx2)
Int64Index([3, 4], dtype='int64')
```

```python
pandas.Index.is_
```

Index.is_ (other)

More flexible, faster check like is but that works through views.

Note: this is not the same as Index.identical(), which checks that metadata is also the same.

Parameters

other [object] Other object to compare against.

Returns

bool True if both have same underlying data, False otherwise.

See also:

Index.identical Works like Index.is_ but also checks metadata.

```python
pandas.Index.is_boolean
```

Index.is_boolean()

Check if the Index only consists of booleans.

Returns

bool Whether or not the Index only consists of booleans.

See also:

is_integer Check if the Index only consists of integers.

is_floating Check if the Index is a floating type.

is_numeric Check if the Index only consists of numeric data.

is_object Check if the Index is of the object dtype.

is_categorical Check if the Index holds categorical data.

is_interval Check if the Index holds Interval objects.
**is_mixed** Check if the Index holds data with mixed data types.

**Examples**

```python
>>> idx = pd.Index([True, False, True])
>>> idx.is_boolean()
True

>>> idx = pd.Index(["True", "False", "True"])
>>> idx.is_boolean()
False

>>> idx = pd.Index([True, False, "True"])
>>> idx.is_boolean()
False
```

**pandas.Index.is_categorical**

Index.is_categorical() Check if the Index holds categorical data.

**Returns**

- **bool** True if the Index is categorical.

**See also:**

- **CategoricalIndex** Index for categorical data.
- **is_boolean** Check if the Index only consists of booleans.
- **is_integer** Check if the Index only consists of integers.
- **is_floating** Check if the Index is a floating type.
- **is_numeric** Check if the Index only consists of numeric data.
- **is_object** Check if the Index is of the object dtype.
- **is_interval** Check if the Index holds Interval objects.
- **is_mixed** Check if the Index holds data with mixed data types.

**Examples**

```python
>>> idx = pd.Index(["Watermelon", "Orange", "Apple", ...
"Watermelon"]).astype("category")
>>> idx.is_categorical()
True

>>> idx = pd.Index([1, 3, 5, 7])
>>> idx.is_categorical()
False
```
```python
>>> s = pd.Series(["Peter", "Victor", "Elisabeth", "Mar"])
>>> s
0    Peter
1     Victor
2  Elisabeth
3      Mar
dtype: object
>>> s.index.is_categorical()
False
```

### pandas.Index.is_floating

`Index.is_floating()`

Check if the Index is a floating type.

The Index may consist of only floats, NaNs, or a mix of floats, integers, or NaNs.

**Returns**

`bool` Whether or not the Index only consists of only consists of floats, NaNs, or a mix of floats, integers, or NaNs.

**See also:**

- `is_boolean` Check if the Index only consists of booleans.
- `is_integer` Check if the Index only consists of integers.
- `is_numeric` Check if the Index only consists of numeric data.
- `is_object` Check if the Index is of the object dtype.
- `is_categorical` Check if the Index holds categorical data.
- `is_interval` Check if the Index holds Interval objects.
- `is_mixed` Check if the Index holds data with mixed data types.

**Examples**

```python
>>> idx = pd.Index([1.0, 2.0, 3.0, 4.0])
>>> idx.is_floating()
True
```

```python
>>> idx = pd.Index([1.0, 2.0, np.nan, 4.0])
>>> idx.is_floating()
True
```

```python
>>> idx = pd.Index([1, 2, 3, 4, np.nan])
>>> idx.is_floating()
True
```

```python
>>> idx = pd.Index([1, 2, 3, 4])
>>> idx.is_floating()
False
```
pandas.Index.is_integer

Index.is_integer()
Check if the Index only consists of integers.

Returns
bool Whether or not the Index only consists of integers.

See also:

is_boolean Check if the Index only consists of booleans.
is_floating Check if the Index is a floating type.
is_numeric Check if the Index only consists of numeric data.
is_object Check if the Index is of the object dtype.
is_categorical Check if the Index holds categorical data.
is_interval Check if the Index holds Interval objects.
is_mixed Check if the Index holds data with mixed data types.

Examples

```python
>>> idx = pd.Index([1, 2, 3, 4])
>>> idx.is_integer()
True

>>> idx = pd.Index([1.0, 2.0, 3.0, 4.0])
>>> idx.is_integer()
False

>>> idx = pd.Index(['Apple', 'Mango', 'Watermelon'])
>>> idx.is_integer()
False
```

pandas.Index.is_interval

Index.is_interval()
Check if the Index holds Interval objects.

Returns
bool Whether or not the Index holds Interval objects.

See also:

IntervalIndex Index for Interval objects.
is_boolean Check if the Index only consists of booleans.
is_integer Check if the Index only consists of integers.
is_floating Check if the Index is a floating type.
is_numeric Check if the Index only consists of numeric data.
is_object Check if the Index is of the object dtype.

is_categorical Check if the Index holds categorical data.

is_mixed Check if the Index holds data with mixed data types.

Examples

```python
>>> idx = pd.Index([pd.Interval(left=0, right=5),
...                   pd.Interval(left=5, right=10)])
>>> idx.is_interval()
True

>>> idx = pd.Index([1, 3, 5, 7])
>>> idx.is_interval()
False
```

pandas.Index.is_mixed

Index.is_mixed() Check if the Index holds data with mixed data types.

Returns

bool Whether or not the Index holds data with mixed data types.

See also:

is_boolean Check if the Index only consists of booleans.

is_integer Check if the Index only consists of integers.

is_floating Check if the Index is a floating type.

is_numeric Check if the Index only consists of numeric data.

is_object Check if the Index is of the object dtype.

is_categorical Check if the Index holds categorical data.

is_interval Check if the Index holds Interval objects.

Examples

```python
>>> idx = pd.Index(['a', np.nan, 'b'])
>>> idx.is_mixed()
True

>>> idx = pd.Index([1.0, 2.0, 3.0, 5.0])
>>> idx.is_mixed()
False
```
**pandas.Index.is_numeric**

`Index.is_numeric()`  
Check if the Index only consists of numeric data.

**Returns**

`bool` Whether or not the Index only consists of numeric data.

**See also:**

- `is_boolean` Check if the Index only consists of booleans.
- `is_integer` Check if the Index only consists of integers.
- `is_floating` Check if the Index is a floating type.
- `is_object` Check if the Index is of the object dtype.
- `is_categorical` Check if the Index holds categorical data.
- `is_interval` Check if the Index holds Interval objects.
- `is_mixed` Check if the Index holds data with mixed data types.

**Examples**

```python
given_idx = pd.Index([1.0, 2.0, 3.0, 4.0])
>>> given_idx.is_numeric()
True

idx = pd.Index([1, 2, 3.0])
>>> idx.is_numeric()
True

idx = pd.Index([1, 2, 3.4])
>>> idx.is_numeric()
True

idx = pd.Index([1, 2, 3.4, np.nan])
>>> idx.is_numeric()
True

idx = pd.Index([1, 2, 3.4, np.nan, "Apple"])
>>> idx.is_numeric()
False
```
**pandas.Index.is_object**

Index.is_object()  
Check if the Index is of the object dtype.

**Returns**

bool Whether or not the Index is of the object dtype.

**See also:**

- is_boolean Check if the Index only consists of booleans.
- is_integer Check if the Index only consists of integers.
- is_floating Check if the Index is a floating type.
- is_numeric Check if the Index only consists of numeric data.
- is_categorical Check if the Index holds categorical data.
- is_interval Check if the Index holds Interval objects.
- is_mixed Check if the Index holds data with mixed data types.

**Examples**

```python
>>> idx = pd.Index(['Apple', 'Mango', 'Watermelon'])
>>> idx.is_object()
True

>>> idx = pd.Index(['Apple', 'Mango', 2.0])
>>> idx.is_object()
True

>>> idx = pd.Index(['Watermelon', 'Orange', 'Apple', ...
                'Watermelon']).astype('category')
>>> idx.is_object()
False

>>> idx = pd.Index([1.0, 2.0, 3.0, 4.0])
>>> idx.is_object()
False
```

**pandas.Index.is_type_compatible**

Index.is_type_compatible(kind)  
Whether the index type is compatible with the provided type.
pandas.Index.isin

Index.<code>isin</code>(values, level=None)

Return a boolean array where the index values are in values.

Compute boolean array of whether each index value is found in the passed set of values. The length of the returned boolean array matches the length of the index.

Parameters

- **values** [set or list-like] Sought values.
- **level** [str or int, optional] Name or position of the index level to use (if the index is a <em>MultiIndex</em>).

Returns

- **is_contained** [ndarray] NumPy array of boolean values.

See also:

<code>Series.isin</code> Same for Series.
<code>DataFrame.isin</code> Same method for DataFrames.

Notes

In the case of <em>MultiIndex</em> you must either specify <em>values</em> as a list-like object containing tuples that are the same length as the number of levels, or specify <em>level</em>. Otherwise it will raise a <code>ValueError</code>.

If <em>level</em> is specified:

- if it is the name of one and only one index level, use that level;
- otherwise it should be a number indicating level position.

Examples

```python
>>> idx = pd.Index([1,2,3])
>>> idx
Int64Index([1, 2, 3], dtype='int64')

Check whether each index value in a list of values.

```python
>>> idx.isin([1, 4])
array([ True, False, False])
```
To check across the levels of a MultiIndex, pass a list of tuples:

```python
>>> midx.isin([(1, 'red'), (3, 'red')])
array([ True, False, False])
```

For a DatetimeIndex, string values in `values` are converted to Timestamps.

```python
>>> dates = ['2000-03-11', '2000-03-12', '2000-03-13']
>>> dti = pd.to_datetime(dates)
>>> dti
DatetimeIndex(['2000-03-11', '2000-03-12', '2000-03-13'], dtype='datetime64[ns]', freq=None)
```

```python
>>> dti.isin(['2000-03-11'])
array([ True, False, False])
```

### pandas.Index.isna

**Index.isna()**

Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as None, numpy.NaN or pd.NaT, get mapped to `True` values. Everything else get mapped to `False` values. Characters such as empty strings `' '` or numpy.inf are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`).

**Returns**

`numpy.ndarray` A boolean array of whether my values are NA.

**See also:**

* `Index.notna` Boolean inverse of isna.
* `Index.dropna` Omit entries with missing values.
* `isna` Top-level isna.
* `Series.isna` Detect missing values in Series object.

### Examples

Show which entries in a pandas.Index are NA. The result is an array.

```python
>>> idx = pd.Index([5.2, 6.0, np.NaN])
>>> idx
Float64Index([5.2, 6.0, nan], dtype='float64')
```

```python
>>> idx.isna()
array([False, False, True])
```

Empty strings are not considered NA values. None is considered an NA value.
pandas: powerful Python data analysis toolkit, Release 1.1.1

```python
>>> idx = pd.Index(['black', '', 'red', None])
>>> idx
Index(['black', '', 'red', None], dtype='object')
>>> idx.isna()
array([False, False, False, True])
```

For datetimes, Na\(T\) (Not a Time) is considered as an NA value.

```python
>>> idx = pd.DatetimeIndex([pd.Timestamp('1940-04-25'),
... pd.Timestamp(''),
... None, pd.NaT])
>>> idx
DatetimeIndex(['1940-04-25', 'NaT', 'NaT', 'NaT'],
              dtype='datetime64[ns]', freq=None)
>>> idx.isna()
array([False, True, True, True])
```

### pandas.Index.isnull

**Index.isnull()**

Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as None, numpy.\(\text{NaN}\) or pd.Na\(T\), get mapped to True values. Everything else get mapped to False values. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.use_inf_as_na = True).

**Returns**

- numpy.ndarray: A boolean array of whether my values are NA.

**See also:**

- Index.notna: Boolean inverse of isna.
- Index.dropna: Omit entries with missing values.
- isna: Top-level isna.
- Series.isna: Detect missing values in Series object.

**Examples**

Show which entries in a pandas.Index are NA. The result is an array.

```python
>>> idx = pd.Index([5.2, 6.0, np.NaN])
>>> idx
Float64Index([5.2, 6.0, nan], dtype='float64')
>>> idx.isna()
array([False, False, True])
```

Empty strings are not considered NA values. None is considered an NA value.

```python
>>> idx = pd.Index(['black', '', 'red', None])
>>> idx
Index(['black', '', 'red', None], dtype='object')
>>> idx.isna()
array([False, False, False, True])
```
For datetimes, *NaT* (Not a Time) is considered as an NA value.

```python
>>> idx = pd.DatetimeIndex([pd.Timestamp('1940-04-25'),
    ... pd.Timestamp(''), None, pd.NaT])
```

```python
>>> idx
DatetimeIndex(['1940-04-25', 'NaT', 'NaT', 'NaT'],
               dtype='datetime64[ns]', freq=None)
```

```python
>>> idx.isna()
array([False, True, True, True])
```

**pandas.Index.item**

*Index.item()*

Return the first element of the underlying data as a python scalar.

**Returns**

- **scalar**  The first element of *%(klass)s*.

**Raises**

- **ValueError**  If the data is not length-1.

**pandas.Index.join**

*Index.join*(other, how='left', level=None, return_indexers=False, sort=False)

Compute join_index and indexers to conform data structures to the new index.

**Parameters**

- **other**  [Index]
- **how**  [{‘left’, ‘right’, ‘inner’, ‘outer’}]
- **level**  [int or level name, default None]
- **return_indexers**  [bool, default False]
- **sort**  [bool, default False]  Sort the join keys lexicographically in the result Index.  If 
  False, the order of the join keys depends on the join type (how keyword).

**Returns**

- **join_index**, *(left_indexer, right_indexer)*

**pandas.Index.map**

*Index.map*(mapper, na_action=None)

Map values using input correspondence (a dict, Series, or function).

**Parameters**

- **mapper**  [function, dict, or Series]  Mapping correspondence.
- **na_action**  [{None, ‘ignore’}]  If ‘ignore’, propagate NA values, without passing them to the mapping correspondence.

**Returns**

3.7. Index objects
applied [Union[Index, MultiIndex], inferred] The output of the mapping function applied to the index. If the function returns a tuple with more than one element a MultiIndex will be returned.

**pandas.Index.max**

```python
Index.max(\text{axis=None, skipna=True, } \ast \text{args, } \ast \ast \text{kwargs})
```

Return the maximum value of the Index.

**Parameters**

- `axis` [int, optional] For compatibility with NumPy. Only 0 or None are allowed.
- `skipna` [bool, default True] Exclude NA/null values when showing the result.
- `\ast \text{args, } \ast \ast \text{kwargs}` Additional arguments and keywords for compatibility with NumPy.

**Returns**

- `scalar` Maximum value.

**See also:**

- `Index.min` Return the minimum value in an Index.
- `Series.max` Return the maximum value in a Series.
- `DataFrame.max` Return the maximum values in a DataFrame.

**Examples**

```python
>>> idx = pd.Index([3, 2, 1])
>>> idx.max()
3

>>> idx = pd.Index(['c', 'b', 'a'])
>>> idx.max()
'c'
```

For a MultiIndex, the maximum is determined lexicographically.

```python
>>> idx = pd.MultiIndex.from_product([('a', 'b'), (2, 1)])
>>> idx.max()
('b', 2)
```

**pandas.Index.memory_usage**

```python
Index.memory_usage(\text{deep=False})
```

Memory usage of the values.

**Parameters**

- `deep` [bool] Introspect the data deeply, interrogate object dtypes for system-level memory consumption.

**Returns**

- `bytes used`
See also:

```
numpy.ndarray.nbytes  Total bytes consumed by the elements of the array.
```

**Notes**

Memory usage does not include memory consumed by elements that are not components of the array if `deep=False` or if used on PyPy.

### pandas.Index.min

```
Index.min(axis=None, skipna=True, *args, **kwargs)
```

Return the minimum value of the Index.

**Parameters**

- `axis` [{None}] Dummy argument for consistency with Series.
- `skipna` [bool, default True] Exclude NA/null values when showing the result.
- `*args, **kwargs` Additional arguments and keywords for compatibility with NumPy.

**Returns**

- `scalar` Minimum value.

See also:

```
Index.max  Return the maximum value of the object.
Series.min  Return the minimum value in a Series.
DataFrame.min  Return the minimum values in a DataFrame.
```

**Examples**

```
>>> idx = pd.Index([3, 2, 1])
>>> idx.min()
1

>>> idx = pd.Index(['c', 'b', 'a'])
>>> idx.min()
'a'
```

For a MultiIndex, the minimum is determined lexicographically.

```
>>> idx = pd.MultiIndex.from_product([['a', 'b'], (2, 1)])
>>> idx.min()
('a', 1)
```
pandas.Index.notna

Index.notna()

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to True. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.use_inf_as_na = True). NA values, such as None or numpy.NaN, get mapped to False values.

Returns

numpy.ndarray Boolean array to indicate which entries are not NA.

See also:

Index.notnull Alias of notna.

Index.isna Inverse of notna.

notna Top-level notna.

Examples

Show which entries in an Index are not NA. The result is an array.

```python
>>> idx = pd.Index([5.2, 6.0, np.NaN])
>>> idx
Float64Index([5.2, 6.0, nan], dtype='float64')
>>> idx.notna()
array([True, True, False])
```

Empty strings are not considered NA values. None is considered a NA value.

```python
>>> idx = pd.Index(['black', '', 'red', None])
>>> idx
Index(['black', '', 'red', None], dtype='object')
>>> idx.notna()
array([True, True, True, False])
```

pandas.Index.notnull

Index.notnull()

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to True. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.use_inf_as_na = True). NA values, such as None or numpy.NaN, get mapped to False values.

Returns

numpy.ndarray Boolean array to indicate which entries are not NA.

See also:

Index.notnull Alias of notna.
**Index.isna** Inverse of notna.

**notna** Top-level notna.

### Examples

Show which entries in an Index are not NA. The result is an array.

```python
>>> idx = pd.Index([5.2, 6.0, np.NaN])
>>> idx
Float64Index([5.2, 6.0, nan], dtype='float64')
>>> idx.notna()
array([ True, True, False])
```

Empty strings are not considered NA values. None is considered a NA value.

```python
>>> idx = pd.Index(['black', '', 'red', None])
>>> idx
Index(['black', '', 'red', None], dtype='object')
>>> idx.notna()
array([ True, True, True, False])
```

### pandas.Index.nunique

**Index.nunique** *(dropna=True)*

Return number of unique elements in the object.

Excludes NA values by default.

**Parameters**

- **dropna** [bool, default True] Don’t include NaN in the count.

**Returns**

- int

**See also:**

- DataFrame.nunique Method nunique for DataFrame.
- Series.count Count non-NA/null observations in the Series.

### Examples

```python
>>> s = pd.Series([1, 3, 5, 7, 7])
>>> s
0  1
1  3
2  5
3  7
4  7
dtype: int64

>>> s.nunique()
4
```
pandas.Index.putmask

Index.putmask (mask, value)
Return a new Index of the values set with the mask.

Returns
Index

See also:

numpy.ndarray.putmask

pandas.Index.ravel

Index.ravel (order='C')
Return an ndarray of the flattened values of the underlying data.

Returns
numpy.ndarray Flattened array.

See also:

numpy.ndarray.ravel

pandas.Index.reindex

Index.reindex (target, method=None, level=None, limit=None, tolerance=None)
Create index with target’s values.

Parameters

target [an iterable]

Returns

ew_index [pd.Index] Resulting index.
indexer [np.ndarray or None] Indices of output values in original index.

pandas.Index.rename

Index.rename (name, inplace=False)
Alter Index or MultiIndex name.

Able to set new names without level. Defaults to returning new index. Length of names must match number of levels in MultiIndex.

Parameters

name [label or list of labels] Name(s) to set.

inplace [bool, default False] Modifies the object directly, instead of creating a new Index or MultiIndex.

Returns

Index The same type as the caller or None if inplace is True.
See also:

**Index.set_names** Able to set new names partially and by level.

**Examples**

```python
>>> idx = pd.Index(['A', 'C', 'A', 'B'], name='score')
>>> idx.rename('grade')
Index(['A', 'C', 'A', 'B'], dtype='object', name='grade')

>>> idx = pd.MultiIndex.from_product([['python', 'cobra'], [2018, 2019]], names=['kind', 'year'])
>>> idx
MultiIndex([('python', 2018), ('python', 2019), ('cobra', 2018), ('cobra', 2019)], names=['kind', 'year'])

>>> idx.rename(['species', 'year'])
MultiIndex([('python', 2018), ('python', 2019), ('cobra', 2018), ('cobra', 2019)], names=['species', 'year'])

>>> idx.rename('species')
Traceback (most recent call last):
  TypeError: Must pass list-like as 'names'.
```

**pandas.Index.repeat**

**Index.repeat** *(repeats, axis=None)*

Repeat elements of a Index.

Returns a new Index where each element of the current Index is repeated consecutively a given number of times.

**Parameters**

- **repeats** [int or array of ints] The number of repetitions for each element. This should be a non-negative integer. Repeating 0 times will return an empty Index.

- **axis** [None] Must be None. Has no effect but is accepted for compatibility with numpy.

**Returns**

- **repeated_index** [Index] Newly created Index with repeated elements.

**See also:**

**Series.repeat** Equivalent function for Series.

**numpy.repeat** Similar method for numpy.ndarray.
Examples

```python
>>> idx = pd.Index(['a', 'b', 'c'])
>>> idx
Index(['a', 'b', 'c'], dtype='object')
>>> idx.repeat(2)
Index(['a', 'a', 'b', 'b', 'c', 'c'], dtype='object')
>>> idx.repeat([1, 2, 3])
Index(['a', 'b', 'b', 'c', 'c', 'c'], dtype='object')
```

**pandas.Index.searchsorted**

`Index.searchsorted(value, side='left', sorter=None)`

Find indices where elements should be inserted to maintain order.

Find the indices into a sorted Index `self` such that, if the corresponding elements in `value` were inserted before the indices, the order of `self` would be preserved.

**Note:** The Index must be monotonically sorted, otherwise wrong locations will likely be returned. Pandas does not check this for you.

**Parameters**

- `value` [array_like] Values to insert into `self`.
- `side` [‘left’, ‘right’], optional] If ‘left’, the index of the first suitable location found is given. If ‘right’, return the last such index. If there is no suitable index, return either 0 or N (where N is the length of `self`).
- `sorter` [1-D array_like, optional] Optional array of integer indices that sort `self` into ascending order. They are typically the result of `np.argsort`.

**Returns**

- `int` or `array of int` A scalar or array of insertion points with the same shape as `value`.

Changed in version 0.24.0: If `value` is a scalar, an int is now always returned. Previously, scalar inputs returned an 1-item array for `Series` and `Categorical`.

**See also:**

- `sort_values` Sort by the values along either axis.
- `numpy.searchsorted` Similar method from NumPy.
Notes

Binary search is used to find the required insertion points.

Examples

```python
>>> ser = pd.Series([1, 2, 3])
>>> ser
0  1
1  2
2  3
dtype: int64

>>> ser.searchsorted(4)
3

>>> ser.searchsorted([0, 4])
array([0, 3])

>>> ser.searchsorted([1, 3], side='left')
array([0, 2])

>>> ser.searchsorted([1, 3], side='right')
array([1, 3])

>>> ser = pd.Categorical(
...    ['apple', 'bread', 'bread', 'cheese', 'milk'], ordered=True
...)

>>> ser
['apple', 'bread', 'bread', 'cheese', 'milk']
Categories (4, object): ['apple' < 'bread' < 'cheese' < 'milk']

>>> ser.searchsorted('bread')
1

>>> ser.searchsorted(['bread'], side='right')
array([3])
```

If the values are not monotonically sorted, wrong locations may be returned:

```python
>>> ser = pd.Series([2, 1, 3])
>>> ser
0  2
1  1
2  3
dtype: int64

>>> ser.searchsorted(1)
0  # wrong result, correct would be 1
```
pandas.Index.set_names

Index.set_names(names, level=None, inplace=False)

Set Index or MultiIndex name.

Able to set new names partially and by level.

Parameters

names [label or list of label] Name(s) to set.

level [int, label or list of int or label, optional] If the index is a MultiIndex, level(s) to set (None for all levels). Otherwise level must be None.

inplace [bool, default False] Modifies the object directly, instead of creating a new Index or MultiIndex.

Returns

Index The same type as the caller or None if inplace is True.

See also:

Index.rename Able to set new names without level.

Examples

```python
>>> idx = pd.Index([1, 2, 3, 4])
>>> idx
Int64Index([1, 2, 3, 4], dtype='int64')
>>> idx.set_names('quarter')
Int64Index([1, 2, 3, 4], dtype='int64', name='quarter')

>>> idx = pd.MultiIndex.from_product([['python', 'cobra'],
... [2018, 2019]])
>>> idx
MultiIndex([('python', 2018),
('python', 2019),
('cobra', 2018),
('cobra', 2019),
],
)
>>> idx.set_names(['kind', 'year'], inplace=True)
>>> idx
MultiIndex([('python', 2018),
('python', 2019),
('cobra', 2018),
('cobra', 2019)],
names=['kind', 'year'])
>>> idx.set_names('species', level=0)
MultiIndex([('python', 2018),
('python', 2019),
('cobra', 2018),
('cobra', 2019),
],
names=['species', 'year'])
```
**pandas.Index.set_value**

Index.set_value(arr, key, value)

Fast lookup of value from 1-dimensional ndarray.

Deprecated since version 1.0.

**Notes**

Only use this if you know what you’re doing.

**pandas.Index.shift**

Index.shift(periods=1, freq=None)

Shift index by desired number of time frequency increments.

This method is for shifting the values of datetime-like indexes by a specified time increment a given number of times.

**Parameters**

- **periods** [int, default 1] Number of periods (or increments) to shift by, can be positive or negative.
- **freq** [pandas.DateOffset, pandas.Timedelta or str, optional] Frequency increment to shift by. If None, the index is shifted by its own freq attribute. Offset aliases are valid strings, e.g., ‘D’, ‘W’, ‘M’ etc.

**Returns**

pandas.Index  Shifted index.

**See also:**

Series.shift  Shift values of Series.

**Notes**

This method is only implemented for datetime-like index classes, i.e., DatetimeIndex, PeriodIndex and TimedeltaIndex.

**Examples**

Put the first 5 month starts of 2011 into an index.

```python
>>> month_starts = pd.date_range('1/1/2011', periods=5, freq='MS')
>>> month_starts
dtype='datetime64[ns]', freq='MS')
```

Shift the index by 10 days.
pandas: powerful Python data analysis toolkit, Release 1.1.1

```
>>> month_starts.shift(10, freq='D')
               '2011-05-11'],
             dtype='datetime64[ns]', freq=None)
```

The default value of `freq` is the `freq` attribute of the index, which is ‘MS’ (month start) in this example.

```
>>> month_starts.shift(10)
DatetimeIndex(['2011-11-01', '2011-12-01', '2012-01-01', '2012-02-01',
               '2012-03-01'],
             dtype='datetime64[ns]', freq='MS')
```

**pandas.Index.slice_indexer**

`Index.slice_indexer(start=None, end=None, step=None, kind=None)`  
Compute the slice indexer for input labels and step.

Index needs to be ordered and unique.

**Parameters**

- **start** [label, default None] If None, defaults to the beginning.
- **end** [label, default None] If None, defaults to the end.
- **step** [int, default None]
- **kind** [str, default None]

**Returns**

- **indexer** [slice]

**Raises**

- **KeyError** [If key does not exist, or key is not unique and index is] not ordered.

**Notes**

This function assumes that the data is sorted, so use at your own peril

**Examples**

This is a method on all index types. For example you can do:

```
>>> idx = pd.Index(list('abcd'))
>>> idx.slice_indexer(start='b', end='c')
slice(1, 3, None)
```

```
>>> idx = pd.MultiIndex.from_arrays([list('abcd'), list('efgh')])
>>> idx.slice_indexer(start='b', end=('c', 'g'))
slice(1, 3, None)
```
pandas.Index.slice_locs

Index.slice_locs(start=None, end=None, step=None, kind=None)
Compute slice locations for input labels.

Parameters

- start [label, default None] If None, defaults to the beginning.
- end [label, default None] If None, defaults to the end.
- step [int, defaults None] If None, defaults to 1.
- kind [['loc', 'getitem'] or None]

Returns

- start, end [int]

See also:

Index.get_loc Get location for a single label.

Notes

This method only works if the index is monotonic or unique.

Examples

```python
>>> idx = pd.Index(list('abcd'))
>>> idx.slice_locs(start='b', end='c')
(1, 3)
```

pandas.Index.sort

Index.sort(*args, **kwargs)
Use sort_values instead.

pandas.Index.sort_values

Index.sort_values(return_indexer=False, ascending=True, key=None)
Return a sorted copy of the index.

Return a sorted copy of the index, and optionally return the indices that sorted the index itself.

Parameters

- return_indexer [bool, default False] Should the indices that would sort the index be returned.
- ascending [bool, default True] Should the index values be sorted in an ascending order.
- key [callable, optional] If not None, apply the key function to the index values before sorting. This is similar to the key argument in the builtin sorted() function, with the notable difference that this key function should be vectorized. It should expect an Index and return an Index of the same shape.
New in version 1.1.0.

Returns

- **sorted_index** [pandas.Index] Sorted copy of the index.
- **indexer** [numpy.ndarray, optional] The indices that the index itself was sorted by.

See also:

- **Series.sort_values** Sort values of a Series.
- **DataFrame.sort_values** Sort values in a DataFrame.

 Examples

```python
>>> idx = pd.Index([10, 100, 1, 1000])
>>> idx
Int64Index([10, 100, 1, 1000], dtype='int64')
```

Sort values in ascending order (default behavior).

```python
>>> idx.sort_values()
Int64Index([1, 10, 100, 1000], dtype='int64')
```

Sort values in descending order, and also get the indices `idx` was sorted by.

```python
>>> idx.sort_values(ascending=False, return_indexer=True)
(Int64Index([1000, 100, 10, 1], dtype='int64'), array([3, 1, 0, 2]))
```

**pandas.Index.sortlevel**

Index.sortlevel(`level=None`, `ascending=True`, `sort_remaining=None`)

For internal compatibility with with the Index API.

Sort the Index. This is for compat with MultiIndex

**Parameters**

- **ascending** [bool, default True] False to sort in descending order

**Returns**

- **Index**

**pandas.Index.str**

Index.str()

Vectorized string functions for Series and Index.

NAs stay NA unless handled otherwise by a particular method. Patterned after Python’s string methods, with some inspiration from R’s stringr package.
Examples

```python
>>> s = pd.Series(["A_Str_Series"]) >>> s
0  A_Str_Series
dtype: object

0  [A, Str, Series]
dtype: object

0  AStrSeries
dtype: object
```

`pandas.Index.symmetric_difference`

`Index.symmetric_difference(other, result_name=None, sort=None)`

Compute the symmetric difference of two Index objects.

**Parameters**

- `other` [Index or array-like]
- `result_name` [str]
- `sort` [False or None, default None] Whether to sort the resulting index. By default, the values are attempted to be sorted, but any TypeError from incomparable elements is caught by pandas.
  - None : Attempt to sort the result, but catch any TypeErrors from comparing incomparable elements.
  - False : Do not sort the result.

New in version 0.24.0.

Changed in version 0.24.1: Changed the default value from True to None (without change in behaviour).

**Returns**

- `symmetric_difference` [Index]

**Notes**

`symmetric_difference` contains elements that appear in either `idx1` or `idx2` but not both. Equivalent to the Index created by `idx1.difference(idx2) | idx2.difference(idx1)` with duplicates dropped.
Examples

```python
>>> idx1 = pd.Index([1, 2, 3, 4])
>>> idx2 = pd.Index([2, 3, 4, 5])
>>> idx1.symmetric_difference(idx2)
Int64Index([1, 5], dtype='int64')
```

You can also use the `^` operator:

```python
>>> idx1 ^ idx2
Int64Index([1, 5], dtype='int64')
```

**pandas.Index.take**

`Index.take(indices, axis=0, allow_fill=True, fill_value=None, **kwargs)`

Return a new Index of the values selected by the indices.

For internal compatibility with numpy arrays.

**Parameters**

- `indices` [list] Indices to be taken.
- `axis` [int, optional] The axis over which to select values, always 0.
- `allow_fill` [bool, default True]
- `fill_value` [bool, default None] If allow_fill=True and fill_value is not None, indices specified by -1 is regarded as NA. If Index doesn’t hold NA, raise ValueError.

**Returns**

- `numpy.ndarray` Elements of given indices.

**See also:**

- `numpy.ndarray.take`

**pandas.Index.to_flat_index**

`Index.to_flat_index()`

Identity method.

New in version 0.24.0.

This is implemented for compatibility with subclass implementations when chaining.

**Returns**

- `pd.Index` Caller.

**See also:**

- `MultiIndex.to_flat_index` Subclass implementation.
pandas.Index.to_frame

Index.to_frame(index=True, name=None)
Create a DataFrame with a column containing the Index.
New in version 0.24.0.

Parameters

index [bool, default True] Set the index of the returned DataFrame as the original Index.

name [object, default None] The passed name should substitute for the index name (if it has one).

Returns

DataFrame DataFrame containing the original Index data.

See also:

Index.to_series Convert an Index to a Series.
Series.to_frame Convert Series to DataFrame.

Examples

```python
>>> idx = pd.Index(['Ant', 'Bear', 'Cow'], name='animal')
>>> idx.to_frame()
   animal
animal  Ant
    Bear
   Cow
```

By default, the original Index is reused. To enforce a new Index:

```python
>>> idx.to_frame(index=False)
   animal
0    Ant
1    Bear
2     Cow
```

To override the name of the resulting column, specify name:

```python
>>> idx.to_frame(index=False, name='zoo')
   zoo
0    Ant
1    Bear
2     Cow
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.Index.to_list

Index.to_list()  
Return a list of the values.  
These are each a scalar type, which is a Python scalar (for str, int, float) or a pandas scalar (for Timestamp/Timedelta/Interval/Period)  
Returns  
list  
See also:  

numpy.ndarray.tolist  Return the array as an a.ndim-levels deep nested list of Python scalars.

pandas.Index.to_native_types

Index.to_native_types(slicer=None, **kwargs)  
Format specified values of self and return them.  
Parameters  

slicer [int, array-like] An indexer into self that specifies which values are used in the formatting process.  

kwargs [dict] Options for specifying how the values should be formatted. These options include the following:  
1) na_rep [str] The value that serves as a placeholder for NULL values  
2) quoting [bool or None] Whether or not there are quoted values in self  
3) date_format [str] The format used to represent date-like values.  
Returns  

numpy.ndarray  Formatted values.

pandas.Index.to_numpy

Index.to_numpy(dtype=None, copy=False, na_value=<object object>, **kwargs)  
A NumPy ndarray representing the values in this Series or Index.  
New in version 0.24.0.  
Parameters  

dtype [str or numpy.dtype, optional] The dtype to pass to numpy.asarray().  

copy [bool, default False] Whether to ensure that the returned value is not a view on another array. Note that copy=False does not ensure that to_numpy() is no-copy. Rather, copy=True ensure that a copy is made, even if not strictly necessary.  

na_value [Any, optional] The value to use for missing values. The default value depends on dtype and the type of the array.  
New in version 1.0.0.
**kwargs Additional keywords passed through to the to_numpy method of the underlying array (for extension arrays).

New in version 1.0.0.

**Returns**
	numpy.ndarray

**See also:**

*Series.array* Get the actual data stored within.

*Index.array* Get the actual data stored within.

*DataFrame.to_numpy* Similar method for DataFrame.

**Notes**

The returned array will be the same up to equality (values equal in self will be equal in the returned array; likewise for values that are not equal). When self contains an ExtensionArray, the dtype may be different. For example, for a category-dtype Series, to_numpy() will return a NumPy array and the categorical dtype will be lost.

For NumPy dtypes, this will be a reference to the actual data stored in this Series or Index (assuming copy=False). Modifying the result in place will modify the data stored in the Series or Index (not that we recommend doing that).

For extension types, to_numpy() may require copying data and coercing the result to a NumPy type (possibly object), which may be expensive. When you need a no-copy reference to the underlying data, Series.array should be used instead.

This table lays out the different dtypes and default return types of to_numpy() for various dtypes within pandas.

<table>
<thead>
<tr>
<th>dtype</th>
<th>array type</th>
</tr>
</thead>
<tbody>
<tr>
<td>category[T]</td>
<td>ndarray[T] (same dtype as input)</td>
</tr>
<tr>
<td>period</td>
<td>ndarray[object] (Periods)</td>
</tr>
<tr>
<td>interval</td>
<td>ndarray[object] (Intervals)</td>
</tr>
<tr>
<td>IntegerNA</td>
<td>ndarray[object]</td>
</tr>
<tr>
<td>datetime64[ns]</td>
<td>datetime64[ns]</td>
</tr>
<tr>
<td>datetime64[ns, tz]</td>
<td>ndarray[object] (Timestamps)</td>
</tr>
</tbody>
</table>

**Examples**

```python
gpd.Series(pd.Categorical(['a', 'b', 'a']))
```

```python
gpd.Series(pd.Categorical(['a', 'b', 'a'], dtype=object))
```

Specify the *dtype* to control how datetime-aware data is represented. Use dtype=object to return an ndarray of pandas Timestamp objects, each with the correct tz.

```python
gpd.Series(pd.date_range('2000', periods=2, tz='CET'))
```

```
gpd.Series(pd.date_range('2000', periods=2, tz='CET'), dtype=object)
```

---

3.7. Index objects 1947
Or dtype='datetime64[ns]' to return an ndarray of native datetime64 values. The values are converted to UTC and the timezone info is dropped.

```python
>>> ser.to_numpy(dtype="datetime64[ns]"
... array(['1999-12-31T23:00:00.000000000', '2000-01-01T23:00:00...',
   dtype='datetime64[ns]')
```

### pandas.Index.to_series

Index.to_series(index=None, name=None)

Create a Series with both index and values equal to the index keys.

Useful with map for returning an indexer based on an index.

**Parameters**

- **index** [Index, optional] Index of resulting Series. If None, defaults to original index.
- **name** [str, optional] Name of resulting Series. If None, defaults to name of original index.

**Returns**

Series The dtype will be based on the type of the Index values.

**See also:**

- Index.to_frame Convert an Index to a DataFrame.
- Series.to_frame Convert Series to DataFrame.

**Examples**

```python
>>> idx = pd.Index(['Ant', 'Bear', 'Cow'], name='animal')
```

By default, the original Index and original name is reused.

```python
>>> idx.to_series()
animal
Ant  Ant
Bear  Bear
Cow  Cow
Name: animal, dtype: object
```

To enforce a new Index, specify new labels to `index`:

```python
>>> idx.to_series(index=[0, 1, 2])
0   Ant
1   Bear
2   Cow
Name: animal, dtype: object
```

To override the name of the resulting column, specify `name`:
```python
>>> idx.to_series(name='zoo')
animal        
Ant    Ant
Bear   Bear
Cow    Cow
Name: zoo, dtype: object
```

### pandas.Index.tolist

**Index.tolist()**

Return a list of the values.

These are each a scalar type, which is a Python scalar (for str, int, float) or a pandas scalar (for Timestamp/Timedelta/Interval/Period)

Returns

list

See also:

- `numpy.ndarray.tolist` Return the array as an a.ndim-levels deep nested list of Python scalars.

### pandas.Index.transpose

**Index.transpose(*args, **kwargs)**

Return the transpose, which is by definition self.

Returns

%(klass)s

### pandas.Index.union

**Index.union(other, sort=None)**

Form the union of two Index objects.

If the Index objects are incompatible, both Index objects will be cast to dtype('object') first.

Changed in version 0.25.0.

**Parameters**

- `other` [Index or array-like]
- `sort` [bool or None, default None] Whether to sort the resulting Index.

  - None : Sort the result, except when
    1. `self` and `other` are equal.
    2. `self` or `other` has length 0.
    3. Some values in `self` or `other` cannot be compared. A RuntimeWarning is issued in this case.
  - False : do not sort the result.
New in version 0.24.0.

Changed in version 0.24.1: Changed the default value from `True` to `None` (without change in behaviour).

**Returns**

```
union [Index]
```

**Examples**

**Union matching dtypes**

```python
g = pd.Index([1, 2, 3, 4])
g.union(h)
```

```
Int64Index([1, 2, 3, 4, 5, 6], dtype='int64')
```

**Union mismatched dtypes**

```python
g = pd.Index([1, 2, 3, 4])
g.union(h)
```

```
Index(['a', 'b', 'c', 'd', 1, 2, 3, 4], dtype='object')
```

**pandas.Index.unique**

```
Index.unique (level=None)
```

Return unique values in the index.

Unique values are returned in order of appearance, this does NOT sort.

**Parameters**

```
level [int or str, optional, default None] Only return values from specified level (for MultiIndex).
```

New in version 0.23.0.

**Returns**

```
Index without duplicates
```

**See also:**

```
unique
Series.unique
```
Index.objects 1951

pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.Index.value_counts

Index.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)

Return a Series containing counts of unique values.

The resulting object will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values by default.

Parameters

- **normalize** [bool, default False] If True then the object returned will contain the relative frequencies of the unique values.
- **sort** [bool, default True] Sort by frequencies.
- **ascending** [bool, default False] Sort in ascending order.
- **bins** [int, optional] Rather than count values, group them into half-open bins, a convenience for pd.cut, only works with numeric data.
- **dropna** [bool, default True] Don’t include counts of NaN.

Returns

Series

See also:

- **Series.count** Number of non-NA elements in a Series.
- **DataFrame.count** Number of non-NA elements in a DataFrame.
- **DataFrame.value_counts** Equivalent method on DataFrames.

Examples

```python
>>> index = pd.Index([3, 1, 2, 3, 4, np.nan])
>>> index.value_counts()
3.0  2
4.0  1
2.0  1
1.0  1
dtype: int64
```

With normalize set to True, returns the relative frequency by dividing all values by the sum of values.

```python
>>> s = pd.Series([3, 1, 2, 3, 4, np.nan])
>>> s.value_counts(normalize=True)
3.0  0.4
4.0  0.2
2.0  0.2
1.0  0.2
dtype: float64
```

**bins**

Bins can be useful for going from a continuous variable to a categorical variable; instead of counting unique apparitions of values, divide the index in the specified number of half-open bins.
pandas: powerful Python data analysis toolkit, Release 1.1.1

```python
>>> s.value_counts(bins=3)
(2.0, 3.0]  2
(0.996, 2.0]  2
(3.0, 4.0]  1
dtype: int64
```

```python
dropna

With `dropna` set to `False` we can also see NaN index values.
```
```python
>>> s.value_counts(dropna=False)
3.0  2
NaN  1
4.0  1
2.0  1
1.0  1
dtype: int64
```

### pandas.Index.where

`Index.where`(cond, other=None)

Replace values where the condition is False.

The replacement is taken from other.

**Parameters**

- **cond** [bool array-like with the same length as self] Condition to select the values on.
- **other** [scalar, or array-like, default None] Replacement if the condition is False.

**Returns**

- **pandas.Index** A copy of self with values replaced from other where the condition is False.

**See also:**

- **Series.where** Same method for Series.
- **DataFrame.where** Same method for DataFrame.

**Examples**

```python
>>> idx = pd.Index(['car', 'bike', 'train', 'tractor'])
>>> idx
Index(['car', 'bike', 'train', 'tractor'], dtype='object')
>>> idx.where(idx.isin(['car', 'train']), 'other')
Index(['car', 'other', 'train', 'other'], dtype='object')
```
Properties

- **Index.values**: Return an array representing the data in the Index.
- **Index.is_monotonic**: Alias for `is_monotonic_increasing`.
- **Index.is_monotonic_increasing**: Return if the index is monotonic increasing (only equal or increasing) values.
- **Index.is_monotonic_decreasing**: Return if the index is monotonic decreasing (only equal or decreasing) values.
- **Index.is_unique**: Return if the index has unique values.
- **Index.has_duplicates**: Check if the Index has duplicate values.
- **Index.hasnans**: Return if I have any nans; enables various perf speedups.
- **Index.dtype**: Return the dtype object of the underlying data.
- **Index.inferred_type**: Return a string of the type inferred from the values.
- **Index.is_all_dates**: Whether or not the index values only consist of dates.
- **Index.shape**: Return a tuple of the shape of the underlying data.
- **Index.name**: Return Index or MultiIndex name.
- **Index.names**: Property
- **Index.nbytes**: Return the number of bytes in the underlying data.
- **Index.ndim**: Number of dimensions of the underlying data, by definition 1.
- **Index.size**: Return the number of elements in the underlying data.
- **Index.empty**: Property
- **Index.T**: Return the transpose, which is by definition self.
- **Index.memory_usage**(*deep*)**: Memory usage of the values.

**pandas.Index.names**

**property Index.names**

**pandas.Index.empty**

**property Index.empty**

Modifying and computations

- **Index.all(**args, **kwargs)**: Return whether all elements are True.
- **Index.any(**args, **kwargs)**: Return whether any element is True.
- **Index.argmin(axis, skipna)**: Return int position of the smallest value in the Series.
- **Index.argmax(axis, skipna)**: Return int position of the largest value in the Series.
- **Index.copy(, deep, dtype, names)**: Make a copy of this object.
- **Index.delete(loc)**: Make new Index with passed location(-s) deleted.
- **Index.drop(labels[, errors])**: Make new Index with passed list of labels deleted.
- **Index.drop_duplicates(keep)**: Return Index with duplicate values removed.
- **Index.duplicated(keep)**: Indicate duplicate index values.
- **Index.equals(other)**: Determine if two Index object are equal.
- **Index.factorize(sort, na_sentinel)**: Encode the object as an enumerated type or categorical variable.

continues on next page
Table 132 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Index.identical(other)</code></td>
<td>Similar to equals, but checks that object attributes and</td>
</tr>
<tr>
<td></td>
<td>types are also equal.</td>
</tr>
<tr>
<td><code>Index.insert(loc, item)</code></td>
<td>Make new Index inserting new item at location.</td>
</tr>
<tr>
<td><code>Index.is_(other)</code></td>
<td>More flexible, faster check like <code>is</code> but that works</td>
</tr>
<tr>
<td></td>
<td>through views.</td>
</tr>
<tr>
<td><code>Index.is_boolean()</code></td>
<td>Check if the Index only consists of booleans.</td>
</tr>
<tr>
<td><code>Index.is_categorical()</code></td>
<td>Check if the Index holds categorical data.</td>
</tr>
<tr>
<td><code>Index.is_floating()</code></td>
<td>Check if the Index is a floating type.</td>
</tr>
<tr>
<td><code>Index.is_integer()</code></td>
<td>Check if the Index only consists of integers.</td>
</tr>
<tr>
<td><code>Index.is_interval()</code></td>
<td>Check if the Index holds Interval objects.</td>
</tr>
<tr>
<td><code>Index.is_mixed()</code></td>
<td>Check if the Index holds data with mixed data types.</td>
</tr>
<tr>
<td><code>Index.is_numeric()</code></td>
<td>Check if the Index only consists of numeric data.</td>
</tr>
<tr>
<td><code>Index.is_object()</code></td>
<td>Check if the Index is of the object dtype.</td>
</tr>
<tr>
<td><code>Index.min([axis, skipna])</code></td>
<td>Return the minimum value of the Index.</td>
</tr>
<tr>
<td><code>Index.max([axis, skipna])</code></td>
<td>Return the maximum value of the Index.</td>
</tr>
<tr>
<td><code>Index.reindex(target[, method, level, ...])</code></td>
<td>Create index with target’s values.</td>
</tr>
<tr>
<td><code>Index.rename(name[, inplace])</code></td>
<td>Alter Index or MultiIndex name.</td>
</tr>
<tr>
<td><code>Index.repeat(repeats[, axis])</code></td>
<td>Repeat elements of a Index.</td>
</tr>
<tr>
<td><code>Index.where(cond[, other])</code></td>
<td>Replace values where the condition is False.</td>
</tr>
<tr>
<td><code>Index.take(indices[, axis, allow_fill, ...])</code></td>
<td>Return a new Index of the values selected by the indices.</td>
</tr>
<tr>
<td><code>Index.putmask(mask, value)</code></td>
<td>Return a new Index of the values set with the mask.</td>
</tr>
<tr>
<td><code>Index.unique([level])</code></td>
<td>Return unique values in the index.</td>
</tr>
<tr>
<td><code>Index.nunique([dropna])</code></td>
<td>Return number of unique elements in the object.</td>
</tr>
<tr>
<td><code>Index.value_counts([normalize, sort, ...])</code></td>
<td>Return a Series containing counts of unique values.</td>
</tr>
</tbody>
</table>

Compatibility with MultiIndex

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Index.set_names(names[, level, inplace])</code></td>
<td>Set Index or MultiIndex name.</td>
</tr>
<tr>
<td><code>Index.droplevel([level])</code></td>
<td>Return index with requested level(s) removed.</td>
</tr>
</tbody>
</table>

Missing values

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Index.fillna([value, downcast])</code></td>
<td>Fill NA/NaN values with the specified value.</td>
</tr>
<tr>
<td><code>Index.dropna([how])</code></td>
<td>Return Index without NA/NaN values.</td>
</tr>
<tr>
<td><code>Index.isna()</code></td>
<td>Detect missing values.</td>
</tr>
<tr>
<td><code>Index.notna()</code></td>
<td>Detect existing (non-missing) values.</td>
</tr>
</tbody>
</table>

Conversion

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Index.astype(dtype[, copy])</code></td>
<td>Create an Index with values cast to dtypes.</td>
</tr>
<tr>
<td><code>Index.item()</code></td>
<td>Return the first element of the underlying data as a python</td>
</tr>
<tr>
<td></td>
<td>scalar.</td>
</tr>
<tr>
<td><code>Index.map(mapper[, na_action])</code></td>
<td>Map values using input correspondence (a dict, Series, or</td>
</tr>
<tr>
<td></td>
<td>function).</td>
</tr>
<tr>
<td><code>Index.ravel([order])</code></td>
<td>Return an ndarray of the flattened values of the underlying</td>
</tr>
<tr>
<td></td>
<td>data.</td>
</tr>
</tbody>
</table>

continues on next page
Table 135 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Index.to_list()</code></td>
<td>Return a list of the values.</td>
</tr>
<tr>
<td><code>Index.to_native_types([slicer])</code></td>
<td>Format specified values of <code>self</code> and return them.</td>
</tr>
<tr>
<td><code>Index.to_series([index, name])</code></td>
<td>Create a Series with both index and values equal to the index keys.</td>
</tr>
<tr>
<td><code>Index.to_frame([index, name])</code></td>
<td>Create a DataFrame with a column containing the Index.</td>
</tr>
</tbody>
</table>

**pandas.Index.view**

`Index.view(cls=None)`

**Sorting**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Index.argsort(*args, **kwargs)</code></td>
<td>Return the integer indices that would sort the index.</td>
</tr>
<tr>
<td><code>Index.searchsorted(value[, side, sorter])</code></td>
<td>Find indices where elements should be inserted to maintain order.</td>
</tr>
<tr>
<td><code>Index.sort_values([return_indexer, . . . ])</code></td>
<td>Return a sorted copy of the index.</td>
</tr>
</tbody>
</table>

**Time-specific operations**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Index.shift([periods, freq])</code></td>
<td>Shift index by desired number of time frequency increments.</td>
</tr>
</tbody>
</table>

**Combining / joining / set operations**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Index.append(other)</code></td>
<td>Append a collection of Index options together.</td>
</tr>
<tr>
<td><code>Index.join(other[, how, level, ...])</code></td>
<td>Compute join_index and indexers to conform data structures to the new index.</td>
</tr>
<tr>
<td><code>Index.intersection(other[, sort])</code></td>
<td>Form the intersection of two Index objects.</td>
</tr>
<tr>
<td><code>Index.union(other[, sort])</code></td>
<td>Form the union of two Index objects.</td>
</tr>
<tr>
<td><code>Index.difference(other[, sort])</code></td>
<td>Return a new Index with elements of index not in <code>other</code>.</td>
</tr>
<tr>
<td><code>Index.symmetric_difference(other[, . . . ])</code></td>
<td>Compute the symmetric difference of two Index objects.</td>
</tr>
</tbody>
</table>

**Selecting**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Index.asof(label)</code></td>
<td>Return the label from the index, or, if not present, the previous one.</td>
</tr>
<tr>
<td><code>Index.asof_locs(where, mask)</code></td>
<td>Return the locations (indices) of labels in the index.</td>
</tr>
<tr>
<td><code>Index.get_indexer(target[, method, limit, . . . ])</code></td>
<td>Compute indexer and mask for new index given the current index.</td>
</tr>
<tr>
<td><code>Index.get_indexer_for(target, **kwargs)</code></td>
<td>Guaranteed return of an indexer even when non-unique.</td>
</tr>
<tr>
<td><code>Index.get_indexer_non_unique(target)</code></td>
<td>Compute indexer and mask for new index given the current index.</td>
</tr>
</tbody>
</table>

continues on next page
Table 139 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>index.get_level_values(level)</code></td>
<td>Return an Index of values for requested level.</td>
</tr>
<tr>
<td><code>index.get_loc(key[, method, tolerance])</code></td>
<td>Get integer location, slice or boolean mask for requested label.</td>
</tr>
<tr>
<td><code>index.get_slice_bound(label, side, kind)</code></td>
<td>Calculate slice bound that corresponds to given label.</td>
</tr>
<tr>
<td><code>index.get_value(series, key)</code></td>
<td>Fast lookup of value from 1-dimensional ndarray.</td>
</tr>
<tr>
<td><code>index.isin(values[, level])</code></td>
<td>Return a boolean array where the index values are in <code>values</code>.</td>
</tr>
<tr>
<td><code>index.slice_indexer([start, end, step, kind])</code></td>
<td>Compute the slice indexer for input labels and step.</td>
</tr>
<tr>
<td><code>index.slice_locs([start, end, step, kind])</code></td>
<td>Compute slice locations for input labels.</td>
</tr>
</tbody>
</table>

3.7.2 Numeric Index

`RangeIndex([start, stop, step, dtype, copy, ...])` Immutable Index implementing a monotonic integer range.

`Int64Index([data, dtype, copy, name])` Immutable ndarray implementing an ordered, sliceable set.

`UInt64Index([data, dtype, copy, name])` Immutable ndarray implementing an ordered, sliceable set.

`Float64Index([data, dtype, copy, name])` Immutable ndarray implementing an ordered, sliceable set.

**pandas.RangeIndex**

**class** `pandas.RangeIndex(start=None, stop=None, step=None, dtype=None, copy=False, name=None)`

Immutable Index implementing a monotonic integer range.

RangeIndex is a memory-saving special case of Int64Index limited to representing monotonic ranges. Using RangeIndex may in some instances improve computing speed.

This is the default index type used by DataFrame and Series when no explicit index is provided by the user.

**Parameters**

- `start` [int (default: 0), or other RangeIndex instance] If int and “stop” is not given, interpreted as “stop” instead.
- `stop` [int (default: 0)]
- `step` [int (default: 1)]
- `name` [object, optional] Name to be stored in the index.
- `copy` [bool, default False] Unused, accepted for homogeneity with other index types.

**See also:**

- `Index` The base pandas Index type.
- `Int64Index` Index of int64 data.
## Attributes

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>start</code></td>
<td>The value of the <code>start</code> parameter (0 if this was not supplied).</td>
</tr>
<tr>
<td><code>stop</code></td>
<td>The value of the <code>stop</code> parameter.</td>
</tr>
<tr>
<td><code>step</code></td>
<td>The value of the <code>step</code> parameter (1 if this was not supplied).</td>
</tr>
</tbody>
</table>

### pandas.RangeIndex.start

RangeIndex.`start`

The value of the `start` parameter (0 if this was not supplied).

### pandas.RangeIndex.stop

RangeIndex.`stop`

The value of the `stop` parameter.

### pandas.RangeIndex.step

RangeIndex.`step`

The value of the `step` parameter (1 if this was not supplied).

## Methods

### from_range(data[, name, dtype])

Create RangeIndex from a range object.

### pandas.RangeIndex.from_range

**classmethod** RangeIndex.`from_range`(data, name=None, dtype=None)

Create RangeIndex from a range object.

**Returns**

RangeIndex

## pandas.Int64Index

**class** pandas.`Int64Index`(data=None, dtype=None, copy=False, name=None)

Immutable ndarray implementing an ordered, sliceable set. The basic object storing axis labels for all pandas objects. Int64Index is a special case of `Index` with purely integer labels.

**Parameters**

- **data** [array-like (1-dimensional)]
- **dtype** [NumPy dtype (default: int64)]
- **copy** [bool] Make a copy of input ndarray.

3.7. Index objects
**name** [object] Name to be stored in the index.

**See also:**

*Index* The base pandas Index type.

**Notes**

An Index instance can only contain hashable objects.

**Attributes**

None

**Methods**

None

---

**pandas.UInt64Index**

**class** pandas.*UInt64Index*(data=None, dtype=None, copy=False, name=None)

Immutable ndarray implementing an ordered, sliceable set. The basic object storing axis labels for all pandas objects. UInt64Index is a special case of Index with purely unsigned integer labels.

**Parameters**

- **data** [array-like (1-dimensional)]
- **dtype** [NumPy dtype (default: uint64)]
- **copy** [bool] Make a copy of input ndarray.
- **name** [object] Name to be stored in the index.

**See also:**

*Index* The base pandas Index type.

**Notes**

An Index instance can only contain hashable objects.

**Attributes**

None
pandas: powerful Python data analysis toolkit, Release 1.1.1

Methods

None

pandas.Float64Index

class pandas.Float64Index(data=None, dtype=None, copy=False, name=None)

Immutable ndarray implementing an ordered, sliceable set. The basic object storing axis labels for all pandas objects. Float64Index is a special case of Index with purely float labels.

Parameters

- data [array-like (1-dimensional)]
- dtype [NumPy dtype (default: float64)]
- copy [bool] Make a copy of input ndarray.
- name [object] Name to be stored in the index.

See also:

Index The base pandas Index type.

Notes

An Index instance can only contain hashable objects.

Attributes

None

Methods

None

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>RangeIndex.start</td>
<td>The value of the start parameter (0 if this was not supplied).</td>
</tr>
<tr>
<td>RangeIndex.stop</td>
<td>The value of the stop parameter.</td>
</tr>
<tr>
<td>RangeIndex.step</td>
<td>The value of the step parameter (1 if this was not supplied).</td>
</tr>
<tr>
<td>RangeIndex.from_range(data[, name, dtype])</td>
<td>Create RangelIndex from a range object.</td>
</tr>
</tbody>
</table>
3.7.3 CategoricalIndex

CategoricalIndex([data, categories, ...])  
Index based on an underlying Categorical.

pandas.CategoricalIndex

class pandas.CategoricalIndex(data=None, categories=None, ordered=None, dtype=None, copy=False, name=None)

Index based on an underlying Categorical.

CategoricalIndex, like Categorical, can only take on a limited, and usually fixed, number of possible values (categories). Also, like Categorical, it might have an order, but numerical operations (additions, divisions, ...) are not possible.

Parameters

- **data** [array-like (1-dimensional)] The values of the categorical. If categories are given, values not in categories will be replaced with NaN.

- **categories** [index-like, optional] The categories for the categorical. Items need to be unique.
  
  If the categories are not given here (and also not in dtype), they will be inferred from the data.

- **ordered** [bool, optional] Whether or not this categorical is treated as an ordered categorical.
  
  If not given here or in dtype, the resulting categorical will be unordered.

- **dtype** [CategoricalDtype or “category”, optional] If CategoricalDtype, cannot be used together with categories or ordered.

- **copy** [bool, default False] Make a copy of input ndarray.

- **name** [object, optional] Name to be stored in the index.

Raises

- **ValueError** If the categories do not validate.

- **TypeError** If an explicit ordered=True is given but no categories and the values are not sortable.

See also:

- **Index** The base pandas Index type.

- **Categorical** A categorical array.

- **CategoricalDtype** Type for categorical data.

Notes

See the user guide for more.
Examples

>>> pd.CategoricalIndex(["a", "b", "c", "a", "b", "c"])
CategoricalIndex(['a', 'b', 'c', 'a', 'b', 'c'], categories=['a', 'b', 'c'], ordered=False, dtype='category')

CategoricalIndex can also be instantiated from a Categorical:

>>> c = pd.Categorical(["a", "b", "c", "a", "b", "c"])
>>> pd.CategoricalIndex(c)
CategoricalIndex(['a', 'b', 'c', 'a', 'b', 'c'], categories=['a', 'b', 'c'], ordered=False, dtype='category')

Ordered CategoricalIndex can have a min and max value.

>>> ci = pd.CategoricalIndex(
...     ["a", "b", "c", "a", "b", "c"], ordered=True, categories=['c', 'b', 'a']
... )
>>> ci
CategoricalIndex(['a', 'b', 'c', 'a', 'b', 'c'], categories=['c', 'b', 'a'], ordered=True, dtype='category')
>>> ci.min()
'c'

Attributes

<table>
<thead>
<tr>
<th>codes</th>
<th>The category codes of this categorical.</th>
</tr>
</thead>
<tbody>
<tr>
<td>categories</td>
<td>The categories of this categorical.</td>
</tr>
<tr>
<td>ordered</td>
<td>Whether the categories have an ordered relationship.</td>
</tr>
</tbody>
</table>

pandas.CategoricalIndex.codes

property CategoricalIndex.codes

The category codes of this categorical.

Codes are an array of integers which are the positions of the actual values in the categories array.

There is no setter, use the other categorical methods and the normal item setter to change values in the categorical.

Returns

    ndarray[int] A non-writable view of the codes array.
pandas.CategoricalIndex.categories

**property** CategoricalIndex.categories
The categories of this categorical.

Setting assigns new values to each category (effectively a rename of each individual category).
The assigned value has to be a list-like object. All items must be unique and the number of items in the new categories must be the same as the number of items in the old categories.
Assigning to categories is an in-place operation!

**Raises**

* ValueError: If the new categories do not validate as categories or if the number of new categories is unequal the number of old categories

**See also:**
- rename_categories Rename categories.
- reorder_categories Reorder categories.
- add_categories Add new categories.
- remove_categories Remove the specified categories.
- remove_unused_categories Remove categories which are not used.
- set_categories Set the categories to the specified ones.

pandas.CategoricalIndex.ordered

**property** CategoricalIndex.ordered
Whether the categories have an ordered relationship.

**Methods**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>rename_categories(*args, **kwags)</td>
<td>Rename categories.</td>
</tr>
<tr>
<td>reorder_categories(*args, **kwags)</td>
<td>Reorder categories as specified in new_categories.</td>
</tr>
<tr>
<td>add_categories(*args, **kwags)</td>
<td>Add new categories.</td>
</tr>
<tr>
<td>remove_categories(*args, **kwags)</td>
<td>Remove the specified categories.</td>
</tr>
<tr>
<td>remove_unused_categories(*args, **kwags)</td>
<td>Remove categories which are not used.</td>
</tr>
<tr>
<td>set_categories(*args, **kwags)</td>
<td>Set the categories to the specified new_categories.</td>
</tr>
<tr>
<td>as_ordered(*args, **kwags)</td>
<td>Set the Categorical to be ordered.</td>
</tr>
<tr>
<td>as_unordered(*args, **kwags)</td>
<td>Set the Categorical to be unordered.</td>
</tr>
<tr>
<td>map(mapper)</td>
<td>Map values using input correspondence (a dict, Series, or function).</td>
</tr>
</tbody>
</table>
pandas.CategoricalIndex.rename_categories

CategoricalIndex.rename_categories(*args, **kwargs)

Rename categories.

Parameters

new_categories [list-like, dict-like or callable] New categories which will replace old categories.

- list-like: all items must be unique and the number of items in the new categories must match the existing number of categories.
- dict-like: specifies a mapping from old categories to new. Categories not contained in the mapping are passed through and extra categories in the mapping are ignored.
- callable: a callable that is called on all items in the old categories and whose return values comprise the new categories.

New in version 0.23.0.

inplace [bool, default False] Whether or not to rename the categories inplace or return a copy of this categorical with renamed categories.

Returns

cat [Categorical or None] With inplace=False, the new categorical is returned. With inplace=True, there is no return value.

Raises

ValueError If new categories are list-like and do not have the same number of items as the current categories or do not validate as categories

See also:

reorder_categories Reorder categories.
add_categories Add new categories.
remove_categories Remove the specified categories.
remove_unused_categories Remove categories which are not used.
set_categories Set the categories to the specified ones.

Examples

>>> c = pd.Categorical(['a', 'a', 'b'])
>>> c.rename_categories([0, 1])
[0, 0, 1]
Categories (2, int64): [0, 1]

For dict-like new_categories, extra keys are ignored and categories not in the dictionary are passed through

>>> c.rename_categories({'a': 'A', 'c': 'C'})
['A', 'A', 'b']
Categories (2, object): ['A', 'b']

3.7. Index objects
You may also provide a callable to create the new categories

```python
>>> c.rename_categories(lambda x: x.upper())
['A', 'A', 'B']
Categories (2, object): ['A', 'B']
```

**pandas.CategoricalIndex.reorder_categories**

CategoricalIndex.reorder_categories (*args, **kwargs)

Reorder categories as specified in new_categories.

new_categories need to include all old categories and no new category items.

**Parameters**

- **new_categories** [Index-like] The categories in new order.
- **ordered** [bool, optional] Whether or not the categorical is treated as an ordered categorical. If not given, do not change the ordered information.
- **inplace** [bool, default False] Whether or not to reorder the categories inplace or return a copy of this categorical with reordered categories.

**Returns**

- **cat** [Categorical with reordered categories or None if inplace.]

**Raises**

ValueError If the new categories do not contain all old category items or any new ones

**See also:**

- rename_categories Rename categories.
- add_categories Add new categories.
- remove_categories Remove the specified categories.
- remove_unused_categories Remove categories which are not used.
- set_categories Set the categories to the specified ones.

**pandas.CategoricalIndex.add_categories**

CategoricalIndex.add_categories (*args, **kwargs)

Add new categories.

new_categories will be included at the last/highest place in the categories and will be unused directly after this call.

**Parameters**

- **new_categories** [category or list-like of category] The new categories to be included.
- **inplace** [bool, default False] Whether or not to add the categories inplace or return a copy of this categorical with added categories.

**Returns**

- **cat** [Categorical with new categories added or None if inplace.]
Raises

* ValueError If the new categories include old categories or do not validate as categories

See also:

rename_categories Rename categories.
reorder_categories Reorder categories.
remove_categories Remove the specified categories.
remove_unused_categories Remove categories which are not used.
set_categories Set the categories to the specified ones.

pandas.CategoricalIndex.remove_categories

CategoricalIndex.remove_categories(*args, **kwargs)
Remove the specified categories.

removals must be included in the old categories. Values which were in the removed categories will be set to NaN

Parameters

removals [category or list of categories] The categories which should be removed.
inplace [bool, default False] Whether or not to remove the categories inplace or return a copy of this categorical with removed categories.

Returns

cat [Categorical with removed categories or None if inplace.]

Raises

* ValueError If the removals are not contained in the categories

See also:

rename_categories Rename categories.
reorder_categories Reorder categories.
add_categories Add new categories.
remove_unused_categories Remove categories which are not used.
set_categories Set the categories to the specified ones.

pandas.CategoricalIndex.remove_unused_categories

CategoricalIndex.remove_unused_categories(*args, **kwargs)
Remove categories which are not used.

Parameters

inplace [bool, default False] Whether or not to drop unused categories inplace or return a copy of this categorical with unused categories dropped.

Returns

3.7. Index objects
cat  [Categorical with unused categories dropped or None if inplace.]

See also:

rename_categories Rename categories.
reorder_categories Reorder categories.
add_categories Add new categories.
remove_categories Remove the specified categories.
set_categories Set the categories to the specified ones.

pandas.CategoricalIndex.set_categories

CategoricalIndex.set_categories(*args, **kwargs)
Set the categories to the specified new_categories.

new_categories can include new categories (which will result in unused categories) or remove old categories (which results in values set to NaN). If rename=True, the categories will simply be renamed (less or more items than in old categories will result in values set to NaN or in unused categories respectively).

This method can be used to perform more than one action of adding, removing, and reordering simultaneously and is therefore faster than performing the individual steps via the more specialised methods.

On the other hand this method does not do checks (e.g., whether the old categories are included in the new categories on a reorder), which can result in surprising changes, for example when using special string dtypes, which does not considers a S1 string equal to a single char python string.

Parameters

new_categories  [Index-like] The categories in new order.
ordered  [bool, default False] Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.
rename  [bool, default False] Whether or not the new_categories should be considered as a rename of the old categories or as reordered categories.
inplace  [bool, default False] Whether or not to reorder the categories in-place or return a copy of this categorical with reordered categories.

Returns

Categorical with reordered categories or None if inplace.

Raises

ValueError  If new_categories does not validate as categories

See also:

rename_categories Rename categories.
reorder_categories Reorder categories.
add_categories Add new categories.
remove_categories Remove the specified categories.
remove_unused_categories Remove categories which are not used.
pandas.CategoricalIndex.as_ordered

CategoricalIndex.as_ordered(*args, **kwargs)
Set the Categorical to be ordered.

Parameters

inplace [bool, default False] Whether or not to set the ordered attribute in-place or return a copy of this categorical with ordered set to True.

Returns

Categorical Ordered Categorical.

pandas.CategoricalIndex.as_unordered

CategoricalIndex.as_unordered(*args, **kwargs)
Set the Categorical to be unordered.

Parameters

inplace [bool, default False] Whether or not to set the ordered attribute in-place or return a copy of this categorical with ordered set to False.

Returns

Categorical Unordered Categorical.

pandas.CategoricalIndex.map

CategoricalIndex.map(mapper)
Map values using input correspondence (a dict, Series, or function).

Maps the values (their categories, not the codes) of the index to new categories. If the mapping correspondence is one-to-one the result is a CategoricalIndex which has the same order property as the original, otherwise an Index is returned.

If a dict or Series is used any unmapped category is mapped to NaN. Note that if this happens an Index will be returned.

Parameters

mapper [function, dict, or Series] Mapping correspondence.

Returns

pandas.CategoricalIndex or pandas.Index Mapped index.

See also:

Index.map Apply a mapping correspondence on an Index.
Series.map Apply a mapping correspondence on a Series.
Series.apply Apply more complex functions on a Series.
Examples

```python
>>> idx = pd.CategoricalIndex(['a', 'b', 'c'])
>>> idx
CategoricalIndex(['a', 'b', 'c'], categories=['a', 'b', 'c'], ordered=False, dtype='category')
>>> idx.map(lambda x: x.upper())
CategoricalIndex(['A', 'B', 'C'], categories=['A', 'B', 'C'], ordered=False, dtype='category')
>>> idx.map({'a': 'first', 'b': 'second', 'c': 'third'})
CategoricalIndex(['first', 'second', 'third'], categories=['first', 'second', 'third'], ordered=False, dtype='category')
```

If the mapping is one-to-one the ordering of the categories is preserved:

```python
>>> idx = pd.CategoricalIndex(['a', 'b', 'c'], ordered=True)
>>> idx
CategoricalIndex(['a', 'b', 'c'], categories=['a', 'b', 'c'], ordered=True, dtype='category')
>>> idx.map({'a': 3, 'b': 2, 'c': 1})
CategoricalIndex([3, 2, 1], categories=[3, 2, 1], ordered=True, dtype='category')
```

If the mapping is not one-to-one an `Index` is returned:

```python
>>> idx.map({'a': 'first', 'b': 'second', 'c': 'first'})
Index(['first', 'second', 'first'], dtype='object')
```

If a `dict` is used, all unmapped categories are mapped to `NaN` and the result is an `Index`:

```python
>>> idx.map({'a': 'first', 'b': 'second'})
Index(['first', 'second', nan], dtype='object')
```

Categorical components

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>CategoricalIndex.codes</td>
<td>The category codes of this categorical.</td>
</tr>
<tr>
<td>CategoricalIndex.categories</td>
<td>The categories of this categorical.</td>
</tr>
<tr>
<td>CategoricalIndex.ordered</td>
<td>Whether the categories have an ordered relationship.</td>
</tr>
<tr>
<td>CategoricalIndex.rename_categories(*args,...)</td>
<td>Rename categories.</td>
</tr>
<tr>
<td>CategoricalIndex.reorder_categories(*args,...)</td>
<td>Reorder categories as specified in new_categories.</td>
</tr>
<tr>
<td>CategoricalIndex.add_categories(*args,**kwargs)</td>
<td>Add new categories.</td>
</tr>
<tr>
<td>CategoricalIndex.remove_categories(*args,...)</td>
<td>Remove the specified categories.</td>
</tr>
<tr>
<td>CategoricalIndex.remove_unused_categories(...)</td>
<td>Remove categories which are not used.</td>
</tr>
<tr>
<td>CategoricalIndex.set_categories(*args,**kwargs)</td>
<td>Set the Categories to the specified new_categories.</td>
</tr>
<tr>
<td>CategoricalIndex.as_ordered(*args,**kwargs)</td>
<td>Set the Categorical to be ordered.</td>
</tr>
</tbody>
</table>
```
Table 147 – continued from previous page

*CategoricalIndex.as_unordered(*args, **kwargs)*
Set the Categorical to be unordered.

Modifying and computations

*CategoricalIndex.map(mapper)*
Map values using input correspondence (a dict, Series, or function).

*CategoricalIndex.equals(other)*
Determine if two CategoricalIndex objects contain the same elements.

**pandas.CategoricalIndex.equals**

*CategoricalIndex.equals(other)*
Determine if two CategoricalIndex objects contain the same elements.

**Returns**

*bool* If two CategoricalIndex objects have equal elements True, otherwise False.

3.7.4 IntervalIndex

*IntervalIndex*(data[, closed, dtype, copy, ...])
Immutable index of intervals that are closed on the same side.

**pandas.IntervalIndex**

**class pandas.IntervalIndex**(data, closed=None, dtype=None, copy=False, name=None, verify_integrity=True)
Immutable index of intervals that are closed on the same side.

New in version 0.23.0.

**Parameters**

* data [array-like (1-dimensional)] Array-like containing Interval objects from which to build the IntervalIndex.

* closed [[‘left’, ‘right’, ‘both’, ‘neither’], default ‘right’] Whether the intervals are closed on the left-side, right-side, both or neither.

* dtype [dtype or None, default None] If None, dtype will be inferred.

* copy [bool, default False] Copy the input data.

* name [object, optional] Name to be stored in the index.

* verify_integrity [bool, default True] Verify that the IntervalIndex is valid.

**See also:**

*Index* The base pandas Index type.

*Interval* A bounded slice-like interval; the elements of an IntervalIndex.

*interval_range* Function to create a fixed frequency IntervalIndex.
**cut** Bin values into discrete Intervals.
**qcut** Bin values into equal-sized Intervals based on rank or sample quantiles.

**Notes**

See the user guide for more.

**Examples**

A new `IntervalIndex` is typically constructed using `interval_range()`:

```python
>>> pd.interval_range(start=0, end=5)
IntervalIndex([(0, 1], (1, 2], (2, 3], (3, 4], (4, 5]],
closed='right',
dtype='interval[int64]')
```

It may also be constructed using one of the constructor methods: `IntervalIndex.from_arrays()`, `IntervalIndex.from_breaks()`, and `IntervalIndex.from_tuples()`.

See further examples in the doc strings of `interval_range` and the mentioned constructor methods.

**Attributes**

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>left</code></td>
<td>Return the left endpoints of each Interval in the IntervalArray as an Index.</td>
</tr>
<tr>
<td><code>right</code></td>
<td>Return the right endpoints of each Interval in the IntervalArray as an Index.</td>
</tr>
<tr>
<td><code>closed</code></td>
<td>Whether the intervals are closed on the left-side, right-side, both or neither.</td>
</tr>
<tr>
<td><code>mid</code></td>
<td>Return the midpoint of each Interval in the IntervalArray as an Index.</td>
</tr>
<tr>
<td><code>length</code></td>
<td>Return an Index with entries denoting the length of each Interval in the IntervalArray.</td>
</tr>
<tr>
<td><code>is_empty</code></td>
<td>Indicates if an interval is empty, meaning it contains no points.</td>
</tr>
<tr>
<td><code>is_non_overlapping_monotonic</code></td>
<td>Return True if the IntervalArray is non-overlapping (no Intervals share points) and is either monotonic increasing or monotonic decreasing, else False.</td>
</tr>
<tr>
<td><code>is_overlapping</code></td>
<td>Return True if the IntervalIndex has overlapping intervals, else False.</td>
</tr>
<tr>
<td><code>values</code></td>
<td>Return the IntervalIndex’s data as an IntervalArray.</td>
</tr>
</tbody>
</table>
**pandas.IntervalIndex.left**

**property IntervalIndex.left**

Return the left endpoints of each Interval in the IntervalArray as an Index.

**pandas.IntervalIndex.right**

**property IntervalIndex.right**

Return the right endpoints of each Interval in the IntervalArray as an Index.

**pandas.IntervalIndex.closed**

IntervalIndex.closed

Whether the intervals are closed on the left-side, right-side, both or neither.

**pandas.IntervalIndex.mid**

IntervalIndex.mid

Return the midpoint of each Interval in the IntervalArray as an Index.

**pandas.IntervalIndex.length**

**property IntervalIndex.length**

Return an Index with entries denoting the length of each Interval in the IntervalArray.

**pandas.IntervalIndex.is_empty**

IntervalIndex.is_empty

Indicates if an interval is empty, meaning it contains no points.

New in version 0.25.0.

**Returns**

bool or ndarray A boolean indicating if a scalar Interval is empty, or a boolean ndarray positionally indicating if an Interval in an IntervalArray or IntervalIndex is empty.

**Examples**

An Interval that contains points is not empty:

```python
>>> pd.Interval(0, 1, closed='right').is_empty
False
```

An Interval that does not contain any points is empty:
An Interval that contains a single point is not empty:

```python
>>> pd.Interval(0, 0, closed='both').is_empty
False
```

An IntervalArray or IntervalIndex returns a boolean ndarray positionally indicating if an Interval is empty:

```python
>>> ivs = [pd.Interval(0, 0, closed='neither'),
         ...        pd.Interval(1, 2, closed='neither')]
>>> pd.arrays.IntervalArray(ivs).is_empty
array([ True, False])
```

Missing values are not considered empty:

```python
>>> ivs = [pd.Interval(0, 0, closed='neither'), np.nan]
>>> pd.IntervalIndex(ivs).is_empty
array([ True, False])
```

**pandas.IntervalIndex.is_non_overlapping_monotonic**

IntervalIndex.is_non_overlapping_monotonic
Return True if the IntervalArray is non-overlapping (no Intervals share points) and is either monotonic increasing or monotonic decreasing, else False.

**pandas.IntervalIndex.is_overlapping**

property IntervalIndex.is_overlapping
Return True if the IntervalIndex has overlapping intervals, else False.

Two intervals overlap if they share a common point, including closed endpoints. Intervals that only have an open endpoint in common do not overlap.

New in version 0.24.0.

Returns

- bool  Boolean indicating if the IntervalIndex has overlapping intervals.

See also:

- Interval.overlaps Check whether two Interval objects overlap.
- IntervalIndex.overlaps Check an IntervalIndex elementwise for overlaps.
Examples

```python
>>> index = pd.IntervalIndex.from_tuples([(0, 2), (1, 3), (4, 5)])
>>> index
IntervalIndex([(0, 2], (1, 3], (4, 5]],
            closed='right',
            dtype='interval[int64]')
>>> index.is_overlapping
True

Intervals that share closed endpoints overlap:

```python
>>> index = pd.interval_range(0, 3, closed='both')
>>> index
IntervalIndex([[0, 1], [1, 2], [2, 3]],
               closed='both',
               dtype='interval[int64]')
>>> index.is_overlapping
True

Intervals that only have an open endpoint in common do not overlap:

```python
>>> index = pd.interval_range(0, 3, closed='left')
>>> index
IntervalIndex([[0, 1), [1, 2), [2, 3)),
               closed='left',
               dtype='interval[int64]')
>>> index.is_overlapping
False
```

**pandas.IntervalIndex.values**

IntervalIndex.values

Return the IntervalIndex’s data as an IntervalArray.

**Methods**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>from_arrays</td>
<td>Construct from two arrays defining the left and right bounds.</td>
</tr>
<tr>
<td>from_tuples</td>
<td>Construct an IntervalIndex from an array-like of tuples.</td>
</tr>
<tr>
<td>from_breaks</td>
<td>Construct an IntervalIndex from an array of splits.</td>
</tr>
<tr>
<td>contains</td>
<td>Check elementwise if the Intervals contain the value.</td>
</tr>
<tr>
<td>overlaps</td>
<td>Check elementwise if an Interval overlaps the values in the IntervalArray.</td>
</tr>
<tr>
<td>set_closed</td>
<td>Return an IntervalArray identical to the current one, but closed on the specified side.</td>
</tr>
<tr>
<td>to_tuples</td>
<td>Return an ndarray of tuples of the form (left, right).</td>
</tr>
</tbody>
</table>
**pandas.IntervalIndex.from_arrays**

**classmethod** IntervalIndex.from_arrays(left, right, closed='right', name=None, copy=False, dtype=None)

Construct from two arrays defining the left and right bounds.

**Parameters**

- **left** [array-like (1-dimensional)] Left bounds for each interval.
- **right** [array-like (1-dimensional)] Right bounds for each interval.
- **closed** [{'left', 'right', 'both', 'neither'}, default 'right'] Whether the intervals are closed on the left-side, right-side, both or neither.
- **copy** [bool, default False] Copy the data.
- **dtype** [dtype, optional] If None, dtype will be inferred.

**Returns**

IntervalIndex

**Raises**

ValueError When a value is missing in only one of left or right. When a value in left is greater than the corresponding value in right.

**See also:**

- `interval_range` Function to create a fixed frequency IntervalIndex.
- IntervalIndex.from_breaks Construct an IntervalIndex from an array of splits.
- IntervalIndex.from_tuples Construct an IntervalIndex from an array-like of tuples.

**Notes**

Each element of left must be less than or equal to the right element at the same position. If an element is missing, it must be missing in both left and right. A TypeError is raised when using an unsupported type for left or right. At the moment, ‘category’, ‘object’, and ‘string’ subtypes are not supported.

**Examples**

```python
>>> pd.IntervalIndex.from_arrays([0, 1, 2], [1, 2, 3])
IntervalIndex([(0, 1], (1, 2], (2, 3]],
closed='right',
dtype='interval[int64]')
```
pandas.IntervalIndex.from_tuples

classmethod IntervalIndex.from_tuples(data, closed='right', name=None, copy=False, dtype=None)

Construct an IntervalIndex from an array-like of tuples.

Parameters

data [array-like (1-dimensional)] Array of tuples.
closed [{'left', 'right', 'both', 'neither'}, default 'right'] Whether the intervals are closed on the left-side, right-side, both or neither.
copy [bool, default False] By-default copy the data, this is compat only and ignored.
dtype [dtype or None, default None] If None, dtype will be inferred.

Returns

IntervalIndex

See also:

interval_range Function to create a fixed frequency IntervalIndex.
IntervalIndex.from_arrays Construct an IntervalIndex from a left and right array.
IntervalIndex.from_breaks Construct an IntervalIndex from an array of splits.

Examples

```python
>>> pd.IntervalIndex.from_tuples([(0, 1), (1, 2)])
IntervalIndex([(0, 1], (1, 2]),
closed='right',
dtype='interval[int64]')
```

pandas.IntervalIndex.from_breaks

classmethod IntervalIndex.from_breaks(breaks, closed='right', name=None, copy=False, dtype=None)

Construct an IntervalIndex from an array of splits.

Parameters

breaks [array-like (1-dimensional)] Left and right bounds for each interval.
closed [{'left', 'right', 'both', 'neither'}, default 'right'] Whether the intervals are closed on the left-side, right-side, both or neither.
copy [bool, default False] Copy the data.
dtype [dtype or None, default None] If None, dtype will be inferred.

Returns

IntervalIndex

See also:
**interval_range** Function to create a fixed frequency IntervalIndex.

**IntervalIndex.from_arrays** Construct from a left and right array.

**IntervalIndex.from_tuples** Construct from a sequence of tuples.

**Examples**

```python
>>> pd.IntervalIndex.from_breaks([0, 1, 2, 3])
IntervalIndex([(0, 1], (1, 2], (2, 3]],
closed='right',
dtype='interval[int64]')
```

**pandas.IntervalIndex.contains**

IntervalIndex.contains(*args, **kwargs)
Check elementwise if the Intervals contain the value.

Return a boolean mask whether the value is contained in the Intervals of the IntervalArray.

New in version 0.25.0.

**Parameters**

other [scalar] The value to check whether it is contained in the Intervals.

**Returns**

boolean array

**See also:**

Interval.contains Check whether Interval object contains value.

IntervalArray.overlaps Check if an Interval overlaps the values in the IntervalArray.

**Examples**

```python
>>> intervals = pd.arrays.IntervalArray.from_tuples([(0, 1), (1, 3), (2, 4)])
>>> intervals
<IntervalArray>
[(0, 1], (1, 3], (2, 4]]
Length: 3, closed: right, dtype: interval[int64]

>>> intervals.contains(0.5)
array([ True, False, False])
```
### pandas.IntervalIndex.overlaps

**IntervalIndex.overlaps(*args, **kwargs)**

Check elementwise if an Interval overlaps the values in the IntervalArray.

Two intervals overlap if they share a common point, including closed endpoints. Intervals that only have an open endpoint in common do not overlap.

New in version 0.24.0.

**Parameters**

- **other** [IntervalArray] Interval to check against for an overlap.

**Returns**

- **ndarray** Boolean array positionally indicating where an overlap occurs.

**See also:**

Interval.overlaps Check whether two Interval objects overlap.

**Examples**

```python
>>> data = [(0, 1), (1, 3), (2, 4)]
>>> intervals = pd.arrays.IntervalArray.from_tuples(data)
>>> intervals
 IntervalArray
[(0, 1], (1, 3], (2, 4]
Length: 3, closed: right, dtype: interval[int64]

>>> intervals.overlaps(pd.Interval(0.5, 1.5))
array([ True,  True, False])

Intervals that share closed endpoints overlap:

```python
>>> intervals.overlaps(pd.Interval(1, 3, closed='left'))
array([ True,  True, True])
```  
Intervals that only have an open endpoint in common do not overlap:

```python
>>> intervals.overlaps(pd.Interval(1, 2, closed='right'))
array([False,  True, False])
```  
### pandas.IntervalIndex.set_closed

**IntervalIndex.set_closed(*args, **kwargs)**

Return an IntervalArray identical to the current one, but closed on the specified side.

New in version 0.24.0.

**Parameters**

- **closed** [{’left’, ’right’, ’both’, ’neither’}] Whether the intervals are closed on the left-side, right-side, both or neither.

**Returns**
**Examples**

```python
>>> index = pd.arrays.IntervalArray.from_breaks(range(4))
>>> index
<IntervalArray>
[(0, 1], (1, 2], (2, 3]]
Length: 3, closed: right, dtype: interval[int64]

```

### pandas.IntervalIndex.to_tuples

`IntervalIndex.to_tuples(*args, **kwargs)`

Return an ndarray of tuples of the form (left, right).

**Parameters**

- `na_tuple` [bool, default True] Returns NA as a tuple if True, (nan, nan), or just as the NA value itself if False, nan.
  
  New in version 0.23.0.

**Returns**

- `tuples`: ndarray

### IntervalIndex components

<table>
<thead>
<tr>
<th><code>IntervalIndex.from_arrays(lef</code></th>
<th>Construct from two arrays defining the left and right bounds.</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>right[....])</code></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><code>IntervalIndex.from_tuples(data, closed, ...)</code></th>
<th>Construct an IntervalIndex from an array-like of tuples.</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th><code>IntervalIndex.from_breaks(breaks, closed, ...)</code></th>
<th>Construct an IntervalIndex from an array of splits.</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th><code>IntervalIndex.left</code></th>
<th>Return the left endpoints of each Interval in the IntervalArray as an Index.</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th><code>IntervalIndex.right</code></th>
<th>Return the right endpoints of each Interval in the IntervalArray as an Index.</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th><code>IntervalIndex.mid</code></th>
<th>Return the midpoint of each Interval in the IntervalArray as an Index.</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th><code>IntervalIndex.closed</code></th>
<th>Whether the intervals are closed on the left-side, right-side, both or neither.</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th><code>IntervalIndex.length</code></th>
<th>Return an Index with entries denoting the length of each Interval in the IntervalArray.</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th><code>IntervalIndex.values</code></th>
<th>Return the IntervalIndex’s data as an IntervalArray.</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th><code>IntervalIndex.is_empty</code></th>
<th>Indicates if an interval is empty, meaning it contains no points.</th>
</tr>
</thead>
</table>

continues on next page
IntervalIndex.is_non_overlapping_monotonic
Return True if the IntervalArray is non-overlapping (no Intervals share points) and is either monotonic increasing or monotonic decreasing, else False.

IntervalIndex.is_overlapping
Return True if the IntervalIndex has overlapping intervals, else False.

IntervalIndex.get_loc(key[, method, tolerance])
Get integer location, slice or boolean mask for requested label.

IntervalIndex.get_indexer(target[, method, ...])
Compute indexer and mask for new index given the current index.

IntervalIndex.set_closed(*args, **kwargs)
Return an IntervalArray identical to the current one, but closed on the specified side.

IntervalIndex.contains(*args, **kwargs)
Check elementwise if the Intervals contain the value.

IntervalIndex.overlaps(*args, **kwargs)
Check elementwise if an Interval overlaps the values in the IntervalArray.

IntervalIndex.to_tuples(*args, **kwargs)
Return an ndarray of tuples of the form (left, right).

### pandas.IntervalIndex.get_loc

**IntervalIndex.get_loc(key, method=None, tolerance=None)**
Get integer location, slice or boolean mask for requested label.

**Parameters**

- **key** [label]
- **method** [{None}, optional]
  - default: matches where the label is within an interval only.

**Returns**

- int if unique index, slice if monotonic index, else mask

**Examples**

```python
>>> i1, i2 = pd.Interval(0, 1), pd.Interval(1, 2)
>>> index = pd.IntervalIndex([i1, i2])
>>> index.get_loc(1)
0
```

You can also supply a point inside an interval.

```python
>>> index.get_loc(1.5)
1
```

If a label is in several intervals, you get the locations of all the relevant intervals.

```python
>>> i3 = pd.Interval(0, 2)
>>> overlapping_index = pd.IntervalIndex([i1, i2, i3])
>>> overlapping_index.get_loc(0.5)
array([ True, False,  True])
```

Only exact matches will be returned if an interval is provided.
>>> index.get_loc(pd.Interval(0, 1))
0

pandas.IntervalIndex.get_indexer

IntervalIndex.get_indexer(target, method=None, limit=None, tolerance=None)

Compute indexer and mask for new index given the current index. The indexer should be then used as an input to ndarray.take to align the current data to the new index.

Parameters

- **target** [IntervalIndex or list of Intervals]
- **method** [[None, 'pad'/'ffill', 'backfill'/'bfill', 'nearest'], optional]
  - default: exact matches only.
  - pad / ffill: find the PREVIOUS index value if no exact match.
  - backfill / bfill: use NEXT index value if no exact match
  - nearest: use the NEAREST index value if no exact match. Tied distances are broken by preferring the larger index value.
- **limit** [int, optional] Maximum number of consecutive labels in target to match for inexact matches.
- **tolerance** [optional] Maximum distance between original and new labels for inexact matches. The values of the index at the matching locations most satisfy the equation abs(index[indexer] - target) <= tolerance.

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index’s type.

Returns

- **indexer** [ndarray of int] Integers from 0 to n - 1 indicating that the index at these positions matches the corresponding target values. Missing values in the target are marked by -1.

Raises

- **NotImplementedError** If any method argument other than the default of None is specified as these are not yet implemented.

Examples

```python
>>> index = pd.Index(['c', 'a', 'b'])
>>> index.get_indexer(['a', 'b', 'x'])
array([ 1, 2, -1])
```

Notice that the return value is an array of locations in index and x is marked by -1, as it is not in index.
### 3.7.5 MultiIndex

| MultiIndex(levels, codes, sortorder, ...) | A multi-level, or hierarchical, index object for pandas objects. |

**pandas.MultiIndex**

```python
class pandas.MultiIndex(levels=None, codes=None, sortorder=None, names=None, dtype=None, copy=False, name=None, verify_integrity=True, _set_identity=True)
```

A multi-level, or hierarchical, index object for pandas objects.

**Parameters**

- **levels** [sequence of arrays] The unique labels for each level.
- **codes** [sequence of arrays] Integers for each level designating which label at each location.
  - New in version 0.24.0.
- **sortorder** [optional int] Level of sortedness (must be lexicographically sorted by that level).
- **names** [optional sequence of objects] Names for each of the index levels. (name is accepted for compat).
- **copy** [bool, default False] Copy the meta-data.
- **verify_integrity** [bool, default True] Check that the levels/codes are consistent and valid.

**See also:**

- `MultiIndex.from_arrays` Convert list of arrays to MultiIndex.
- `MultiIndex.from_product` Create a MultiIndex from the cartesian product of iterables.
- `MultiIndex.from_tuples` Convert list of tuples to a MultiIndex.
- `MultiIndex.from_frame` Make a MultiIndex from a DataFrame.
- `Index` The base pandas Index type.

**Notes**

See the user guide for more.

**Examples**

A new `MultiIndex` is typically constructed using one of the helper methods `MultiIndex.from_arrays()`, `MultiIndex.from_product()` and `MultiIndex.from_tuples()`. For example (using `from_arrays`):

```python
>>> arrays = [[1, 1, 2, 2], ['red', 'blue', 'red', 'blue']]
>>> pd.MultiIndex.from_arrays(arrays, names=('number', 'color'))
MultiIndex([(1, 'red'),
            (1, 'blue'),
            (2, 'red'),
            (2, 'blue')], names=['number', 'color'])
```

See further examples for how to construct a MultiIndex in the doc strings of the mentioned helper methods.
pandas: powerful Python data analysis toolkit, Release 1.1.1

Attributes

<table>
<thead>
<tr>
<th>names</th>
<th>Names of levels in MultiIndex.</th>
</tr>
</thead>
<tbody>
<tr>
<td>nlevels</td>
<td>Integer number of levels in this MultiIndex.</td>
</tr>
<tr>
<td>levshape</td>
<td>A tuple with the length of each level.</td>
</tr>
</tbody>
</table>

pandas.MultiIndex.names

property MultiIndex.names
Names of levels in MultiIndex.

pandas.MultiIndex.nlevels

property MultiIndex.nlevels
Integer number of levels in this MultiIndex.

pandas.MultiIndex.levshape

property MultiIndex.levshape
A tuple with the length of each level.

<table>
<thead>
<tr>
<th>levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>codes</td>
</tr>
</tbody>
</table>

Methods

from_arrays(arrays[, sortorder, names]) Convert arrays to MultiIndex.

from_tuples(tuples[, sortorder, names]) Convert list of tuples to MultiIndex.

from_product(iterables[, sortorder, names]) Make a MultiIndex from the cartesian product of multiple iterables.

from_frame(df[, sortorder, names]) Make a MultiIndex from a DataFrame.

set_levels(levels[, level, inplace, ...]) Set new levels on MultiIndex.

set_codes(codes[, level, inplace, ...]) Set new codes on MultiIndex.

to_frame([index, name]) Create a DataFrame with the levels of the MultiIndex as columns.

to_flat_index() Convert a MultiIndex to an Index of Tuples containing the level values.

is_lexsorted() Return True if the codes are lexicographically sorted.

sortlevel([level, ascending, sort_remaining]) Sort MultiIndex at the requested level.

droplevel([level]) Return index with requested level(s) removed.

swaplevel([i, j]) Swap level i with level j.

reorder_levels(order) Rearrange levels using input order.

remove_unused_levels() Create new MultiIndex from current that removes unused levels.

get_locs(seq) Get location for a sequence of labels.
pandas.MultiIndex.from_arrays

classmethod  MultiIndex.from_arrays(arrays, sortorder=None, names=<object object>)
Convert arrays to MultiIndex.

Parameters
arrays  [list / sequence of array-likes] Each array-like gives one level’s value for each
data point. len(arrays) is the number of levels.

sortorder  [int or None] Level of sortedness (must be lexicographically sorted by that
level).

names  [list / sequence of str, optional] Names for the levels in the index.

Returns
MultiIndex

See also:

MultiIndex.from_tuples  Convert list of tuples to MultiIndex.
MultiIndex.from_product  Make a MultiIndex from cartesian product of iterables.
MultiIndex.from_frame  Make a MultiIndex from a DataFrame.

Examples

```python
>>> arrays = [[1, 1, 2, 2], ['red', 'blue', 'red', 'blue']]
>>> pd.MultiIndex.from_arrays(arrays, names=('number', 'color'))
MultiIndex([(1, 'red'),
           (1, 'blue'),
           (2, 'red'),
           (2, 'blue')],
          names=['number', 'color'])
```

pandas.MultiIndex.from_tuples

classmethod  MultiIndex.from_tuples(tuples, sortorder=None, names=None)
Convert list of tuples to MultiIndex.

Parameters
tuples  [list / sequence of tuple-likes] Each tuple is the index of one row/column.

sortorder  [int or None] Level of sortedness (must be lexicographically sorted by that
level).

names  [list / sequence of str, optional] Names for the levels in the index.

Returns
MultiIndex

See also:

MultiIndex.from_arrays  Convert list of arrays to MultiIndex.
MultiIndex.from_product  Make a MultiIndex from cartesian product of iterables.
**MultiIndex.from_frame** Make a MultiIndex from a DataFrame.

**Examples**

```python
>>> tuples = [(1, 'red'), (1, 'blue'),
...            (2, 'red'), (2, 'blue')]
>>> pd.MultiIndex.from_tuples(tuples, names=('number', 'color'))
MultiIndex([(1, 'red'),
            (1, 'blue'),
            (2, 'red'),
            (2, 'blue')],
           names=['number', 'color'])
```

**pandas.MultiIndex.from_product**

**classmethod** MultiIndex.from_product(*iterables*, sortorder=None, names=<object object>)

Make a MultiIndex from the cartesian product of multiple iterables.

**Parameters**

- **iterables** [list / sequence of iterables] Each iterable has unique labels for each level of the index.
- **sortorder** [int or None] Level of sortedness (must be lexicographically sorted by that level).
- **names** [list / sequence of str, optional] Names for the levels in the index.

Changed in version 1.0.0: If not explicitly provided, names will be inferred from the elements of iterables if an element has a name attribute

**Returns**

MultiIndex

**See also:**

**MultiIndex.from_arrays** Convert list of arrays to MultiIndex.

**MultiIndex.from_tuples** Convert list of tuples to MultiIndex.

**MultiIndex.from_frame** Make a MultiIndex from a DataFrame.

**Examples**

```python
>>> numbers = [0, 1, 2]
>>> colors = ['green', 'purple']
>>> pd.MultiIndex.from_product([numbers, colors],
                             names=['number', 'color'])
MultiIndex([(0, 'green'),
            (0, 'purple'),
            (1, 'green'),
            (1, 'purple'),
            (2, 'green'),
            (2, 'purple')],
           names=['number', 'color'])
```
pandas.MultiIndex.from_frame

**classmethod**  

`MultiIndex.from_frame(df, sortorder=None, names=None)`  
Make a MultiIndex from a DataFrame.  
New in version 0.24.0.

**Parameters**

- `df` [DataFrame] DataFrame to be converted to MultiIndex.
- `sortorder` [int, optional] Level of sortedness (must be lexicographically sorted by that level).
- `names` [list-like, optional] If no names are provided, use the column names, or tuple of column names if the columns is a MultiIndex. If a sequence, overwrite names with the given sequence.

**Returns**

`MultiIndex` The MultiIndex representation of the given DataFrame.

**See also:**

- `MultiIndex.from_arrays` Convert list of arrays to MultiIndex.
- `MultiIndex.from_tuples` Convert list of tuples to MultiIndex.
- `MultiIndex.from_product` Make a MultiIndex from cartesian product of iterables.

**Examples**

```python
>>> df = pd.DataFrame([[['HI', 'Temp'], ['HI', 'Precip']],
                    [['NJ', 'Temp'], ['NJ', 'Precip']],
                    columns=['a', 'b'])
>>> df
   a    b
0  HI  Temp
1  HI  Precip
2  NJ  Temp
3  NJ  Precip
```

```python
>>> pd.MultiIndex.from_frame(df)
MultiIndex([('HI', 'Temp'),
            ('HI', 'Precip'),
            ('NJ', 'Temp'),
            ('NJ', 'Precip')],
           names=['a', 'b'])
```

Using explicit names, instead of the column names

```python
>>> pd.MultiIndex.from_frame(df, names=['state', 'observation'])
MultiIndex([('HI', 'Temp'),
            ('HI', 'Precip'),
            ('NJ', 'Temp'),
            ('NJ', 'Precip')],
           names=['state', 'observation'])
```
pandas.MultiIndex.set_levels

```
MultiIndex.set_levels(levels, level=None, inplace=False, verify_integrity=True)
```

Set new levels on MultiIndex. Defaults to returning new index.

**Parameters**

- `levels` [sequence or list of sequence] New level(s) to apply.
- `level` [int, level name, or sequence of int/level names (default None)] Level(s) to set (None for all levels).
- `inplace` [bool] If True, mutates in place.
- `verify_integrity` [bool, default True] If True, checks that levels and codes are compatible.

**Returns**

- new index (of same type and class...etc)

**Examples**

```python
>>> idx = pd.MultiIndex.from_tuples(
...     [(1, "one"),
...      (1, "two"),
...      (2, "one"),
...      (2, "two"),
...      (3, "one"),
...      (3, "two")],
...     names=['foo', 'bar'])
```

```python
>>> idx.set_levels([['a', 'b', 'c'], [1, 2]])
```

```python
>>> idx.set_levels([['a', 'b', 'c'], [1, 2]], level=0)
```

(continues on next page)
names=['foo', 'bar'])
>>> idx.set_levels([['a', 'b'], [1, 2, 3, 4]], level=[0, 1])
MultiIndex([['a', 'b', 'c'], [1, 2, 3, 4]], level=[0, 1])
>>> idx.set_levels([['a', 'b', 'c'], [1, 2, 3, 4]], level=[0, 1]).levels
FrozenList([['a', 'b', 'c'], [1, 2, 3, 4]])

pandas.MultiIndex.set_codes

MultiIndex.set_codes(codes, level=None, inplace=False, verify_integrity=True)

Set new codes on MultiIndex. Defaults to returning new index.

New in version 0.24.0: New name for deprecated method set_labels.

Parameters

codes [sequence or list of sequence] New codes to apply.

level [int, level name, or sequence of int/level names (default None)] Level(s) to set (None for all levels).

inplace [bool] If True, mutates in place.

verify_integrity [bool (default True)] If True, checks that levels and codes are compatible.

Returns

new index (of same type and class... etc)
Examples

```python
>>> idx = pd.MultiIndex.from_tuples(
...     [(1, "one"), (1, "two"), (2, "one"), (2, "two")], names=["foo", "bar"]
... )
>>> idx
MultiIndex([(1, 'one'),
             (1, 'two'),
             (2, 'one'),
             (2, 'two')],
            names=['foo', 'bar'])
```

```python
>>> idx.set_codes([[1, 0, 1, 0], [0, 0, 1, 1]])
MultiIndex([(2, 'one'),
             (1, 'two'),
             (2, 'one'),
             (1, 'two')],
            names=['foo', 'bar'])
```

```python
>>> idx.set_codes([1, 0, 1, 0], level=0)
MultiIndex([(2, 'one'),
             (1, 'two'),
             (2, 'one'),
             (1, 'two')],
            names=['foo', 'bar'])
```

```python
>>> idx.set_codes([0, 0, 1, 1], level='bar')
MultiIndex([(1, 'one'),
             (1, 'one'),
             (2, 'two'),
             (2, 'two')],
            names=['foo', 'bar'])
```

```python
>>> idx.set_codes([[1, 0, 1, 0], [0, 0, 1, 1]], level=[0, 1])
MultiIndex([(2, 'one'),
             (1, 'one'),
             (2, 'two'),
             (1, 'two')],
            names=['foo', 'bar'])
```

**pandas.MultiIndex.to_frame**

`MultiIndex.to_frame(index=True, name=None)`

Create a DataFrame with the levels of the MultiIndex as columns.

Column ordering is determined by the DataFrame constructor with data as a dict.

New in version 0.24.0.

**Parameters**

- `index` [bool, default True] Set the index of the returned DataFrame as the original MultiIndex.
- `name` [list / sequence of str, optional] The passed names should substitute index level names.

**Returns**

- `DataFrame` [a DataFrame containing the original MultiIndex data.]
See also:

DataFrame Two-dimensional, size-mutable, potentially heterogeneous tabular data.

pandas.MultiIndex.to_flat_index

MultiIndex.to_flat_index()
Convert a MultiIndex to an Index of Tuples containing the level values.
New in version 0.24.0.

Returns

pd.Index Index with the MultiIndex data represented in Tuples.

Notes

This method will simply return the caller if called by anything other than a MultiIndex.

Examples

```python
>>> index = pd.MultiIndex.from_product(
...     [['foo', 'bar'], ['baz', 'qux']],
...     names=['a', 'b'])
>>> index.to_flat_index()
Index([('foo', 'baz'), ('foo', 'qux'),
     ('bar', 'baz'), ('bar', 'qux')],
     dtype='object')
```

pandas.MultiIndex.is_lexsorted

MultiIndex.is_lexsorted()
Return True if the codes are lexicographically sorted.

Returns

bool

Examples

In the below examples, the first level of the MultiIndex is sorted because a<b<c, so there is no need to look at the next level.

```python
>>> pd.MultiIndex.from_arrays([['a', 'b', 'c'], ['d', 'e', 'f']]).is_lexsorted()
True
>>> pd.MultiIndex.from_arrays([['a', 'b', 'c'], ['d', 'f', 'e']]).is_lexsorted()
True
```

In case there is a tie, the lexicographical sorting looks at the next level of the MultiIndex.
>>> pd.MultiIndex.from_arrays([[0, 1, 1], ['a', 'b', 'c']]).is_lexsorted()
True
>>> pd.MultiIndex.from_arrays([[0, 1, 1], ['a', 'c', 'b']]).is_lexsorted()
False
>>> pd.MultiIndex.from_arrays([['a', 'a', 'b', 'b'], ['aa', 'aa', 'bb', 'bb']]).is_lexsorted()
True
>>> pd.MultiIndex.from_arrays([['a', 'a', 'b', 'b'], ['bb', 'aa', 'aa', 'bb']]).is_lexsorted()
False

pandas.MultiIndex.sortlevel

MultiIndex.sortlevel(level=0, ascending=True, sort_remaining=True)
Sort MultiIndex at the requested level.

The result will respect the original ordering of the associated factor at that level.

Parameters

- **level** [list-like, int or str, default 0] If a string is given, must be a name of the level. If list-like must be names or ints of levels.
- **ascending** [bool, default True] False to sort in descending order. Can also be a list to specify a directed ordering.
- **sort_remaining** [sort by the remaining levels after level]

Returns

- **sorted_index** [pd.MultiIndex] Resulting index.
- **indexer** [np.ndarray] Indices of output values in original index.

pandas.MultiIndex.droplevel

MultiIndex.droplevel(level=0)
Return index with requested level(s) removed.

If resulting index has only 1 level left, the result will be of Index type, not MultiIndex.

New in version 0.23.1: (support for non-MultiIndex)

Parameters

- **level** [int, str, or list-like, default 0] If a string is given, must be the name of a level If list-like, elements must be names or indexes of levels.

Returns

- **Index or MultiIndex**
pandas.MultiIndex.swaplevel

MultiIndex.swaplevel(i=-2, j=-1)

Swap level i with level j.

Calling this method does not change the ordering of the values.

Parameters

- **i** [int, str, default -2] First level of index to be swapped. Can pass level name as string. Type of parameters can be mixed.
- **j** [int, str, default -1] Second level of index to be swapped. Can pass level name as string. Type of parameters can be mixed.

Returns

- **MultiIndex** A new MultiIndex.

See also:

Series.swaplevel Swap levels i and j in a MultiIndex.

DataFrame.swaplevel Swap levels i and j in a MultiIndex on a particular axis.

Examples

```python
>>> mi = pd.MultiIndex(levels=[['a', 'b'], ['bb', 'aa']],
                     codes=[[0, 0, 1, 1], [0, 1, 0, 1]])
>>> mi
MultiIndex([('a', 'bb'),
            ('a', 'aa'),
            ('b', 'bb'),
            ('b', 'aa')],
           )
>>> mi.swaplevel(0, 1)
MultiIndex([('bb', 'a'),
            ('aa', 'a'),
            ('bb', 'b'),
            ('aa', 'b')],
           )
```

pandas.MultiIndex.reorder_levels

MultiIndex.reorder_levels(order)

Rearrange levels using input order. May not drop or duplicate levels.

Parameters

- **order** [list of int or list of str] List representing new level order. Reference level by number (position) or by key (label).

Returns

- **MultiIndex**
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.MultiIndex.remove_unused_levels

MultiIndex.remove_unused_levels()
Create new MultiIndex from current that removes unused levels.
Unused level(s) means levels that are not expressed in the labels. The resulting MultiIndex will have the
same outward appearance, meaning the same .values and ordering. It will also be .equals() to the original.

Returns
MultiIndex

Examples

```python
>>> mi = pd.MultiIndex.from_product([range(2), list('ab')]
>>> mi
MultiIndex([(0, 'a'),
            (0, 'b'),
            (1, 'a'),
            (1, 'b')],
           )

>>> mi[2:]
MultiIndex([(l, 'a'),
            (l, 'b')],
           )

The 0 from the first level is not represented and can be removed

>>> mi2 = mi[2:].remove_unused_levels()
>>> mi2.levels
FrozenList([[[1], ['a', 'b']]])
```

pandas.MultiIndex.get_locs

MultiIndex.get_locs(seq)
Get location for a sequence of labels.

Parameters

seq [label, slice, list, mask or a sequence of such] You should use one of the above for
each level. If a level should not be used, set it to slice(None).

Returns
numpy.ndarray NumPy array of integers suitable for passing to iloc.

See also:

MultiIndex.get_loc Get location for a label or a tuple of labels.
MultiIndex.slice_locs Get slice location given start label(s) and end label(s).
Examples

```python
>>> mi = pd.MultiIndex.from_arrays([list('abb'), list('def')])

>>> mi.get_locs('b')
array([1, 2], dtype=int64)

>>> mi.get_locs([slice(None), ['e', 'f']])
array([1, 2], dtype=int64)

>>> mi.get_locs([[True, False, True], slice('e', 'f')])
array([2], dtype=int64)
```

IndexSlice
Create an object to more easily perform multi-index slicing.

```python
pandas.IndexSlice
pandas.IndexSlice = <pandas.core.indexing._IndexSlice object>
Create an object to more easily perform multi-index slicing.

See also:

```
MultiIndex.remove_unused_levels
```
New MultiIndex with no unused levels.

Notes

See Defined Levels for further info on slicing a MultiIndex.

Examples

```python
>>> midx = pd.MultiIndex.from_product([['A0','A1'], ['B0','B1','B2','B3']])
>>> columns = ['foo', 'bar']
>>> dfmi = pd.DataFrame(np.arange(16).reshape((len(midx), len(columns))),
                      index=midx, columns=columns)

Using the default slice command:

```python
>>> dfmi.loc[(slice(None), slice('B0', 'B1')), :]
   foo  bar
A0  B0   0  1
  B1  2  3
A1  B0   8  9
  B1 10 11
```

Using the IndexSlice class for a more intuitive command:

```python
>>> idx = pd.IndexSlice
>>> dfmi.loc[idx[:, 'B0':'B1'], :]
   foo  bar
A0  B0   0  1
  B1  2  3
```
MultiIndex constructors

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>MultiIndex.from_arrays</td>
<td>Convert arrays to MultiIndex.</td>
</tr>
<tr>
<td>MultiIndex.from_tuples</td>
<td>Convert list of tuples to MultiIndex.</td>
</tr>
<tr>
<td>MultiIndex.from_product</td>
<td>Make a MultiIndex from the cartesian product of multiple iterables.</td>
</tr>
<tr>
<td>MultiIndex.from_frame</td>
<td>Make a MultiIndex from a DataFrame.</td>
</tr>
</tbody>
</table>

MultiIndex properties

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>MultiIndex.names</td>
<td>Names of levels in MultiIndex.</td>
</tr>
<tr>
<td>MultiIndex.levels</td>
<td></td>
</tr>
<tr>
<td>MultiIndex.codes</td>
<td></td>
</tr>
<tr>
<td>MultiIndex.nlevels</td>
<td>Integer number of levels in this MultiIndex.</td>
</tr>
<tr>
<td>MultiIndex.levshape</td>
<td>A tuple with the length of each level.</td>
</tr>
</tbody>
</table>

pandas.MultiIndex.levels

MultiIndex.levels

pandas.MultiIndex.codes

property pandas.MultiIndex.codes

MultiIndex components

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>MultiIndex.set_levels</td>
<td>Set new levels on MultiIndex.</td>
</tr>
<tr>
<td>MultiIndex.set_codes</td>
<td>Set new codes on MultiIndex.</td>
</tr>
<tr>
<td>MultiIndex.to_flat_index</td>
<td>Convert a MultiIndex to an Index of Tuples containing the level values.</td>
</tr>
<tr>
<td>MultiIndex.to_frame</td>
<td>Create a DataFrame with the levels of the MultiIndex as columns.</td>
</tr>
<tr>
<td>MultiIndex.is_lexsorted</td>
<td>Return True if the codes are lexicographically sorted.</td>
</tr>
<tr>
<td>MultiIndex.sortlevel</td>
<td>Sort MultiIndex at the requested level.</td>
</tr>
<tr>
<td>MultiIndex.drop_level</td>
<td>Return index with requested level(s) removed.</td>
</tr>
<tr>
<td>MultiIndex.swaplevel</td>
<td>Swap level i with level j.</td>
</tr>
<tr>
<td>MultiIndex.reorder_levels</td>
<td>Rearrange levels using input order.</td>
</tr>
<tr>
<td>MultiIndex.remove_unused_levels</td>
<td>Create new MultiIndex from current that removes unused levels.</td>
</tr>
</tbody>
</table>

(continued from previous page)
MultiIndex selecting

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>MultiIndex.get_loc(key[, method])</td>
<td>Get location for a label or a tuple of labels.</td>
</tr>
<tr>
<td>MultiIndex.get_locs(seq)</td>
<td>Get location for a sequence of labels.</td>
</tr>
<tr>
<td>MultiIndex.get_loc_level(key[, level, ...])</td>
<td>Get location and sliced index for requested label(s)/level(s).</td>
</tr>
<tr>
<td>MultiIndex.get_indexer(target[, method, ...])</td>
<td>Compute indexer and mask for new index given the current index.</td>
</tr>
<tr>
<td>MultiIndex.get_level_values(level)</td>
<td>Return vector of label values for requested level.</td>
</tr>
</tbody>
</table>

pandas.MultiIndex.get_loc

MultiIndex.get_loc(key, method=None)

Get location for a label or a tuple of labels.

The location is returned as an integer/slice or boolean mask.

Parameters

- **key** [label or tuple of labels (one for each level)]
- **method** [None]

Returns

- **loc** [int, slice object or boolean mask] If the key is past the lexsort depth, the return may be a boolean mask array, otherwise it is always a slice or int.

See also:

- Index.get_loc The get_loc method for (single-level) index.
- MultiIndex.slice_locs Get slice location given start label(s) and end label(s).
- MultiIndex.get_locs Get location for a label/slice/list/mask or a sequence of such.

Notes

The key cannot be a slice, list of same-level labels, a boolean mask, or a sequence of such. If you want to use those, use MultiIndex.get_locs() instead.

Examples

```python
>>> mi = pd.MultiIndex.from_arrays([list('abb'), list('def')])

>>> mi.get_loc('b')
slice(1, 3, None)

>>> mi.get_loc(('b', 'e'))
1
```
pandas.MultiIndex.get_loc_level

**MultiIndex.get_loc_level** *(key, level=0, drop_level=True)*
Get location and sliced index for requested label(s)/level(s).

**Parameters**
- **key** [label or sequence of labels]
- **level** [int/level name or list thereof, optional]
- **drop_level** [bool, default True] If False, the resulting index will not drop any level.

**Returns**
- **loc** [A 2-tuple where the elements are:] Element 0: int, slice object or boolean array Element 1: The resulting sliced multiindex/index. If the key contains all levels, this will be None.

**See also:**
- **MultiIndex.get_loc** Get location for a label or a tuple of labels.
- **MultiIndex.get_locs** Get location for a label/slice/list/mask or a sequence of such.

**Examples**

```python
>>> mi = pd.MultiIndex.from_arrays([[list('abb'), list('def')],
                                  ...
                                  names=['A', 'B'])

>>> mi.get_loc_level('b')
(slice(1, 3, None), Index(['e', 'f'], dtype='object', name='B'))

>>> mi.get_loc_level('e', level='B')
(array([False, True, False]), Index(['b'], dtype='object', name='A'))

>>> mi.get_loc_level(['b', 'e'])
(1, None)
```

pandas.MultiIndex.get_indexer

**MultiIndex.get_indexer** *(target, method=None, limit=None, tolerance=None)*
Compute indexer and mask for new index given the current index. The indexer should be then used as an input to ndarray.take to align the current data to the new index.

**Parameters**
- **target** [MultiIndex or list of tuples]
- **method** [{None, 'pad'/'ffill', 'backfill'/'bfill', 'nearest'}, optional]
  - default: exact matches only.
  - pad / ffill: find the PREVIOUS index value if no exact match.
  - backfill / bfill: use NEXT index value if no exact match
  - nearest: use the NEAREST index value if no exact match. Tied distances are broken by preferring the larger index value.
limit [int, optional] Maximum number of consecutive labels in target to match for inexact matches.

tolerance [optional] Maximum distance between original and new labels for inexact matches. The values of the index at the matching locations most satisfy the equation
abs(index[indexer] - target) <= tolerance.

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index’s type.

Returns

indexer [ndarray of int] Integers from 0 to n - 1 indicating that the index at these positions matches the corresponding target values. Missing values in the target are marked by -1.

Examples

```python
>>> index = pd.Index(['c', 'a', 'b'])
>>> index.get_indexer(['a', 'b', 'x'])
array([ 1, 2, -1])
```

Notice that the return value is an array of locations in index and x is marked by -1, as it is not in index.

pandas.MultiIndex.get_level_values

MultiIndex.get_level_values(level)

Return vector of label values for requested level.

Length of returned vector is equal to the length of the index.

Parameters

level [int or str] level is either the integer position of the level in the MultiIndex, or the name of the level.

Returns

values [Index] Values is a level of this MultiIndex converted to a single Index (or subclass thereof).

Examples

Create a MultiIndex:

```python
>>> mi = pd.MultiIndex.from_arrays((list('abc'), list('def')))
>>> mi.names = ['level_1', 'level_2']
```

Get level values by supplying level as either integer or name:

```python
>>> mi.get_level_values(0)
Index(['a', 'b', 'c'], dtype='object', name='level_1')
>>> mi.get_level_values('level_2')
Index(['d', 'e', 'f'], dtype='object', name='level_2')
```
3.7.6 DatetimeIndex

DatetimeIndex([data, freq, tz, normalize, ...])  
Immutable ndarray-like of datetime64 data.

pandas.DatetimeIndex

class pandas.DatetimeIndex(data=None, freq=<object object>, tz=None, normalize=False, closed=None, ambiguous='raise', dayfirst=False, yearfirst=False, dtype=None, copy=False, name=None)

Immutable ndarray-like of datetime64 data.

Represented internally as int64, and which can be boxed to Timestamp objects that are subclasses of datetime and carry metadata.

Parameters

data [array-like (1-dimensional), optional] Optional datetime-like data to construct index with.

freq [str or pandas offset object, optional] One of pandas date offset strings or corresponding objects. The string ‘infer’ can be passed in order to set the frequency of the index as the inferred frequency upon creation.

tz [pytz.timezone or dateutil.tz.tzfile or datetime.tzinfo or str] Set the Timezone of the data.

normalize [bool, default False] Normalize start/end dates to midnight before generating date range.

closed [[‘left’, ‘right’], optional] Set whether to include start and end that are on the boundary. The default includes boundary points on either end.

ambiguous [‘infer’, bool-ndarray, ‘NaT’, default ‘raise’] When clocks moved backward due to DST, ambiguous times may arise. For example in Central European Time (UTC+01), when going from 03:00 DST to 02:00 non-DST, 02:30:00 local time occurs both at 00:30:00 UTC and at 01:30:00 UTC. In such a situation, the ambiguous parameter dictates how ambiguous times should be handled.

• ‘infer’ will attempt to infer fall dst-transition hours based on order
• bool-ndarray where True signifies a DST time, False signifies a non-DST time (note that this flag is only applicable for ambiguous times)
• ‘NaT’ will return NaT where there are ambiguous times
• ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

dayfirst [bool, default False] If True, parse dates in data with the day first order.

yearfirst [bool, default False] If True parse dates in data with the year first order.

dtype [numpy.dtype or DatetimeTZDtype or str, default None] Note that the only NumPy dtype allowed is ‘datetime64[ns]’.

copy [bool, default False] Make a copy of input ndarray.

name [label, default None] Name to be stored in the index.

See also:

Index The base pandas Index type.
TimedeltaIndex Index of timedelta64 data.
PeriodIndex Index of Period data.
to_datetime Convert argument to datetime.
**date_range** Create a fixed-frequency DatetimeIndex.

**Notes**

To learn more about the frequency strings, please see this link.

**Attributes**

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>year</td>
<td>The year of the datetime.</td>
</tr>
<tr>
<td>month</td>
<td>The month as January=1, December=12.</td>
</tr>
<tr>
<td>day</td>
<td>The day of the datetime.</td>
</tr>
<tr>
<td>hour</td>
<td>The hours of the datetime.</td>
</tr>
<tr>
<td>minute</td>
<td>The minutes of the datetime.</td>
</tr>
<tr>
<td>second</td>
<td>The seconds of the datetime.</td>
</tr>
<tr>
<td>microsecond</td>
<td>The microseconds of the datetime.</td>
</tr>
<tr>
<td>nanosecond</td>
<td>The nanoseconds of the datetime.</td>
</tr>
<tr>
<td>date</td>
<td>Returns numpy array of python datetime.date objects (namely, the date part of Timestamps without timezone information).</td>
</tr>
<tr>
<td>time</td>
<td>Returns numpy array of datetime.time.</td>
</tr>
<tr>
<td>timetz</td>
<td>Returns numpy array of datetime.time also containing timezone information.</td>
</tr>
<tr>
<td>dayofyear</td>
<td>The ordinal day of the year.</td>
</tr>
<tr>
<td>weekofyear</td>
<td>(DEPRECATED) The week ordinal of the year.</td>
</tr>
<tr>
<td>week</td>
<td>(DEPRECATED) The week ordinal of the year.</td>
</tr>
<tr>
<td>dayofweek</td>
<td>The day of the week with Monday=0, Sunday=6.</td>
</tr>
<tr>
<td>weekday</td>
<td>The day of the week with Monday=0, Sunday=6.</td>
</tr>
<tr>
<td>quarter</td>
<td>The quarter of the date.</td>
</tr>
<tr>
<td>tz</td>
<td>Return timezone, if any.</td>
</tr>
<tr>
<td>freq</td>
<td>Return the frequency object if it is set, otherwise None.</td>
</tr>
<tr>
<td>freqstr</td>
<td>Return the frequency object as a string if its set, otherwise None.</td>
</tr>
<tr>
<td>is_month_start</td>
<td>Indicates whether the date is the first day of the month.</td>
</tr>
<tr>
<td>is_month_end</td>
<td>Indicates whether the date is the last day of the month.</td>
</tr>
<tr>
<td>is_quarter_start</td>
<td>Indicator for whether the date is the first day of a quarter.</td>
</tr>
<tr>
<td>is_quarter_end</td>
<td>Indicator for whether the date is the last day of a quarter.</td>
</tr>
<tr>
<td>is_year_start</td>
<td>Indicate whether the date is the first day of a year.</td>
</tr>
<tr>
<td>is_year_end</td>
<td>Indicate whether the date is the last day of the year.</td>
</tr>
<tr>
<td>is_leap_year</td>
<td>Boolean indicator if the date belongs to a leap year.</td>
</tr>
<tr>
<td>inferred_freq</td>
<td>Tries to return a string representing a frequency guess, generated by infer_freq.</td>
</tr>
</tbody>
</table>
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.DatetimeIndex.year

**property** DatetimeIndex.year
The year of the datetime.

**Examples**

```python
>>> datetime_series = pd.Series(
    ...     pd.date_range("2000-01-01", periods=3, freq="Y")
    ... )
>>> datetime_series
0 2000-12-31
1 2001-12-31
2 2002-12-31
dtype: datetime64[ns]
>>> datetime_series.dt.year
0 2000
1 2001
2 2002
dtype: int64
```

pandas.DatetimeIndex.month

**property** DatetimeIndex.month
The month as January=1, December=12.

**Examples**

```python
>>> datetime_series = pd.Series(
    ...     pd.date_range("2000-01-01", periods=3, freq="M")
    ... )
>>> datetime_series
0 2000-01-31
1 2000-02-29
2 2000-03-31
dtype: datetime64[ns]
>>> datetime_series.dt.month
0 1
1 2
2 3
dtype: int64
```
pandas.DatetimeIndex.day

**property** DatetimeIndex.day
The day of the datetime.

**Examples**

```python
>>> datetime_series = pd.Series(
...     pd.date_range("2000-01-01", periods=3, freq="D")
... )
>>> datetime_series
0 2000-01-01
1 2000-01-02
2 2000-01-03
dtype: datetime64[ns]
>>> datetime_series.dt.day
0 1
1 2
2 3
dtype: int64
```

pandas.DatetimeIndex.hour

**property** DatetimeIndex.hour
The hours of the datetime.

**Examples**

```python
>>> datetime_series = pd.Series(
...     pd.date_range("2000-01-01", periods=3, freq="h")
... )
>>> datetime_series
0 2000-01-01 00:00:00
1 2000-01-01 01:00:00
2 2000-01-01 02:00:00
dtype: datetime64[ns]
>>> datetime_series.dt.hour
0 0
1 1
2 2
dtype: int64
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.DatetimeIndex.minute

**property** DatetimeIndex.minute
The minutes of the datetime.

**Examples**

```python
>>> datetime_series = pd.Series(
...   ...   pd.date_range("2000-01-01", periods=3, freq="T")
... )
>>> datetime_series
datetime_series
dtype: datetime64[ns]
>>> datetime_series.dt.minute
0 0
1 1
2 2
dtype: int64
```

pandas.DatetimeIndex.second

**property** DatetimeIndex.second
The seconds of the datetime.

**Examples**

```python
>>> datetime_series = pd.Series(
...   ...   pd.date_range("2000-01-01", periods=3, freq="s")
... )
>>> datetime_series
datetime_series
dtype: datetime64[ns]
>>> datetime_series.dt.second
0 0
1 1
2 2
dtype: int64
```
pandas.DatetimeIndex.microsecond

property DatetimeIndex.microsecond
The microseconds of the datetime.

Examples

```python
>>> datetime_series = pd.Series(
...    pd.date_range("2000-01-01", periods=3, freq="us")
... )
>>> datetime_series
0 2000-01-01 00:00:00.000000
1 2000-01-01 00:00:00.000001
2 2000-01-01 00:00:00.000002
dtype: datetime64[ns]
>>> datetime_series.dt.microsecond
0 0
1 1
2 2
dtype: int64
```

pandas.DatetimeIndex.nanosecond

property DatetimeIndex.nanosecond
The nanoseconds of the datetime.

Examples

```python
>>> datetime_series = pd.Series(
...    pd.date_range("2000-01-01", periods=3, freq="ns")
... )
>>> datetime_series
0 2000-01-01 00:00:00.000000000
1 2000-01-01 00:00:00.000000001
2 2000-01-01 00:00:00.000000002
dtype: datetime64[ns]
>>> datetime_series.dt.nanosecond
0 0
1 1
2 2
dtype: int64
```
`pandas.DatetimeIndex.date`

**property** `DatetimeIndex.date`  
Returns numpy array of python datetime.date objects (namely, the date part of Timestamps without timezone information).

`pandas.DatetimeIndex.time`

**property** `DatetimeIndex.time`  
Returns numpy array of datetime.time. The time part of the Timestamps.

`pandas.DatetimeIndex.timetz`

**property** `DatetimeIndex.timetz`  
Returns numpy array of datetime.time also containing timezone information. The time part of the Timestamps.

`pandas.DatetimeIndex.dayofyear`

**property** `DatetimeIndex.dayofyear`  
The ordinal day of the year.

`pandas.DatetimeIndex.weekofyear`

**property** `DatetimeIndex.weekofyear`  
The week ordinal of the year.  
Deprecated since version 1.1.0.  
weekofyear and week have been deprecated. Please use DatetimeIndex.isocalendar().week instead.

`pandas.DatetimeIndex.week`

**property** `DatetimeIndex.week`  
The week ordinal of the year.  
Deprecated since version 1.1.0.  
weekofyear and week have been deprecated. Please use DatetimeIndex.isocalendar().week instead.

`pandas.DatetimeIndex.dayofweek`

**property** `DatetimeIndex.dayofweek`  
The day of the week with Monday=0, Sunday=6.  
Return the day of the week. It is assumed the week starts on Monday, which is denoted by 0 and ends on Sunday which is denoted by 6. This method is available on both Series with datetime values (using the `dt` accessor) or DatetimeIndex.
Series or Index  Containing integers indicating the day number.

See also:

Series.dt.dayofweek  Alias.
Series.dt.weekday  Alias.
Series.dt.day_name  Returns the name of the day of the week.

Examples

```python
>>> s = pd.date_range('2016-12-31', '2017-01-08', freq='D').to_series()
>>> s.dt.dayofweek
2016-12-31  5
2017-01-01  6
2017-01-02  0
2017-01-03  1
2017-01-04  2
2017-01-05  3
2017-01-06  4
2017-01-07  5
2017-01-08  6
Freq: D, dtype: int64
```

pandas.DatetimeIndex.weekday

property DatetimeIndex.weekday
The day of the week with Monday=0, Sunday=6.

Return the day of the week. It is assumed the week starts on Monday, which is denoted by 0 and ends on Sunday which is denoted by 6. This method is available on both Series with datetime values (using the dt accessor) or DatetimeIndex.

Returns

Series or Index  Containing integers indicating the day number.

See also:

Series.dt.dayofweek  Alias.
Series.dt.weekday  Alias.
Series.dt.day_name  Returns the name of the day of the week.

Examples

```python
>>> s = pd.date_range('2016-12-31', '2017-01-08', freq='D').to_series()
>>> s.dt.dayofweek
2016-12-31  5
2017-01-01  6
2017-01-02  0
2017-01-03  1
2017-01-04  2
2017-01-05  3
```

(continues on next page)
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.DatetimeIndex.quarter

**property**  
DatetimeIndex.quarter

The quarter of the date.

pandas.DatetimeIndex.tz

**property**  
DatetimeIndex.tz

Return timezone, if any.

Returns

- `datetime.tzinfo`, `pytz.tzinfo.BaseTZInfo`, `dateutil.tz.tzfile`, or `None`  
  Returns `None` when the array is tz-naive.

pandas.DatetimeIndex.freq

**property**  
DatetimeIndex.freq

Return the frequency object if it is set, otherwise None.

pandas.DatetimeIndex.freqstr

**property**  
DatetimeIndex.freqstr

Return the frequency object as a string if its set, otherwise None.

pandas.DatetimeIndex.is_month_start

**property**  
DatetimeIndex.is_month_start

Indicates whether the date is the first day of the month.

Returns

- Series or array  
  For Series, returns a Series with boolean values. For DatetimeIndex, returns a boolean array.

**See also:**

- `is_month_start`  
  Return a boolean indicating whether the date is the first day of the month.

- `is_month_end`  
  Return a boolean indicating whether the date is the last day of the month.
Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```python
>>> s = pd.Series(pd.date_range("2018-02-27", periods=3))
>>> s
0 2018-02-27
1 2018-02-28
2 2018-03-01
dtype: datetime64[ns]
>>> s.dt.is_month_start
0 False
1 False
2 True
dtype: bool
>>> s.dt.is_month_end
0 False
1 True
2 False
dtype: bool
```

```python
>>> idx = pd.date_range("2018-02-27", periods=3)
>>> idx.is_month_start
array([False, False, True])
>>> idx.is_month_end
array([False, True, False])
```

### pandas.DatetimeIndex.is_month_end

**property** DatetimeIndex.is_month_end

Indicates whether the date is the last day of the month.

**Returns**

- **Series or array** For Series, returns a Series with boolean values. For DatetimeIndex, returns a boolean array.

**See also:**

- is_month_start Return a boolean indicating whether the date is the first day of the month.
- is_month_end Return a boolean indicating whether the date is the last day of the month.

**Examples**

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```python
>>> s = pd.Series(pd.date_range("2018-02-27", periods=3))
>>> s
0 2018-02-27
1 2018-02-28
2 2018-03-01
dtype: datetime64[ns]
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

(continued from previous page)

```python
>>> s.dt.is_month_start
0   False
1   False
2    True
dtype: bool
>>> s.dt.is_month_end
0   False
1    True
2   False
dtype: bool
```

```python
>>> idx = pd.date_range("2018-02-27", periods=3)
>>> idx.is_month_start
array([False, False, True])
>>> idx.is_month_end
array([False, True, False])
```

pandas.DatetimeIndex.is_quarter_start

**property** DatetimeIndex.is_quarter_start

Indicator for whether the date is the first day of a quarter.

**Returns**

is_quarter_start [Series or DatetimeIndex] The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

**See also:**

quarter Return the quarter of the date.

is_quarter_end Similar property for indicating the quarter start.

**Examples**

This method is available on Series with datetime values under the .dt accessor, and directly on DatetimeIndex.

```python
>>> df = pd.DataFrame({"dates": pd.date_range("2017-03-30", periods=4)})
>>> df.assign(quarter=df.dates.dt.quarter,
...            is_quarter_start=df.dates.dt.is_quarter_start)
   dates    quarter  is_quarter_start
0 2017-03-30      1          False
1 2017-03-31      1          False
2 2017-04-01      2           True
3 2017-04-02      2          False
```

```python
>>> idx = pd.date_range('2017-03-30', periods=4)
>>> idx
DatetimeIndex(['2017-03-30', '2017-03-31', '2017-04-01', '2017-04-02'],
              dtype='datetime64[ns]', freq='D')
```
pandas.DatetimeIndex.is_quarter_end

property DatetimeIndex.is_quarter_end
    Indicator for whether the date is the last day of a quarter.

Returns
    is_quarter_end [Series or DatetimeIndex] The same type as the original data with
    boolean values. Series will have the same name and index. DatetimeIndex will
    have the same name.

See also:
    quarter Return the quarter of the date.
    is_quarter_start Similar property indicating the quarter start.

Examples

This method is available on Series with datetime values under the .dt accessor, and directly on DatetimeIndex.

```python
>>> df = pd.DataFrame({'dates': pd.date_range("2017-03-30", ... periods=4)})
>>> df.assign(quarter=df.dates.dt.quarter, ... is_quarter_end=df.dates.dt.is_quarter_end)
```

```
        dates  quarter  is_quarter_end
0  2017-03-30      1        False
1  2017-03-31      1        True
2  2017-04-01      2        False
3  2017-04-02      2        False
```

```python
>>> idx = pd.date_range('2017-03-30', periods=4)
>>> idx
DatetimeIndex(['2017-03-30', '2017-03-31', '2017-04-01', '2017-04-02'],
               dtype='datetime64[ns]', freq='D')
```

```python
>>> idx.is_quarter_end
array([False, True, False, False])
```

pandas.DatetimeIndex.is_year_start

property DatetimeIndex.is_year_start
    Indicate whether the date is the first day of a year.

Returns
    Series or DatetimeIndex The same type as the original data with boolean values. Se-
    ries will have the same name and index. DatetimeIndex will have the same name.

See also:
**is_year_end** Similar property indicating the last day of the year.

**Examples**

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```python
dates = pd.Series(pd.date_range("2017-12-30", periods=3))
dates
0 2017-12-30
1 2017-12-31
2 2018-01-01
dtype: datetime64[ns]
```

```python
dates.dt.is_year_start
0 False
1 False
2 True
dtype: bool
```

```python
idx = pd.date_range("2017-12-30", periods=3)
datetimeIndex(['2017-12-30', '2017-12-31', '2018-01-01'],
dtype='datetime64[ns]', freq='D')
```

```python
idx.is_year_start
array([False, False, True])
```

**pandas.DatetimeIndex.is_year_end**

**property** `DatetimeIndex.is_year_end`  Indicate whether the date is the last day of the year.

**Returns**

Series or DatetimeIndex  The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

**See also:**

**is_year_start**  Similar property indicating the start of the year.

**Examples**

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```python
dates = pd.Series(pd.date_range("2017-12-30", periods=3))
dates
0 2017-12-30
1 2017-12-31
2 2018-01-01
dtype: datetime64[ns]
```
>>> dates.dt.is_year_end
0   False
1    True
2   False
dtype: bool

>>> idx = pd.date_range("2017-12-30", periods=3)
>>> idx
DatetimeIndex(['2017-12-30', '2017-12-31', '2018-01-01'],
dtype='datetime64[ns]', freq='D')

>>> idx.is_year_end
array([False,  True, False])

pandas.DatetimeIndex.is_leap_year

property DatetimeIndex.is_leap_year
Boolean indicator if the date belongs to a leap year.

A leap year is a year, which has 366 days (instead of 365) including 29th of February as an intercalary
day. Leap years are years which are multiples of four with the exception of years divisible by 100 but not
by 400.

Returns

Series or ndarray  Booleans indicating if dates belong to a leap year.

Examples

This method is available on Series with datetime values under the .dt accessor, and directly on Date-
timeIndex.

>>> idx = pd.date_range("2012-01-01", "2015-01-01", freq="Y")
>>> idx
DatetimeIndex(['2012-12-31', '2013-12-31', '2014-12-31'],
dtype='datetime64[ns]', freq='A-DEC')

>>> idx.is_leap_year
array([ True, False, False])

>>> dates_series = pd.Series(idx)
>>> dates_series
0 2012-12-31
1 2013-12-31
2 2014-12-31
dtype: datetime64[ns]

>>> dates_series.dt.is_leap_year
0   True
1   False
2   False
dtype: bool
**pandas.DatetimeIndex.inferred_freq**

`DatetimeIndex.inferred_freq`  
Tries to return a string representing a frequency guess, generated by infer_freq. Returns None if it can’t autodetect the frequency.

**Methods**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>normalize(*args, **kwargs)</code></td>
<td>Convert times to midnight.</td>
</tr>
<tr>
<td><code>strftime(*args, **kwargs)</code></td>
<td>Convert to Index using specified date_format.</td>
</tr>
<tr>
<td><code>snap(freq)</code></td>
<td>Snap time stamps to nearest occurring frequency.</td>
</tr>
<tr>
<td><code>tz_convert(*args, **kwargs)</code></td>
<td>Convert tz-aware Datetime Array/Index from one time zone to another.</td>
</tr>
<tr>
<td><code>tz_localize(tz [, ambiguous, nonexistent])</code></td>
<td>Localize tz-naive Datetime Array/Index to tz-aware Datetime Array/Index.</td>
</tr>
<tr>
<td><code>round(*args, **kwargs)</code></td>
<td>Perform round operation on the data to the specified freq.</td>
</tr>
<tr>
<td><code>floor(*args, **kwargs)</code></td>
<td>Perform floor operation on the data to the specified freq.</td>
</tr>
<tr>
<td><code>ceil(*args, **kwargs)</code></td>
<td>Perform ceil operation on the data to the specified freq.</td>
</tr>
<tr>
<td><code>to_period(*args, **kwargs)</code></td>
<td>Cast to PeriodArray/Index at a particular frequency.</td>
</tr>
<tr>
<td><code>to_perioddelta(*args, **kwargs)</code></td>
<td>Calculate TimedeltaArray of difference between index values and index converted to PeriodArray at specified freq.</td>
</tr>
<tr>
<td><code>to_pydatetime(*args, **kwargs)</code></td>
<td>Return Datetime Array/Index as object ndarray of datetime.datetime objects.</td>
</tr>
<tr>
<td><code>to_series([keep_tz, index, name])</code></td>
<td>Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index.</td>
</tr>
<tr>
<td><code>to_frame([index, name])</code></td>
<td>Create a DataFrame with a column containing the Index.</td>
</tr>
<tr>
<td><code>month_name(*args, **kwargs)</code></td>
<td>Return the month names of the DateTimeIndex with specified locale.</td>
</tr>
<tr>
<td><code>day_name(*args, **kwargs)</code></td>
<td>Return the day names of the DateTimeIndex with specified locale.</td>
</tr>
<tr>
<td><code>mean(*args, **kwargs)</code></td>
<td>Return the mean value of the Array.</td>
</tr>
</tbody>
</table>

**pandas.DatetimeIndex.normalize**

`DatetimeIndex.normalize(*args, **kwargs)`  
Convert times to midnight.

The time component of the date-time is converted to midnight i.e. 00:00:00. This is useful in cases, when the time does not matter. Length is unaltered. The timezones are unaffected.

This method is available on Series with datetime values under the `.dt` accessor, and directly on Datetime Array/Index.

**Returns**

`DatetimeArray, DatetimeIndex or Series`  The same type as the original data. Series
will have the same name and index. DatetimeIndex will have the same name.

See also:

floor  Floor the datetimes to the specified freq.
ceil  Ceil the datetimes to the specified freq.
round  Round the datetimes to the specified freq.

Examples

```python
>>> idx = pd.date_range(start='2014-08-01 10:00', freq='H',
...                      periods=3, tz='Asia/Calcutta')
>>> idx
DatetimeIndex(['2014-08-01 10:00:00+05:30',
               '2014-08-01 11:00:00+05:30',
               '2014-08-01 12:00:00+05:30'],
               dtype='datetime64[ns, Asia/Calcutta]', freq='H')
>>> idx.normalize()
DatetimeIndex(['2014-08-01 00:00:00+05:30',
               '2014-08-01 00:00:00+05:30',
               '2014-08-01 00:00:00+05:30'],
               dtype='datetime64[ns, Asia/Calcutta]', freq=None)
```

pandas.DatetimeIndex.strftime

```
DatetimeIndex.strftime(*args, **kwargs)
```

Convert to Index using specified date_format.

Return an Index of formatted strings specified by date_format, which supports the same string format as the python standard library. Details of the string format can be found in python string format doc.

Parameters

- **date_format** [str] Date format string (e.g. “%Y-%m-%d”).

Returns

- **ndarray** NumPy ndarray of formatted strings.

See also:

to_datetime  Convert the given argument to datetime.

```
DatetimeIndex.normalize  Return DatetimeIndex with times to midnight.
```

```
DatetimeIndex.round  Round the DatetimeIndex to the specified freq.
```

```
DatetimeIndex.floor  Floor the DatetimeIndex to the specified freq.
```
Examples

```python
>>> rng = pd.date_range(pd.Timestamp("2018-03-10 09:00"),
...                       periods=3, freq='s')
>>> rng.strftime('%B %d, %Y, %r')
Index(['March 10, 2018, 09:00:00 AM', 'March 10, 2018, 09:00:01 AM',
      'March 10, 2018, 09:00:02 AM'],
      dtype='object')
```

pandas.DatetimeIndex.snap

DatetimeIndex.snap(freq='S')

Snap time stamps to nearest occurring frequency.

Returns

DatetimeIndex

pandas.DatetimeIndex.tz_convert

DatetimeIndex.tz_convert(*args, **kwargs)

Convert tz-aware Datetime Array/Index from one time zone to another.

Parameters

- **tz** [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone for time. Corresponding timestamps would be converted to this time zone of the Datetime Array/Index. A tz of None will convert to UTC and remove the timezone information.

Returns

Array or Index

Raises

- TypeError If Datetime Array/Index is tz-naive.

See also:

- DatetimeIndex.tz A timezone that has a variable offset from UTC.
- DatetimeIndex.tz_localize Localize tz-naive DatetimeIndex to a given time zone, or remove timezone from a tz-aware DatetimeIndex.

Examples

With the tz parameter, we can change the DatetimeIndex to other time zones:

```python
>>> dti = pd.date_range(start='2014-08-01 09:00',
...                      freq='H', periods=3, tz='Europe/Berlin')
```

```python
>>> dti
DatetimeIndex(['2014-08-01 09:00:00+02:00', '2014-08-01 10:00:00+02:00',
               '2014-08-01 11:00:00+02:00'],
               dtype='datetime64[ns, Europe/Berlin]', freq='H')
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

```python
>>> dti.tz_convert('US/Central')
DatetimeIndex(['2014-08-01 02:00:00-05:00',
               '2014-08-01 03:00:00-05:00',
               '2014-08-01 04:00:00-05:00'],
              dtype='datetime64[ns, US/Central]', freq='H')
```

With the `tz=None`, we can remove the timezone (after converting to UTC if necessary):

```python
>>> dti = pd.date_range(start='2014-08-01 09:00', freq='H',
                      periods=3, tz='Europe/Berlin')
```

```python
>>> dti
DatetimeIndex(['2014-08-01 09:00:00+02:00',
               '2014-08-01 10:00:00+02:00',
               '2014-08-01 11:00:00+02:00'],
              dtype='datetime64[ns, Europe/Berlin]', freq='H')
```

```python
>>> dti.tz_convert(None)
DatetimeIndex(['2014-08-01 07:00:00',
               '2014-08-01 08:00:00',
               '2014-08-01 09:00:00'],
              dtype='datetime64[ns]', freq='H')
```

### pandas.DatetimeIndex.tz_localize

**Datet imeIndex.tz_localize** *(tz, ambiguous='raise', nonexistent='raise')*

Localize tz-naive Datetime Array/Index to tz-aware Datetime Array/Index.

This method takes a time zone (tz) naive Datetime Array/Index object and makes this time zone aware. It does not move the time to another time zone. Time zone localization helps to switch from time zone aware to time zone unaware objects.

**Parameters**

- **tz** [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone to convert timestamps to. Passing `None` will remove the time zone information preserving local time.
- **ambiguous** ['infer', 'NaT', bool array, default 'raise'] When clocks moved backward due to DST, ambiguous times may arise. For example in Central European Time (UTC+01), when going from 03:00 DST to 02:00 non-DST, 02:30:00 local time occurs both at 00:30:00 UTC and at 01:30:00 UTC. In such a situation, the ambiguous parameter dictates how ambiguous times should be handled.
  - ‘infer’ will attempt to infer fall dst-transition hours based on order
  - bool-ndarray where True signifies a DST time, False signifies a non-DST time (note that this flag is only applicable for ambiguous times)
  - ‘NaT’ will return NaT where there are ambiguous times
  - ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.
- **nonexistent** ['shift_forward', 'shift_backward, 'NaT', timedelta, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.
  - ‘shift_forward’ will shift the nonexistent time forward to the closest existing time

3.7. Index objects 2015
• ‘shift_backward’ will shift the nonexistent time backward to the closest existing time
• ‘NaT’ will return NaT where there are nonexistent times
• timedelta objects will shift nonexistent times by the timedelta
• ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

Same type as self  Array/Index converted to the specified time zone.

Raises

TypeError  If the Datetime Array/Index is tz-aware and tz is not None.

See also:

DatetimeIndex.tz_convert  Convert tz-aware DatetimeIndex from one time zone to another.

Examples

```python
>>> tz_naive = pd.date_range('2018-03-01 09:00', periods=3)
>>> tz_naive
DatetimeIndex(['2018-03-01 09:00:00', '2018-03-02 09:00:00',
               '2018-03-03 09:00:00'], dtype='datetime64[ns]', freq='D')

Localize DatetimeIndex in US/Eastern time zone:

```python
>>> tz_aware = tz_naive.tz_localize(tz='US/Eastern')
>>> tz_aware
DatetimeIndex(['2018-03-01 09:00:00-05:00',
               '2018-03-02 09:00:00-05:00',
               '2018-03-03 09:00:00-05:00'], dtype='datetime64[ns, US/Eastern]', freq=None)
```

With the tz=None, we can remove the time zone information while keeping the local time (not converted to UTC):

```python
>>> tz_aware.tz_localize(None)
DatetimeIndex(['2018-03-01 09:00:00', '2018-03-02 09:00:00',
               '2018-03-03 09:00:00'], dtype='datetime64[ns]', freq=None)
```

Be careful with DST changes. When there is sequential data, pandas can infer the DST time:

```python
>>> s = pd.to_datetime(pd.Series(['2018-10-28 01:30:00',
                                ...    '2018-10-28 02:00:00',
                                ...    '2018-10-28 02:30:00',
                                ...    '2018-10-28 02:00:00',
                                ...    '2018-10-28 02:30:00',
                                ...    '2018-10-28 03:00:00',
                                ...    '2018-10-28 03:30:00']))
>>> s.dt.tz_localize('CET', ambiguous='infer')
0    2018-10-28 01:30:00+02:00
(continues on next page)
In some cases, inferring the DST is impossible. In such cases, you can pass an ndarray to the ambiguous parameter to set the DST explicitly

```python
>>> s = pd.to_datetime(pd.Series(['2018-10-28 01:20:00',
                               '2018-10-28 02:36:00',
                               '2018-10-28 03:46:00']))
>>> s.dt.tz_localize('CET', ambiguous=np.array([True, True, False]))
0 2018-10-28 01:20:00+02:00
1 2018-10-28 02:36:00+02:00
2 2018-10-28 03:46:00+01:00
dtype: datetime64[ns, CET]
```

If the DST transition causes nonexistent times, you can shift these dates forward or backwards with a timedelta object or ‘shift_forward’ or ‘shift_backwards’.

```python
>>> s = pd.to_datetime(pd.Series(['2015-03-29 02:30:00',
                               '2015-03-29 03:30:00']))
>>> s.dt.tz_localize('Europe/Warsaw', nonexistent='shift_forward')
0 2015-03-29 03:00:00+02:00
1 2015-03-29 03:30:00+02:00
dtype: datetime64[ns, Europe/Warsaw]

>>> s.dt.tz_localize('Europe/Warsaw', nonexistent='shift_backward')
0 2015-03-29 01:59:59.999999999+01:00
1 2015-03-29 03:30:00+02:00
dtype: datetime64[ns, Europe/Warsaw]

>>> s.dt.tz_localize('Europe/Warsaw', nonexistent=pd.Timedelta('1H'))
0 2015-03-29 03:30:00+02:00
1 2015-03-29 03:30:00+02:00
dtype: datetime64[ns, Europe/Warsaw]
```

**pandas.DatetimeIndex.round**

```
DatetimeIndex.round(*args, **kwargs)
```

Perform round operation on the data to the specified freq.

**Parameters**

- `freq` [str or Offset] The frequency level to round the index to. Must be a fixed frequency like ‘S’ (second) not ‘ME’ (month end). See frequency aliases for a list of possible freq values.

- `ambiguous` ['infer', bool-ndarray, ‘NaT’, default ‘raise’] Only relevant for DatetimeIndex:
  - ‘infer’ will attempt to infer fall dst-transition hours based on order
• bool-ndarray where True signifies a DST time, False designates a non-DST
time (note that this flag is only applicable for ambiguous times)

• ‘NaT’ will return NaT where there are ambiguous times

• ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

nonexistent ['shift_forward', 'shift_backward', ‘NaT’, timedelta, default ‘raise’] A
nonexistent time does not exist in a particular timezone where clocks moved for-
ward due to DST.

• ‘shift_forward’ will shift the nonexistent time forward to the closest existing
time

• ‘shift_backward’ will shift the nonexistent time backward to the closest exist-
ing time

• ‘NaT’ will return NaT where there are nonexistent times

• timedelta objects will shift nonexistent times by the timedelta

• ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

DatetimeIndex, TimedeltaIndex, or Series Index of the same type for a DatetimeIn-
dex or TimedeltaIndex, or a Series with the same index for a Series.

Raises

ValueError if the freq cannot be converted.

Examples

DatetimeIndex

```python
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(["2018-01-01 11:59:00", '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
              dtype='datetime64[ns]', freq='T')
>>> rng.round('H')
DatetimeIndex(["2018-01-01 12:00:00", '2018-01-01 12:00:00',
               '2018-01-01 12:00:00'],
              dtype='datetime64[ns]', freq=None)
```

Series

```python
>>> pd.Series(rng).dt.round("H")
0  2018-01-01 12:00:00
1  2018-01-01 12:00:00
2  2018-01-01 12:00:00
dtype: datetime64[ns]
```
pandas.DatetimeIndex.floor

DatetimeIndex.floor(*args, **kwargs)
Perform floor operation on the data to the specified freq.

Parameters

freq [str or Offset] The frequency level to floor the index to. Must be a fixed frequency like ‘S’ (second) not ‘ME’ (month end). See frequency aliases for a list of possible freq values.

ambiguous ['infer', bool-ndarray, ‘NaT’, default ‘raise’] Only relevant for DatetimeIndex:
- ‘infer’ will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- ‘NaT’ will return NaT where there are ambiguous times
- ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

nonexistent ['shift_forward', ‘shift_backward’, ‘NaT’, timedelta, default ‘raise’] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.
- ‘shift_forward’ will shift the nonexistent time forward to the closest existing time
- ‘shift_backward’ will shift the nonexistent time backward to the closest existing time
- ‘NaT’ will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

DatetimeIndex, TimedeltaIndex, or Series Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

Raises

ValueError if the freq cannot be converted.

Examples

DatetimeIndex

```python
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
                '2018-01-01 12:01:00'], dtype='datetime64[ns]', freq='T')
>>> rng.floor('H')
```
Series

```python
>>> pd.Series(rng).dt.floor("H")
0 2018-01-01 11:00:00
1 2018-01-01 12:00:00
2 2018-01-01 12:00:00
dtype: datetime64[ns]
```

pandas.DatetimeIndex.ceil

```python
datetimeIndex.ceil(*args, **kwargs)
```

Perform ceil operation on the data to the specified `freq`.

**Parameters**

- **freq** [str or Offset] The frequency level to ceil the index to. Must be a fixed frequency like `‘S’` (second) not `‘ME’` (month end). See frequency aliases for a list of possible `freq` values.
- **ambiguous** ['infer', bool-ndarray, 'NaT', default 'raise'] Only relevant for DatetimeIndex:
  - ‘infer’ will attempt to infer fall dst-transition hours based on order
  - bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
  - ‘NaT’ will return NaT where there are ambiguous times
  - ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

- **nonexistent** ['shift_forward', 'shift_backward', 'NaT', timedelta, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.
  - ‘shift_forward’ will shift the nonexistent time forward to the closest existing time
  - ‘shift_backward’ will shift the nonexistent time backward to the closest existing time
  - ‘NaT’ will return NaT where there are nonexistent times
  - timedelta objects will shift nonexistent times by the timedelta
  - ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

**Returns**

- DatetimeIndex, TimedeltaIndex, or Series Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.
ValueError if the *freq* cannot be converted.

Examples

**DatetimeIndex**

```python
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
               dtype='datetime64[ns]', freq='T')
```

```python
>>> rng.ceil('H')
DatetimeIndex(['2018-01-01 12:00:00', '2018-01-01 12:00:00',
               '2018-01-01 13:00:00'],
               dtype='datetime64[ns]', freq=None)
```

**Series**

```python
>>> pd.Series(rng).dt.ceil("H")
0  2018-01-01 12:00:00
1  2018-01-01 12:00:00
2  2018-01-01 13:00:00
dtype: datetime64[ns]
```

**pandas.DatetimeIndex.to_period**

```
DatetimeIndex.to_period(*args, **kwargs)
```

Cast to PeriodArray/Index at a particular frequency.

Converts DatetimeArray/Index to PeriodArray/Index.

**Parameters**

- *freq* [str or Offset, optional] One of pandas’ offset strings or an Offset object. Will be inferred by default.

**Returns**

- PeriodArray/Index

**Raises**

- ValueError When converting a DatetimeArray/Index with non-regular values, so that a frequency cannot be inferred.

**See also:**

- *PeriodIndex* Immutable ndarray holding ordinal values.
- *DatetimeIndex.to_pydatetime* Return DatetimeIndex as object.
Examples

```python
>>> df = pd.DataFrame({"y": [1, 2, 3]},
                    index=pd.to_datetime(["2000-03-31 00:00:00",
                                          "2000-05-31 00:00:00",
                                          "2000-08-31 00:00:00"]))
>>> df.index.to_period("M")
PeriodIndex(['2000-03', '2000-05', '2000-08'],
            dtype='period[M]', freq='M')
```

Infer the daily frequency

```python
>>> idx = pd.date_range("2017-01-01", periods=2)
>>> idx.to_period()
PeriodIndex(['2017-01-01', '2017-01-02'],
            dtype='period[D]', freq='D')
```

**pandas.DatetimeIndex.to_perioddelta**

`DatetimeIndex.to_perioddelta(*args, **kwargs)`

Calculate TimedeltaArray of difference between index values and index converted to PeriodArray at specified freq. Used for vectorized offsets.

**Parameters**

freq [Period frequency]

**Returns**

TimedeltaArray/Index

**pandas.DatetimeIndex.to_pydatetime**

`DatetimeIndex.to_pydatetime(*args, **kwargs)`

Return Datetime Array/Index as object ndarray of datetime.datetime objects.

**Returns**

datetimes [ndarray]

**pandas.DatetimeIndex.to_series**

`DatetimeIndex.to_series(keep_tz=<object object>, index=None, name=None)`

Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index.

**Parameters**

keep_tz [optional, defaults True] Return the data keeping the timezone.

If keep_tz is True:

If the timezone is not set, the resulting Series will have a datetime64[ns] dtype.

Otherwise the Series will have an datetime64[ns, tz] dtype; the tz will be preserved.
If keep_tz is False:

Series will have a datetime64[ns] dtype. TZ aware objects will have the tz removed.

Changed in version 1.0.0: The default value is now True. In a future version, this keyword will be removed entirely. Stop passing the argument to obtain the future behavior and silence the warning.

**index** [Index, optional] Index of resulting Series. If None, defaults to original index.

**name** [str, optional] Name of resulting Series. If None, defaults to name of original index.

Returns

Series

```
pandas.DatetimeIndex.to_frame
```

**DatetimeIndex.to_frame** (*index=True, name=None*)

Create a DataFrame with a column containing the Index.

New in version 0.24.0.

Parameters

**index** [bool, default True] Set the index of the returned DataFrame as the original Index.

**name** [object, default None] The passed name should substitute for the index name (if it has one).

Returns

**DataFrame** DataFrame containing the original Index data.

See also:

- **Index.to_series** Convert an Index to a Series.
- **Series.to_frame** Convert Series to DataFrame.

Examples

```python
>>> idx = pd.Index(['Ant', 'Bear', 'Cow'], name='animal')
>>> idx.to_frame()
    animal
   0    Ant
   1   Bear
   2   Cow
```

By default, the original Index is reused. To enforce a new Index:

```python
>>> idx.to_frame(index=False)
   animal
  0      Ant
  1     Bear
  2      Cow
```
To override the name of the resulting column, specify `name`:

```python
>>> idx.to_frame(index=False, name='zoo')
zoo
0  Ant
1  Bear
2  Cow
```

### pandas.DatetimeIndex.month_name

`DatetimeIndex.month_name(*args, **kwargs)`

Return the month names of the `DateTimeIndex` with specified locale.

New in version 0.23.0.

**Parameters**

- `locale` [str, optional] Locale determining the language in which to return the month name. Default is English locale.

**Returns**

- `Index` Index of month names.

**Examples**

```python
>>> idx = pd.date_range(start='2018-01', freq='M', periods=3)
>>> idx
DatetimeIndex(['2018-01-31', '2018-02-28', '2018-03-31'],
               dtype='datetime64[ns]', freq='M')
>>> idx.month_name()
Index(['January', 'February', 'March'], dtype='object')
```

### pandas.DatetimeIndex.day_name

`DatetimeIndex.day_name(*args, **kwargs)`

Return the day names of the `DateTimeIndex` with specified locale.

New in version 0.23.0.

**Parameters**

- `locale` [str, optional] Locale determining the language in which to return the day name. Default is English locale.

**Returns**

- `Index` Index of day names.
Examples

```python
>>> idx = pd.date_range(start='2018-01-01', freq='D', periods=3)
>>> idx
DatetimeIndex(['2018-01-01', '2018-01-02', '2018-01-03'],
dtype='datetime64[ns]', freq='D')
```

```
>>> idx.day_name()
Index(['Monday', 'Tuesday', 'Wednesday'], dtype='object')
```

**pandas.DatetimeIndex.mean**

```
DatetimeIndex.mean(*args, **kwargs)
```

Return the mean value of the Array.

New in version 0.25.0.

**Parameters**

- `skipna` [bool, default True] Whether to ignore any NaT elements.

**Returns**

- `scalar` Timestamp or Timedelta.

**See also:**

- `numpy.ndarray.mean` Returns the average of array elements along a given axis.
- `Series.mean` Return the mean value in a Series.

**Notes**

mean is only defined for Datetime and Timedelta dtypes, not for Period.

**Time/date components**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>DatetimeIndex.year</code></td>
<td>The year of the datetime.</td>
</tr>
<tr>
<td><code>DatetimeIndex.month</code></td>
<td>The month as January=1, December=12.</td>
</tr>
<tr>
<td><code>DatetimeIndex.day</code></td>
<td>The day of the datetime.</td>
</tr>
<tr>
<td><code>DatetimeIndex.hour</code></td>
<td>The hours of the datetime.</td>
</tr>
<tr>
<td><code>DatetimeIndex.minute</code></td>
<td>The minutes of the datetime.</td>
</tr>
<tr>
<td><code>DatetimeIndex.second</code></td>
<td>The seconds of the datetime.</td>
</tr>
<tr>
<td><code>DatetimeIndex.microsecond</code></td>
<td>The microseconds of the datetime.</td>
</tr>
<tr>
<td><code>DatetimeIndex.nanosecond</code></td>
<td>The nanoseconds of the datetime.</td>
</tr>
<tr>
<td><code>DatetimeIndex.date</code></td>
<td>Returns numpy array of python datetime.date objects (namely, the date part of Timestamps without timezone information).</td>
</tr>
<tr>
<td><code>DatetimeIndex.time</code></td>
<td>Returns numpy array of datetime.time.</td>
</tr>
<tr>
<td><code>DatetimeIndex.timetz</code></td>
<td>Returns numpy array of datetime.time also containing timezone information.</td>
</tr>
<tr>
<td><code>DatetimeIndex.dayofyear</code></td>
<td>The ordinal day of the year.</td>
</tr>
<tr>
<td><code>DatetimeIndex.weekofyear</code></td>
<td>(DEPRECATED) The week ordinal of the year.</td>
</tr>
</tbody>
</table>

continues on next page
Table 164 – continued from previous page

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DatetimeIndex.week</td>
<td>(DEPRECATED) The week ordinal of the year.</td>
</tr>
<tr>
<td>DatetimeIndex.dayofweek</td>
<td>The day of the week with Monday=0, Sunday=6.</td>
</tr>
<tr>
<td>DatetimeIndex.weekday</td>
<td>The day of the week with Monday=0, Sunday=6.</td>
</tr>
<tr>
<td>DatetimeIndex.quarter</td>
<td>The quarter of the date.</td>
</tr>
<tr>
<td>DatetimeIndex.tz</td>
<td>Return timezone, if any.</td>
</tr>
<tr>
<td>DatetimeIndex.freq</td>
<td>Return the frequency object if it is set, otherwise None.</td>
</tr>
<tr>
<td>DatetimeIndex.freqstr</td>
<td>Return the frequency object as a string if its set, otherwise None.</td>
</tr>
<tr>
<td>DatetimeIndex.is_month_start</td>
<td>Indicates whether the date is the first day of the month.</td>
</tr>
<tr>
<td>DatetimeIndex.is_month_end</td>
<td>Indicates whether the date is the last day of the month.</td>
</tr>
<tr>
<td>DatetimeIndex.is_quarter_start</td>
<td>Indicator for whether the date is the first day of a quarter.</td>
</tr>
<tr>
<td>DatetimeIndex.is_quarter_end</td>
<td>Indicator for whether the date is the last day of a quarter.</td>
</tr>
<tr>
<td>DatetimeIndex.is_year_start</td>
<td>Indicate whether the date is the first day of a year.</td>
</tr>
<tr>
<td>DatetimeIndex.is_year_end</td>
<td>Indicate whether the date is the last day of the year.</td>
</tr>
<tr>
<td>DatetimeIndex.is_leap_year</td>
<td>Boolean indicator if the date belongs to a leap year.</td>
</tr>
<tr>
<td>DatetimeIndex.inferred_freq</td>
<td>Tries to return a string representing a frequency guess, generated by infer_freq.</td>
</tr>
</tbody>
</table>

Selecting

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DatetimeIndex.indexer_at_time(time[, asof])</td>
<td>Return index locations of values at particular time of day (e.g. 9:30AM).</td>
</tr>
<tr>
<td>DatetimeIndex.indexer_between_time(…[, …])</td>
<td>Return index locations of values between particular times of day (e.g., 9:00-9:30AM).</td>
</tr>
</tbody>
</table>

pandas.DatetimeIndex.indexer_at_time

```
DatetimeIndex.indexer_at_time(time[, asof=False])
```

Return index locations of values at particular time of day (e.g. 9:30AM).

**Parameters**

- `time` [datetime.time or str] Time passed in either as object (datetime.time) or as string in appropriate format ("%H:%M", "%H%M", "%I:%M%p", "%I%M%p", "%H:%M:%S", "%H%M%S", "%I:%M:%S%p", "%I%M%S%p").

**Returns**

- `values_at_time` [array of integers]

**See also:**

- `indexer_between_time` Get index locations of values between particular times of day.
- `DataFrame.at_time` Select values at particular time of day.
pandas.datetime.indexer_between_time

pandas.DatetimeIndex.indexer_between_time(start_time, end_time, include_start=True, include_end=True)

Return index locations of values between particular times of day (e.g., 9:00-9:30AM).

Parameters

- **start_time**, **end_time** [datetime.time, str] Time passed either as object (datetime.time) or as string in appropriate format (“%H:%M”, “%H%M”, “%I:%M%p”, “%I%M%p”, “%H:%M:%S”, “%H%M%S”, “%I:%M:%S%p”, “%I%M%S%p”).
- **include_start** [bool, default True]
- **include_end** [bool, default True]

Returns

- **values_between_time** [array of integers]

See also:

- **indexer_at_time** Get index locations of values at particular time of day.
- **DataFrame.between_time** Select values between particular times of day.

Time-specific operations

- **DatetimeIndex.normalize(*args, **kwargs)** Convert times to midnight.
- **DatetimeIndex.strftime(*args, **kwargs)** Convert to Index using specified date_format.
- **DatetimeIndex.snap([freq])** Snap time stamps to nearest occurring frequency.
- **DatetimeIndex.tz_convert(*args, **kwargs)** Convert tz-aware Datetime Array/Index from one time zone to another.
- **DatetimeIndex.tz_localize(tz[, ambiguous, ...])** Localize tz-naive Datetime Array/Index to tz-aware Datetime Array/Index.
- **DatetimeIndex.round(*args, **kwargs)** Perform round operation on the data to the specified freq.
- **DatetimeIndex.floor(*args, **kwargs)** Perform floor operation on the data to the specified freq.
- **DatetimeIndex.ceil(*args, **kwargs)** Perform ceil operation on the data to the specified freq.
- **DatetimeIndex.month_name(*args, **kwargs)** Return the month names of the DateTimeIndex with specified locale.
- **DatetimeIndex.day_name(*args, **kwargs)** Return the day names of the DateTimeIndex with specified locale.

Conversion

- **DatetimeIndex.to_period(*args, **kwargs)** Cast to PeriodArray/Index at a particular frequency.
- **DatetimeIndex.to_perioddelta(*args, **kwargs)** Calculate TimedeltaArray of difference between index values and index converted to PeriodArray at specified freq.
- **DatetimeIndex.to_pydatetime(*args, **kwargs)** Return Datetime Array/Index as object ndarray of datetime.datetime objects.
- **DatetimeIndex.to_series([keep_tz, index, name])** Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index.

continues on next page
Table 167 – continued from previous page

| DatetimeIndex.to_frame | Create a DataFrame with a column containing the Index. |

Methods

| DatetimeIndex.mean | Return the mean value of the Array. |

3.7.7 TimedeltaIndex

| TimedeltaIndex | Immutable ndarray of timedelta64 data, represented internally as int64, and which can be boxed to timedelta objects. |

pandas.TimedeltaIndex

class pandas.TimedeltaIndex(data=None, unit=None, freq=<object object>, closed=None, dtype=\texttt{dtype('\textless m8[ns]\textgreater')}, copy=False, name=None)

Immutable ndarray of timedelta64 data, represented internally as int64, and which can be boxed to timedelta objects.

Parameters

- **data** [array-like (1-dimensional), optional] Optional timedelta-like data to construct index with.
- **unit** [unit of the arg (D,h,m,s,ms,us,ns) denote the unit, optional] Which is an integer/float number.
- **freq** [str or pandas offset object, optional] One of pandas date offset strings or corresponding objects. The string ‘infer’ can be passed in order to set the frequency of the index as the inferred frequency upon creation.
- **copy** [bool] Make a copy of input ndarray.
- **name** [object] Name to be stored in the index.

See also:

- **Index** The base pandas Index type.
- **Timedelta** Represents a duration between two dates or times.
- **DatetimeIndex** Index of datetime64 data.
- **PeriodIndex** Index of Period data.
- **timedelta_range** Create a fixed-frequency TimedeltaIndex.
Notes

To learn more about the frequency strings, please see this link.

Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>days</td>
<td>Number of days for each element.</td>
</tr>
<tr>
<td>seconds</td>
<td>Number of seconds (&gt;= 0 and less than 1 day) for each element.</td>
</tr>
<tr>
<td>microseconds</td>
<td>Number of microseconds (&gt;= 0 and less than 1 second) for each element.</td>
</tr>
<tr>
<td>nanoseconds</td>
<td>Number of nanoseconds (&gt;= 0 and less than 1 microsecond) for each element.</td>
</tr>
<tr>
<td>components</td>
<td>Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds) of the Timedeltas.</td>
</tr>
<tr>
<td>inferred_freq</td>
<td>Tries to return a string representing a frequency guess, generated by infer_freq.</td>
</tr>
</tbody>
</table>

*pandas.TimedeltaIndex.days*

**property** TimedeltaIndex.days

Number of days for each element.

*pandas.TimedeltaIndex.seconds*

**property** TimedeltaIndex.seconds

Number of seconds (>= 0 and less than 1 day) for each element.

*pandas.TimedeltaIndex.microseconds*

**property** TimedeltaIndex.microseconds

Number of microseconds (>= 0 and less than 1 second) for each element.

*pandas.TimedeltaIndex.nanoseconds*

**property** TimedeltaIndex.nanoseconds

Number of nanoseconds (>= 0 and less than 1 microsecond) for each element.
**pandas.TimedeltaIndex.components**

**property TimedeltaIndex.components**

Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds) of the Timedeltas.

**Returns**

a DataFrame

**pandas.TimedeltaIndex.inferred_freq**

**TimedeltaIndex.inferred_freq**

Tries to return a string representing a frequency guess, generated by infer_freq. Returns None if it can’t autodetect the frequency.

**Methods**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>to_pytimedelta(*args, **kwargs)</td>
<td>Return Timedelta Array/Index as object ndarray of datetime.timedelta objects.</td>
</tr>
<tr>
<td>to_series(index=None, name=None)</td>
<td>Create a Series with both index and values equal to the index keys.</td>
</tr>
<tr>
<td>round(*args, **kwargs)</td>
<td>Perform round operation on the data to the specified freq.</td>
</tr>
<tr>
<td>floor(*args, **kwargs)</td>
<td>Perform floor operation on the data to the specified freq.</td>
</tr>
<tr>
<td>ceil(*args, **kwargs)</td>
<td>Perform ceil operation on the data to the specified freq.</td>
</tr>
<tr>
<td>to_frame(index=None, name=None)</td>
<td>Create a DataFrame with a column containing the Index.</td>
</tr>
<tr>
<td>mean(*args, **kwargs)</td>
<td>Return the mean value of the Array.</td>
</tr>
</tbody>
</table>

**pandas.TimedeltaIndex.to_pytimedelta**

**TimedeltaIndex.to_pytimedelta(*args, **kwargs)**

Return Timedelta Array/Index as object ndarray of datetime.timedelta objects.

**Returns**

datetimes [ndarray]

**pandas.TimedeltaIndex.to_series**

**TimedeltaIndex.to_series(index=None, name=None)**

Create a Series with both index and values equal to the index keys.

Useful with map for returning an indexer based on an index.

**Parameters**

index [Index, optional] Index of resulting Series. If None, defaults to original index.
name [str, optional] Name of resulting Series. If None, defaults to name of original index.

Returns

Series The dtype will be based on the type of the Index values.

See also:

Index.to_frame Convert an Index to a DataFrame.
Series.to_frame Convert Series to DataFrame.

Examples

>>> idx = pd.Index(['Ant', 'Bear', 'Cow'], name='animal')

By default, the original Index and original name is reused.

>>> idx.to_series()
animal
 Ant Ant
Bear Bear
Cow  Cow
Name: animal, dtype: object

To enforce a new Index, specify new labels to index:

>>> idx.to_series(index=[0, 1, 2])
0  Ant
1  Bear
2  Cow
Name: animal, dtype: object

To override the name of the resulting column, specify name:

>>> idx.to_series(name='zoo')
animal
Ant  Ant
Bear Bear
Cow  Cow
Name: zoo, dtype: object

pandas.TimedeltaIndex.round

TimedeltaIndex.round(*args, **kwargs)
Perform round operation on the data to the specified freq.

Parameters

freq [str or Offset] The frequency level to round the index to. Must be a fixed frequency like ‘S’ (second) not ‘ME’ (month end). See frequency aliases for a list of possible freq values.

ambiguous ['infer', boolndarray, ‘NaT’, default ‘raise’] Only relevant for DatetimeIndex:
- ‘infer’ will attempt to infer fall dst-transition hours based on order
**bool-ndarray** where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)

- ‘NaT’ will return NaT where there are ambiguous times
- ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

**nonexistent** ['shift_forward', 'shift_backward', 'NaT', timedelta, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- ‘shift_forward’ will shift the nonexistent time forward to the closest existing time
- ‘shift_backward’ will shift the nonexistent time backward to the closest existing time
- ‘NaT’ will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

**Returns**

**DatetimeIndex, TimedeltaIndex, or Series** Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

**Raises**

ValueError if the freq cannot be converted.

**Examples**

**DatetimeIndex**

```python
g = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
gng = g
gng.round('H')
gng.round('H')
```

**Series**

```python
pd.Series(g).dt.round("H")
```

<table>
<thead>
<tr>
<th>0</th>
<th>2018-01-01 12:00:00</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2018-01-01 12:00:00</td>
</tr>
<tr>
<td>2</td>
<td>2018-01-01 12:00:00</td>
</tr>
</tbody>
</table>

dtype: datetime64[ns]
TimedeltaIndex.floor(*args, **kwargs)

Perform floor operation on the data to the specified freq.

Parameters

- **freq** [str or Offset] The frequency level to floor the index to. Must be a fixed frequency like ‘S’ (second) not ‘ME’ (month end). See frequency aliases for a list of possible freq values.

- **ambiguous** ['infer', bool-ndarray, ‘NaT’, default ‘raise’] Only relevant for DatetimeIndex:
  - ‘infer’ will attempt to infer fall dst-transition hours based on order
  - bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
  - ‘NaT’ will return NaT where there are ambiguous times
  - ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

- **nonexistent** ['shift_forward', 'shift_backward', ‘NaT’, timedelta, default ‘raise’] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.
  - ‘shift_forward’ will shift the nonexistent time forward to the closest existing time
  - ‘shift_backward’ will shift the nonexistent time backward to the closest existing time
  - ‘NaT’ will return NaT where there are nonexistent times
  - timedelta objects will shift nonexistent times by the timedelta
  - ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

Returns

- **DatetimeIndex, TimedeltaIndex, or Series** Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

Raises

- **ValueError if the freq cannot be converted.**

Examples

**DatetimelIndex**

```python
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00', '2018-01-01 12:01:00'], dtype='datetime64[ns]', freq='T')
>>> rng.floor('H')
```
Series

```python
>>> pd.Series(rng).dt.floor("H")
0  2018-01-01 11:00:00
1  2018-01-01 12:00:00
2  2018-01-01 12:00:00
dtype: datetime64[ns]
```

**pandas.TimedeltaIndex.ceil**

*TimedeltaIndex.ceil(*args, **kwargs)*

Perform ceil operation on the data to the specified `freq`.

**Parameters**

- `freq` [str or Offset] The frequency level to ceil the index to. Must be a fixed frequency like ‘S’ (second) not ‘ME’ (month end). See *frequency aliases* for a list of possible `freq` values.

- `ambiguous` [‘infer’, bool-ndarray, ‘NaT’, default ‘raise’] Only relevant for DatetimeIndex:
  - ‘infer’ will attempt to infer fall dst-transition hours based on order
  - bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
  - ‘NaT’ will return NaT where there are ambiguous times
  - ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

- `nonexistent` [‘shift_forward’, ‘shift_backward’, ‘NaT’, timedelta, default ‘raise’] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.
  - ‘shift_forward’ will shift the nonexistent time forward to the closest existing time
  - ‘shift_backward’ will shift the nonexistent time backward to the closest existing time
  - ‘NaT’ will return NaT where there are nonexistent times
  - timedelta objects will shift nonexistent times by the timedelta
  - ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

**Returns**

- `DatetimeIndex`, `TimedeltaIndex`, or `Series` Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

**Raises**
ValueError if the freq cannot be converted.

Examples

**DatetimeIndex**

```python
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
              dtype='datetime64[ns]', freq='T')

>>> rng.ceil('H')
DatetimeIndex(['2018-01-01 12:00:00', '2018-01-01 12:00:00',
               '2018-01-02 00:00:00'],
              dtype='datetime64[ns]', freq=None)
```

**Series**

```python
>>> pd.Series(rng).dt.ceil("H")
0  2018-01-01 12:00:00
1  2018-01-01 12:00:00
2  2018-01-02 00:00:00
dtype: datetime64[ns]
```

**pandas.TimedeltaIndex.to_frame**

TimedeltaIndex.to_frame(index=True, name=None)  
Create a DataFrame with a column containing the Index.  
New in version 0.24.0.

**Parameters**

index [bool, default True] Set the index of the returned DataFrame as the original Index.

name [object, default None] The passed name should substitute for the index name (if it has one).

**Returns**

DataFrame DataFrame containing the original Index data.

See also:

* Index.to_series Convert an Index to a Series.
* Series.to_frame Convert Series to DataFrame.
Examples

```python
>>> idx = pd.Index(['Ant', 'Bear', 'Cow'], name='animal')
>>> idx.to_frame()
       animal
animal  Ant
       Bear
       Cow

By default, the original Index is reused. To enforce a new Index:

```python
>>> idx.to_frame(index=False)
        animal
         0  Ant
         1  Bear
         2  Cow
```

To override the name of the resulting column, specify `name`:

```python
>>> idx.to_frame(index=False, name='zoo')
         zoo
         0  Ant
         1  Bear
         2  Cow
```

**pandas.TimedeltaIndex.mean**

`TimedeltaIndex.mean(*args, **kwargs)`

Return the mean value of the Array.

New in version 0.25.0.

**Parameters**

- `skipna` [bool, default True] Whether to ignore any NaT elements.

**Returns**

- scalar Timestamp or Timedelta.

**See also:**

- `numpy.ndarray.mean` Returns the average of array elements along a given axis.
- `Series.mean` Return the mean value in a Series.

**Notes**

mean is only defined for Datetime and Timedelta dtypes, not for Period.
**Components**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>TimedeltaIndex.days</td>
<td>Number of days for each element.</td>
</tr>
<tr>
<td>TimedeltaIndex.seconds</td>
<td>Number of seconds (&gt;= 0 and less than 1 day) for each element.</td>
</tr>
<tr>
<td>TimedeltaIndex.microseconds</td>
<td>Number of microseconds (&gt;= 0 and less than 1 second) for each element.</td>
</tr>
<tr>
<td>TimedeltaIndex.nanoseconds</td>
<td>Number of nanoseconds (&gt;= 0 and less than 1 microsecond) for each element.</td>
</tr>
<tr>
<td>TimedeltaIndex.components</td>
<td>Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds) of the Timedeltas.</td>
</tr>
<tr>
<td>TimedeltaIndex.inferred_freq</td>
<td>Tries to return a string representing a frequency guess, generated by infer_freq.</td>
</tr>
</tbody>
</table>

**Conversion**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>TimedeltaIndex.to_pytimedelta(*args, **kwargs)</td>
<td>Return Timedelta Array/Index as object ndarray of datetime.timedelta objects.</td>
</tr>
<tr>
<td>TimedeltaIndex.to_series([index, name])</td>
<td>Create a Series with both index and values equal to the index keys.</td>
</tr>
<tr>
<td>TimedeltaIndex.round(*args, **kwargs)</td>
<td>Perform round operation on the data to the specified freq.</td>
</tr>
<tr>
<td>TimedeltaIndex.floor(*args, **kwargs)</td>
<td>Perform floor operation on the data to the specified freq.</td>
</tr>
<tr>
<td>TimedeltaIndex.ceil(*args, **kwargs)</td>
<td>Perform ceil operation on the data to the specified freq.</td>
</tr>
<tr>
<td>TimedeltaIndex.to_frame([index, name])</td>
<td>Create a DataFrame with a column containing the Index.</td>
</tr>
</tbody>
</table>

**Methods**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>TimedeltaIndex.mean(*args, **kwargs)</td>
<td>Return the mean value of the Array.</td>
</tr>
</tbody>
</table>

### 3.7.8 PeriodIndex

**PeriodIndex**([data, ordinal, freq, tz, ...]) Immutable ndarray holding ordinal values indicating regular periods in time.

**pandas.PeriodIndex**

```python
class pandas.PeriodIndex(data=None, ordinal=None, freq=None, tz=None, dtype=None, copy=False, name=None, **fields)
```

Immutable ndarray holding ordinal values indicating regular periods in time.

Index keys are boxed to Period objects which carries the metadata (eg, frequency information).

**Parameters**

- **data** [array-like (1d int np.ndarray or PeriodArray), optional] Optional period-like data to construct index with.
copy [bool] Make a copy of input ndarray.

freq [str or period object, optional] One of pandas period strings or corresponding objects.

year [int, array, or Series, default None]
month [int, array, or Series, default None]
quarter [int, array, or Series, default None]
day [int, array, or Series, default None]
hour [int, array, or Series, default None]
minute [int, array, or Series, default None]
second [int, array, or Series, default None]
tz [object, default None] Timezone for converting datetime64 data to Periods.
dtype [str or PeriodDtype, default None]

See also:

Index The base pandas Index type.
Period Represents a period of time.
DatetimeIndex Index with datetime64 data.
TimedeltaIndex Index of timedelta64 data.
period_range Create a fixed-frequency PeriodIndex.

Examples

```python
>>> idx = pd.PeriodIndex(year=[2000, 2002], quarter=[1, 3])
>>> idx
PeriodIndex(['2000Q1', '2002Q3'], dtype='period[Q-DEC]', freq='Q-DEC')
```

Attributes

- `day` The days of the period.
- `dayofweek` The day of the week with Monday=0, Sunday=6.
- `dayofyear` The ordinal day of the year.
- `days_in_month` The number of days in the month.
- `daysinmonth` The number of days in the month.
- `freq` Return the frequency object if it is set, otherwise None.
- `freqstr` Return the frequency object as a string if its set, otherwise None.
- `hour` The hour of the period.
- `is_leap_year` Logical indicating if the date belongs to a leap year.
- `minute` The minute of the period.
- `month` The month as January=1, December=12.
- `quarter` The quarter of the date.
- `second` The second of the period.
- `week` The week ordinal of the year.
- `weekday` The day of the week with Monday=0, Sunday=6.
- `weekofyear` The week ordinal of the year.
Table 176 – continued from previous page

<table>
<thead>
<tr>
<th>year</th>
<th>The year of the period.</th>
</tr>
</thead>
</table>

**pandas.PeriodIndex.day**

**property** PeriodIndex.day
The days of the period.

**pandas.PeriodIndex.dayofweek**

**property** PeriodIndex.dayofweek
The day of the week with Monday=0, Sunday=6.

**pandas.PeriodIndex.dayofyear**

**property** PeriodIndex.dayofyear
The ordinal day of the year.

**pandas.PeriodIndex.days_in_month**

**property** PeriodIndex.days_in_month
The number of days in the month.

**pandas.PeriodIndex.daysinmonth**

**property** PeriodIndex.daysinmonth
The number of days in the month.

**pandas.PeriodIndex.freq**

**property** PeriodIndex.freq
Return the frequency object if it is set, otherwise None.

**pandas.PeriodIndex.freqstr**

**property** PeriodIndex.freqstr
Return the frequency object as a string if it is set, otherwise None.
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.PeriodIndex.hour

property PeriodIndex.hour
   The hour of the period.

pandas.PeriodIndex.is_leap_year

property PeriodIndex.is_leap_year
   Logical indicating if the date belongs to a leap year.

pandas.PeriodIndex.minute

property PeriodIndex.minute
   The minute of the period.

pandas.PeriodIndex.month

property PeriodIndex.month
   The month as January=1, December=12.

pandas.PeriodIndex.quarter

property PeriodIndex.quarter
   The quarter of the date.

pandas.PeriodIndex.second

property PeriodIndex.second
   The second of the period.

pandas.PeriodIndex.week

property PeriodIndex.week
   The week ordinal of the year.

pandas.PeriodIndex.weekday

property PeriodIndex.weekday
   The day of the week with Monday=0, Sunday=6.
pandas.PeriodIndex.weekofyear

**property** `PeriodIndex.weekofyear`  
The week ordinal of the year.

pandas.PeriodIndex.year

**property** `PeriodIndex.year`  
The year of the period.

<table>
<thead>
<tr>
<th>end_time</th>
<th>qyear</th>
<th>start_time</th>
</tr>
</thead>
</table>

**Methods**

<table>
<thead>
<tr>
<th><code>asfreq([freq, how])</code></th>
<th>Convert the Period Array/Index to the specified frequency <code>freq</code>.</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>strftime(*args, **kwargs)</code></td>
<td>Convert to Index using specified date_format.</td>
</tr>
<tr>
<td><code>to_timestamp(*args, **kwargs)</code></td>
<td>Cast to DatetimeArray/Index.</td>
</tr>
</tbody>
</table>

**pandas.PeriodIndex.asfreq**

`PeriodIndex.asfreq(freq=None, how='E')`  
Convert the Period Array/Index to the specified frequency `freq`.

**Parameters**

- `freq` [str] A frequency.
- `how` [str {‘E’, ‘S’}] Whether the elements should be aligned to the end or start within a period.
  - ‘E’, ‘END’, or ‘FINISH’ for end,
  - ‘S’, ‘START’, or ‘BEGIN’ for start.
  January 31st (‘END’) vs. January 1st (‘START’) for example.

**Returns**

- **Period Array/Index**  Constructed with the new frequency.
## Examples

```
>>> pidx = pd.period_range('2010-01-01', '2015-01-01', freq='A')
>>> pidx
dtype='period[A-DEC]', freq='A-DEC')
```

```
>>> pidx.asfreq('M')
PeriodIndex(['2010-12', '2011-12', '2012-12', '2013-12', '2014-12',
             '2015-12'], dtype='period[M]', freq='M')
```

```
>>> pidx.asfreq('M', how='S')
             '2015-01'], dtype='period[M]', freq='M')
```

### pandas.PeriodIndex.strftime

PeriodIndex.\texttt{strftime}(\*\textit{args}, \*\*\textit{kwargs})

Convert to Index using specified date\_format.

Return an Index of formatted strings specified by date\_format, which supports the same string format as the python standard library. Details of the string format can be found in python string format doc.

**Parameters**

- \texttt{date\_format} [str] Date format string (e.g. \texttt{"\%Y-\%m-\%d"}).

**Returns**

- \texttt{ndarray} NumPy ndarray of formatted strings.

**See also:**

- \texttt{to\_datetime} Convert the given argument to datetime.
- \texttt{DatetimeIndex.normalize} Return DatetimeIndex with times to midnight.
- \texttt{DatetimeIndex.round} Round the DatetimeIndex to the specified freq.
- \texttt{DatetimeIndex.floor} Floor the DatetimeIndex to the specified freq.

### Examples

```
>>> rng = pd.date_range(pd.Timestamp("2018-03-10 09:00"),
                      periods=3, freq='s')
>>> rng.strftime('%B %d, %Y, %r')
Index(['March 10, 2018, 09:00:00 AM', 'March 10, 2018, 09:00:01 AM',
      'March 10, 2018, 09:00:02 AM'],
      dtype='object')
```
pandas.PeriodIndex.to_timestamp

PeriodIndex.to_timestamp(*args, **kwargs)
Cast to DatetimeArray/Index.

Parameters

freq [str or DateOffset, optional] Target frequency. The default is 'D' for week or longer, 'S' otherwise.

how [{‘s’, ‘e’, ‘start’, ‘end’}] Whether to use the start or end of the time period being converted.

Returns

DatetimeArray/Index

Properties

PeriodIndex.day
The days of the period.

PeriodIndex.dayofweek
The day of the week with Monday=0, Sunday=6.

PeriodIndex.dayofyear
The ordinal day of the year.

PeriodIndex.days_in_month
The number of days in the month.

PeriodIndex.daysinmonth
The number of days in the month.

PeriodIndex.end_time

PeriodIndex.freq
Return the frequency object if it is set, otherwise None.

PeriodIndex.freqstr
Return the frequency object as a string if its set, otherwise None.

PeriodIndex.hour
The hour of the period.

PeriodIndex.is_leap_year
Logical indicating if the date belongs to a leap year.

PeriodIndex.minute
The minute of the period.

PeriodIndex.month
The month as January=1, December=12.

PeriodIndex.quarter
The quarter of the date.

PeriodIndex.qyear

PeriodIndex.second
The second of the period.

PeriodIndex.start_time

PeriodIndex.week
The week ordinal of the year.

PeriodIndex.weekday
The day of the week with Monday=0, Sunday=6.

PeriodIndex.weekofyear
The week ordinal of the year.

PeriodIndex.year
The year of the period.

pandas.PeriodIndex.end_time

property PeriodIndex.end_time
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.PeriodIndex.qyear

property PeriodIndex.qyear

pandas.PeriodIndex.start_time

property PeriodIndex.start_time

Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>PeriodIndex.asfreq(freq, how)</td>
<td>Convert the Period Array/Index to the specified frequency freq.</td>
</tr>
<tr>
<td>PeriodIndex.strftime(*args, **kwargs)</td>
<td>Convert to Index using specified date_format.</td>
</tr>
<tr>
<td>PeriodIndex.to_timestamp(*args, **kwargs)</td>
<td>Cast to DatetimeArray/Index.</td>
</tr>
</tbody>
</table>

3.8 Date offsets

3.8.1 DateOffset

<table>
<thead>
<tr>
<th>Class</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DateOffset</td>
<td>Standard kind of date increment used for a date range.</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.DateOffset

class pandas.tseries.offsets.DateOffset

Standard kind of date increment used for a date range.

Works exactly like relativedelta in terms of the keyword args you pass in, use of the keyword n is discouraged—you would be better off specifying n in the keywords you use, but regardless it is there for you. n is needed for DateOffset subclasses.

DateOffset work as follows. Each offset specify a set of dates that conform to the DateOffset. For example, Bday defines this set to be the set of dates that are weekdays (M-F). To test if a date is in the set of a DateOffset dateOffset we can use the is_on_offset method: dateOffset.is_on_offset(date).

If a date is not on a valid date, the rollback and rollforward methods can be used to roll the date to the nearest valid date before/after the date.

DateOffsets can be created to move dates forward a given number of valid dates. For example, Bday(2) can be added to a date to move it two business days forward. If the date does not start on a valid date, first it is moved to a valid date. Thus pseudo code is:

def __add__(date): date = rollback(date) # does nothing if date is valid return date + <n number of periods>

When a date offset is created for a negative number of periods, the date is first rolled forward. The pseudo code is:

def __add__(date): date = rollforward(date) # does nothing is date is valid return date + <n number of periods>

Zero presents a problem. Should it roll forward or back? We arbitrarily have it rollforward:

date + BDay(0) == BDay.rollforward(date)

Since 0 is a bit weird, we suggest avoiding its use.

Parameters
n [int, default 1] The number of time periods the offset represents.

normalize [bool, default False] Whether to round the result of a DateOffset addition down to the previous midnight.

**kwds** Temporal parameter that add to or replace the offset value.

Parameters that **add** to the offset (like Timedelta):

- years
- months
- weeks
- days
- hours
- minutes
- seconds
- microseconds
- nanoseconds

Parameters that **replace** the offset value:

- year
- month
- day
- weekday
- hour
- minute
- second
- microsecond
- nanosecond.

See also:

dateutil.relativedelta.relativedelta The relativedelta type is designed to be applied to an existing datetime and can replace specific components of that datetime, or represents an interval of time.

Examples

```python
>>> from pandas.tseries.offsets import DateOffset
>>> ts = pd.Timestamp('2017-01-01 09:10:11')
>>> ts + DateOffset(months=3)
Timestamp('2017-04-01 09:10:11')

>>> ts = pd.Timestamp('2017-01-01 09:10:11')
>>> ts + DateOffset(months=2)
Timestamp('2017-03-01 09:10:11')
```
Attributes

| base   | Returns a copy of the calling offset object with n=1 and all other attributes equal. |

`pandas.tseries.offsets.DateOffset.base`

DateOffset . `base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<table>
<thead>
<tr>
<th>freqstr</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>kwds</td>
<td></td>
</tr>
<tr>
<td>n</td>
<td></td>
</tr>
<tr>
<td>name</td>
<td></td>
</tr>
<tr>
<td>nanos</td>
<td></td>
</tr>
<tr>
<td>normalize</td>
<td></td>
</tr>
<tr>
<td>rule_code</td>
<td></td>
</tr>
</tbody>
</table>

Methods

<table>
<thead>
<tr>
<th><code>__call__</code>(*args, **kwargs)</th>
<th>Call self as a function.</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>rollback</code></td>
<td>Roll provided date backward to next offset only if not on offset.</td>
</tr>
<tr>
<td><code>rollforward</code></td>
<td>Roll provided date forward to next offset only if not on offset.</td>
</tr>
</tbody>
</table>

`pandas.tseries.offsets.DateOffset.__call__`

DateOffset . `__call__`(*args, **kwargs)

Call self as a function.

`pandas.tseries.offsets.DateOffset.rollback`

DateOffset . `rollback`

Roll provided date backward to next offset only if not on offset.

Returns

*TimeStamp* Rolled timestamp if not on offset, otherwise unchanged timestamp.
**pandas.tseries.offsets.DateOffset.rollforward**

```python
DateOffset.rollforward()
```

Roll provided date forward to next offset only if not on offset.

**Returns**

<table>
<thead>
<tr>
<th>Returns</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>TimeStamp</strong></td>
<td>Rolled timestamp if not on offset, otherwise unchanged timestamp.</td>
</tr>
</tbody>
</table>

**Properties**

- `DateOffset.freqstr`
- `DateOffset.kwds`
- `DateOffset.name`
- `DateOffset.nanos`
- `DateOffset.normalize`
- `DateOffset.rule_code`
- `DateOffset.n`

**pandas.tseries.offsets.DateOffset.freqstr**

```python
DateOffset.freqstr
```

**pandas.tseries.offsets.DateOffset.kwds**

```python
DateOffset.kwds
```
`pandas`: powerful Python data analysis toolkit, Release 1.1.1

`pandas.tseries.offsets.DateOffset.name`

`DateOffset.name`

`pandas.tseries.offsets.DateOffset.nanos`

`DateOffset.nanos`

`pandas.tseries.offsets.DateOffset.normalize`

`DateOffset.normalize`

`pandas.tseries.offsets.DateOffset.rule_code`

`DateOffset.rule_code`

`pandas.tseries.offsets.DateOffset.n`

`DateOffset.n`

**Methods**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>DateOffset.apply(other)</code></td>
<td></td>
</tr>
<tr>
<td><code>DateOffset.apply_index(other)</code></td>
<td></td>
</tr>
<tr>
<td><code>DateOffset.copy</code></td>
<td></td>
</tr>
<tr>
<td><code>DateOffset.isAnchored</code></td>
<td></td>
</tr>
<tr>
<td><code>DateOffset.onOffset</code></td>
<td></td>
</tr>
<tr>
<td><code>DateOffset.is_anchored</code></td>
<td></td>
</tr>
<tr>
<td><code>DateOffset.is_on_offset</code></td>
<td></td>
</tr>
<tr>
<td><code>DateOffset.__call__(*args, **kwargs)</code></td>
<td>Call self as a function.</td>
</tr>
</tbody>
</table>

`pandas.tseries.offsets.DateOffset.apply`

`DateOffset.apply(other)`
pandas.tseries.offsets.DateOffset.apply_index

DateOffset.apply_index(other)

pandas.tseries.offsets.DateOffset.copy

DateOffset.copy()

pandas.tseries.offsets.DateOffset.isAnchored

DateOffset.isAnchored()

pandas.tseries.offsets.DateOffset.onOffset

DateOffset.onOffset()

pandas.tseries.offsets.DateOffset.is_anchored

DateOffset.is_anchored()

pandas.tseries.offsets.DateOffset.is_on_offset

DateOffset.is_on_offset()

3.8.2 BusinessDay

<table>
<thead>
<tr>
<th>BusinessDay</th>
<th>DateOffset subclass representing possibly n business days.</th>
</tr>
</thead>
</table>

pandas.tseries.offsets.BusinessDay

class pandas.tseries.offsets.BusinessDay

DateOffset subclass representing possibly n business days.

Attributes

<table>
<thead>
<tr>
<th>base</th>
<th>Returns a copy of the calling offset object with n=1 and all other attributes equal.</th>
</tr>
</thead>
<tbody>
<tr>
<td>offset</td>
<td>Alias for self._offset.</td>
</tr>
</tbody>
</table>
pandas.tseries.offsets.BusinessDay.base

BusinessDay.base
   Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.BusinessDay.offset

BusinessDay.offset
   Alias for self._offset.

Methods

__call__(*args, **kwargs)  Call self as a function.
rollback
   Roll provided date backward to next offset only if not on offset.
rollforward
   Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.BusinessDay.__call__

BusinessDay.__call__(*args, **kwargs)
   Call self as a function.

pandas.tseries.offsets.BusinessDay.rollback

BusinessDay.rollback()
   Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp  Rolled timestamp if not on offset, otherwise unchanged timestamp.
pandas.tseries.offsets.BusinessDay.rollforward

BusinessDay.rollforward()
    Roll provided date forward to next offset only if not on offset.

    Returns
    TimeStamp  Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>apply</th>
<th>copy</th>
<th>isAnchored</th>
<th>is_anchored</th>
<th>is_on_offset</th>
<th>onOffset</th>
</tr>
</thead>
</table>

Alias:

BDay                     alias of pandas._libs.tslibs.offsets.BusinessDay

3.8. Date offsets
pandas: powerful Python data analysis toolkit, Release 1.1.1

- `pandas.tseries.offsets.BusinessDay.freqstr`
- `BusinessDay.freqstr`
- `pandas.tseries.offsets.BusinessDay.kwds`
- `BusinessDay.kwds`
- `pandas.tseries.offsets.BusinessDay.name`
- `BusinessDay.name`
- `pandas.tseries.offsets.BusinessDay.nanos`
- `BusinessDay.nanos`
- `pandas.tseries.offsets.BusinessDay.normalize`
- `BusinessDay.normalize`
- `pandas.tseries.offsets.BusinessDay.rule_code`
- `BusinessDay.rule_code`
- `pandas.tseries.offsets.BusinessDay.n`
- `BusinessDay.n`
- `pandas.tseries.offsets.BusinessDay.weekmask`
- `BusinessDay.weekmask`
- `pandas.tseries.offsets.BusinessDay.holidays`
- `BusinessDay.holidays`
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.BusinessDay.calendar

Methods

- BusinessDay.apply
- BusinessDay.apply_index
- BusinessDay.copy
- BusinessDay.isAnchored
- BusinessDay.onOffset
- BusinessDay.is_on_offset
- BusinessDay._apply(*args, **kwargs) Call self as a function.

pandas.tseries.offsets.BusinessDay.apply

BusinessDay.apply(other)

pandas.tseries.offsets.BusinessDay.apply_index

BusinessDay.apply_index(other)

pandas.tseries.offsets.BusinessDay.copy

BusinessDay.copy()

pandas.tseries.offsets.BusinessDay.isAnchored

BusinessDay.isAnchored()

pandas.tseries.offsets.BusinessDay.onOffset

BusinessDay.onOffset()

pandas.tseries.offsets.BusinessDay.is_anchored

BusinessDay.is_anchored()
3.8.3 BusinessHour

`BusinessHour` is a subclass of `DateOffset` representing possibly n business hours.

**Attributes**

- `base`: Returns a copy of the calling offset object with n=1 and all other attributes equal.
- `next_bday`: Used for moving to next business day.
- `offset`: Alias for `self._offset`.

```python
BusinessHour.base
Return a copy of the calling offset object with n=1 and all other attributes equal.

BusinessHour.next_bday
Used for moving to next business day.

BusinessHour.offset
Alias for self._offset.
```
pandas.tseries.offsets.BusinessHour.offset

BusinessHour.offset

Alias for self._offset.

Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>call</strong>(*args, **kwargs)</td>
<td>Call self as a function.</td>
</tr>
<tr>
<td>rollback(other)</td>
<td>Roll provided date backward to next offset only if not on offset.</td>
</tr>
<tr>
<td>rollforward(other)</td>
<td>Roll provided date forward to next offset only if not on offset.</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.BusinessHour.__call__

BusinessHour.__call__(*args, **kwargs)

Call self as a function.

pandas.tseries.offsets.BusinessHour.rollback

BusinessHour.rollback(other)

Roll provided date backward to next offset only if not on offset.

pandas.tseries.offsets.BusinessHour.rollforward

BusinessHour.rollback(other)

Roll provided date forward to next offset only if not on offset.
Properties

<table>
<thead>
<tr>
<th>BusinessHour.freqstr</th>
</tr>
</thead>
<tbody>
<tr>
<td>BusinessHour.kwds</td>
</tr>
<tr>
<td>BusinessHour.name</td>
</tr>
<tr>
<td>BusinessHour.nanos</td>
</tr>
<tr>
<td>BusinessHour.normalize</td>
</tr>
<tr>
<td>BusinessHour.rule_code</td>
</tr>
<tr>
<td>BusinessHour.n</td>
</tr>
<tr>
<td>BusinessHour.start</td>
</tr>
<tr>
<td>BusinessHour.end</td>
</tr>
<tr>
<td>BusinessHour.weekmask</td>
</tr>
<tr>
<td>BusinessHour.holidays</td>
</tr>
<tr>
<td>BusinessHour.calendar</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.BusinessHour.freqstr

BusinessHour.freqstr

pandas.tseries.offsets.BusinessHour.kwds

BusinessHour.kwds

pandas.tseries.offsets.BusinessHour.name

BusinessHour.name

pandas.tseries.offsets.BusinessHour.nanos

BusinessHour.nanos
### pandas.tseries.offsets.BusinessHour

- **normalize**
- **rule_code**
- **n**
- **start**
- **end**
- **weekmask**
- **holidays**
- **calendar**

#### Methods

- `BusinessHour.apply(other)`
- `BusinessHour.apply_index(other)`
- `BusinessHour.copy`
- `BusinessHour.isAnchored`
- `BusinessHour.onOffset`
- `BusinessHour.is_anchored`
- `BusinessHour.is_on_offset`
- `BusinessHour.__call__(*args, **kwargs)` Call self as a function.

### 3.8. Date offsets
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.BusinessHour.apply

BusinessHour.apply(other)

pandas.tseries.offsets.BusinessHour.apply_index

BusinessHour.apply_index(other)

pandas.tseries.offsets.BusinessHour.copy

BusinessHour.copy()

pandas.tseries.offsets.BusinessHour.isAnchored

BusinessHour.isAnchored()

pandas.tseries.offsets.BusinessHour.onOffset

BusinessHour.onOffset()

pandas.tseries.offsets.BusinessHour.is_anchored

BusinessHour.is_anchored()

pandas.tseries.offsets.BusinessHour.is_on_offset

BusinessHour.is_on_offset()

3.8.4 CustomBusinessDay

<table>
<thead>
<tr>
<th>CustomBusinessDay</th>
<th>DateOffset subclass representing custom business days excluding holidays.</th>
</tr>
</thead>
</table>

pandas.tseries.offsets.CustomBusinessDay

class pandas.tseries.offsets.CustomBusinessDay

DateOffset subclass representing custom business days excluding holidays.

Parameters

n [int, default 1]

normalize [bool, default False] Normalize start/end dates to midnight before generating date range.

weekmask [str, Default ‘Mon Tue Wed Thu Fri’] Weekmask of valid business days, passed to numpy.busdaycalendar.
**holidays** [list] List/array of dates to exclude from the set of valid business days, passed to `numpy.busdaycalendar`.

**calendar** [pd.HolidayCalendar or np.busdaycalendar]

**offset** [timedelta, default timedelta(0)]

### Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>base</code></td>
<td>Returns a copy of the calling offset object with n=1 and all other attributes equal.</td>
</tr>
<tr>
<td><code>offset</code></td>
<td>Alias for self._offset.</td>
</tr>
</tbody>
</table>

#### pandas.tseries.offsets.CustomBusinessDay.base

**CustomBusinessDay.base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

#### pandas.tseries.offsets.CustomBusinessDay.offset

**CustomBusinessDay.offset**

Alias for self._offset.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>calendar</code></td>
<td></td>
</tr>
<tr>
<td><code>freqstr</code></td>
<td></td>
</tr>
<tr>
<td><code>holidays</code></td>
<td></td>
</tr>
<tr>
<td><code>kwds</code></td>
<td></td>
</tr>
<tr>
<td><code>n</code></td>
<td></td>
</tr>
<tr>
<td><code>name</code></td>
<td></td>
</tr>
<tr>
<td><code>nanos</code></td>
<td></td>
</tr>
<tr>
<td><code>normalize</code></td>
<td></td>
</tr>
<tr>
<td><code>rule_code</code></td>
<td></td>
</tr>
<tr>
<td><code>weekmask</code></td>
<td></td>
</tr>
</tbody>
</table>

### Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>__call__(args, **kwargs)</code></td>
<td>Call self as a function.</td>
</tr>
<tr>
<td><code>rollback</code></td>
<td>Roll provided date backward to next offset only if not on offset.</td>
</tr>
<tr>
<td><code>rollforward</code></td>
<td>Roll provided date forward to next offset only if not on offset.</td>
</tr>
</tbody>
</table>
pandas.tseries.offsets.CustomBusinessDay.__call__

CustomBusinessDay.__call__(*args, **kwargs)
Call self as a function.

pandas.tseries.offsets.CustomBusinessDay.rollback

CustomBusinessDay.rollback()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.CustomBusinessDay.rollforward

CustomBusinessDay.rollforward()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>apply</th>
<th>apply_index</th>
</tr>
</thead>
<tbody>
<tr>
<td>copy</td>
<td></td>
</tr>
<tr>
<td>isAnchored</td>
<td>is_anchored</td>
</tr>
<tr>
<td>is_on_offset</td>
<td>onOffset</td>
</tr>
</tbody>
</table>

Alias:

CDay alias of pandas._libs.tslibs.offsets.CustomBusinessDay

pandas.tseries.offsets.CDay

pandas.tseries.offsets.CDay
alias of pandas._libs.tslibs.offsets.CustomBusinessDay

Properties

<table>
<thead>
<tr>
<th>CustomBusinessDay.freqstr</th>
</tr>
</thead>
<tbody>
<tr>
<td>CustomBusinessDay.kwds</td>
</tr>
<tr>
<td>CustomBusinessDay.name</td>
</tr>
<tr>
<td>CustomBusinessDay.nanos</td>
</tr>
<tr>
<td>CustomBusinessDay.normalize</td>
</tr>
<tr>
<td>CustomBusinessDay.rule_code</td>
</tr>
</tbody>
</table>
Table 200 – continued from previous page

<table>
<thead>
<tr>
<th>CustomBusinessDay.n</th>
</tr>
</thead>
<tbody>
<tr>
<td>CustomBusinessDay.weekmask</td>
</tr>
<tr>
<td>CustomBusinessDay.calendar</td>
</tr>
<tr>
<td>CustomBusinessDay.holidays</td>
</tr>
</tbody>
</table>

```python
pandas.tseries.offsets.CustomBusinessDay.freqstr

CustomBusinessDay.freqstr

pandas.tseries.offsets.CustomBusinessDay.kwds

CustomBusinessDay.kwds

pandas.tseries.offsets.CustomBusinessDay.name

CustomBusinessDay.name

pandas.tseries.offsets.CustomBusinessDay.nanos

CustomBusinessDay.nanos

pandas.tseries.offsets.CustomBusinessDay.normalize

CustomBusinessDay.normalize

pandas.tseries.offsets.CustomBusinessDay.rule_code

CustomBusinessDay.rule_code

pandas.tseries.offsets.CustomBusinessDay.n

CustomBusinessDay.n

pandas.tseries.offsets.CustomBusinessDay.weekmask

CustomBusinessDay.weekmask
```

3.8. Date offsets
CustomBusinessDay.calendar

CustomBusinessDay.holidays

Methods

CustomBusinessDay.apply_index
CustomBusinessDay.apply(\(other\))
CustomBusinessDay.copy
CustomBusinessDay.isAnchored
CustomBusinessDay.onOffset
CustomBusinessDay.is_anchored
CustomBusinessDay.is_on_offset
CustomBusinessDay.__call__(\(*args, \**kwargs\))

Call self as a function.
pandas.tseries.offsets.CustomBusinessDay.is_anchored

CustomBusinessDay.is_anchored()

pandas.tseries.offsets.CustomBusinessDay.is_on_offset

CustomBusinessDay.is_on_offset()

### 3.8.5 CustomBusinessHour

<table>
<thead>
<tr>
<th>CustomBusinessHour</th>
<th>DateOffset subclass representing possibly n custom business days.</th>
</tr>
</thead>
</table>

pandas.tseries.offsets.CustomBusinessHour

```python
class pandas.tseries.offsets.CustomBusinessHour
    DateOffset subclass representing possibly n custom business days.
```

**Attributes**

<table>
<thead>
<tr>
<th>base</th>
<th>Returns a copy of the calling offset object with n=1 and all other attributes equal.</th>
</tr>
</thead>
<tbody>
<tr>
<td>next_bday</td>
<td>Used for moving to next business day.</td>
</tr>
<tr>
<td>offset</td>
<td>Alias for self._offset.</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.CustomBusinessHour.base

CustomBusinessHour.base

    Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.CustomBusinessHour.next_bday

CustomBusinessHour.next_bday

    Used for moving to next business day.

pandas.tseries.offsets.CustomBusinessHour.offset

CustomBusinessHour.offset

    Alias for self._offset.
Methods

```
_pcall_(*args, **kwargs) Call self as a function.
rollback(other) Roll provided date backward to next offset only if not on offset.
rollforward(other) Roll provided date forward to next offset only if not on offset.
```

**pandas.tseries.offsets.CustomBusinessHour._call_**

CustomBusinessHour._call_(*args, **kwargs)
Call self as a function.

**pandas.tseries.offsets.CustomBusinessHour.rollback**

CustomBusinessHour.rollback(other)
Roll provided date backward to next offset only if not on offset.

**pandas.tseries.offsets.CustomBusinessHour.rollforward**

CustomBusinessHour.rollforward(other)
Roll provided date forward to next offset only if not on offset.
Properties

<table>
<thead>
<tr>
<th>Property</th>
</tr>
</thead>
<tbody>
<tr>
<td>CustomBusinessHour.freqstr</td>
</tr>
<tr>
<td>CustomBusinessHour.kwds</td>
</tr>
<tr>
<td>CustomBusinessHour.name</td>
</tr>
<tr>
<td>CustomBusinessHour.nanos</td>
</tr>
<tr>
<td>CustomBusinessHour.normalize</td>
</tr>
<tr>
<td>CustomBusinessHour.rule_code</td>
</tr>
<tr>
<td>CustomBusinessHour.n</td>
</tr>
<tr>
<td>CustomBusinessHour.weekmask</td>
</tr>
<tr>
<td>CustomBusinessHour.calendar</td>
</tr>
<tr>
<td>CustomBusinessHour.holidays</td>
</tr>
<tr>
<td>CustomBusinessHour.start</td>
</tr>
<tr>
<td>CustomBusinessHour.end</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.CustomBusinessHour.freqstr

CustomBusinessHour.freqstr

pandas.tseries.offsets.CustomBusinessHour.kwds

CustomBusinessHour.kwds

pandas.tseries.offsets.CustomBusinessHour.name

CustomBusinessHour.name

pandas.tseries.offsets.CustomBusinessHour.nanos

CustomBusinessHour.nanos

pandas.tseries.offsets.CustomBusinessHour.normalize

CustomBusinessHour.normalize

pandas.tseries.offsets.CustomBusinessHour.rule_code

CustomBusinessHour.rule_code
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.CustomBusinessHour.n

CustomBusinessHour.n

pandas.tseries.offsets.CustomBusinessHour.weekmask

CustomBusinessHour.weekmask

pandas.tseries.offsets.CustomBusinessHour.calendar

CustomBusinessHour.calendar

pandas.tseries.offsets.CustomBusinessHour.holidays

CustomBusinessHour.holidays

pandas.tseries.offsets.CustomBusinessHour.start

CustomBusinessHour.start

pandas.tseries.offsets.CustomBusinessHour.end

CustomBusinessHour.end

Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Signature</th>
</tr>
</thead>
<tbody>
<tr>
<td>CustomBusinessHour.apply</td>
<td>(other)</td>
</tr>
<tr>
<td>CustomBusinessHour.apply_index</td>
<td>(other)</td>
</tr>
<tr>
<td>CustomBusinessHour.copy</td>
<td></td>
</tr>
<tr>
<td>CustomBusinessHour.isAnchored</td>
<td></td>
</tr>
<tr>
<td>CustomBusinessHour.onOffset</td>
<td></td>
</tr>
<tr>
<td>CustomBusinessHour.is_anchored</td>
<td></td>
</tr>
<tr>
<td>CustomBusinessHour.is_on_offset</td>
<td></td>
</tr>
<tr>
<td>CustomBusinessHour.<strong>call</strong></td>
<td>(*args, **kwargs)</td>
</tr>
<tr>
<td></td>
<td>Call self as a function.</td>
</tr>
</tbody>
</table>
pandas.tseries.offsets.CustomBusinessHour.apply

CustomBusinessHour.apply(other)

pandas.tseries.offsets.CustomBusinessHour.apply_index

CustomBusinessHour.apply_index(other)

pandas.tseries.offsets.CustomBusinessHour.copy

CustomBusinessHour.copy()

pandas.tseries.offsets.CustomBusinessHour.isAnchored

CustomBusinessHour.isAnchored()

pandas.tseries.offsets.CustomBusinessHour.onOffset

CustomBusinessHour.onOffset()

pandas.tseries.offsets.CustomBusinessHour.is_anchored

CustomBusinessHour.is_anchored()

pandas.tseries.offsets.CustomBusinessHour.is_on_offset

CustomBusinessHour.is_on_offset()

3.8.6 MonthEnd

<table>
<thead>
<tr>
<th>MonthEnd</th>
<th>DateOffset of one month end.</th>
</tr>
</thead>
</table>

pandas.tseries.offsets.MonthEnd

class pandas.tseries.offsets.MonthEnd
    DateOffset of one month end.
Attributes

```
base
Returns a copy of the calling offset object with n=1
and all other attributes equal.
```

```
pandas.tseries.offsets.MonthEnd.base
MonthEnd.base
Returns a copy of the calling offset object with n=1 and all other attributes equal.
```

```
freqstr
kwds
n
name
nanos
normalize
rule_code
```

Methods

```
__call__(*args, **kwargs)
Call self as a function.
```

```
rollback
Roll provided date backward to next offset only if
not on offset.
```

```
rollforward
Roll provided date forward to next offset only if not
on offset.
```

```
pandas.tseries.offsets.MonthEnd.__call__
MonthEnd.__call__(*args, **kwargs)
Call self as a function.
```

```
pandas.tseries.offsets.MonthEnd.rollback
MonthEnd.rollback()
Roll provided date backward to next offset only if not on offset.
```

Returns

```
TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.
```

pandas.tseries.offsets.MonthEnd.rollforward

MonthEnd.rollforward()
    Roll provided date forward to next offset only if not on offset.

Returns

    TimeStamp  Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>apply</th>
<th>copy</th>
<th>isAnchored</th>
<th>is_anchored</th>
<th>is_on_offset</th>
<th>onOffset</th>
</tr>
</thead>
</table>

Properties

- MonthEnd.freqstr
- MonthEnd.kwds
- MonthEnd.name
- MonthEnd.nanos
- MonthEnd.normalize
- MonthEnd.rule_code
- MonthEnd.n

pandas.tseries.offsets.MonthEnd.freqstr

MonthEnd.freqstr

pandas.tseries.offsets.MonthEnd.kwds

MonthEnd.kwds
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.MonthEnd.name

MonthEnd.name

pandas.tseries.offsets.MonthEnd.nanos

MonthEnd.nanos

pandas.tseries.offsets.MonthEnd.normalize

MonthEnd.normalize

pandas.tseries.offsets.MonthEnd.rule_code

MonthEnd.rule_code

pandas.tseries.offsets.MonthEnd.n

MonthEnd.n

Methods

- MonthEnd.apply(other)
- MonthEnd.apply_index(other)
- MonthEnd.copy
- MonthEnd.isAnchored
- MonthEnd.onOffset
- MonthEnd.is_anchored
- MonthEnd.is_on_offset
- MonthEnd.__call__(*args, **kwargs) Call self as a function.

pandas.tseries.offsets.MonthEnd.apply

MonthEnd.apply(other)
pandas.tseries.offsets.MonthEnd.apply_index

MonthEnd.apply_index(other)

pandas.tseries.offsets.MonthEnd.copy

MonthEnd.copy()

pandas.tseries.offsets.MonthEnd.isAnchored

MonthEnd.isAnchored()

pandas.tseries.offsets.MonthEnd.onOffset

MonthEnd.onOffset()

pandas.tseries.offsets.MonthEnd.is_anchored

MonthEnd.is_anchored()

3.8.7 MonthBegin

<table>
<thead>
<tr>
<th>MonthBegin</th>
<th>DateOffset of one month at beginning.</th>
</tr>
</thead>
</table>

pandas.tseries.offsets.MonthBegin

class pandas.tseries.offsets.MonthBegin
    DateOffset of one month at beginning.

Attributes

| base | Returns a copy of the calling offset object with n=1 and all other attributes equal. |
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.MonthBegin.base

MonthBegin.base

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<table>
<thead>
<tr>
<th>freqstr</th>
<th>kwds</th>
</tr>
</thead>
<tbody>
<tr>
<td>n</td>
<td>name</td>
</tr>
<tr>
<td>normalize</td>
<td>nanos</td>
</tr>
<tr>
<td>rule_code</td>
<td></td>
</tr>
</tbody>
</table>

Methods

__call__(*args, **kwargs) Call self as a function.

rollback

Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.MonthBegin.rollback

MonthBegin.rollback()

Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

rollforward

Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.
**Properties**

<table>
<thead>
<tr>
<th>MonthBegin.freqstr</th>
</tr>
</thead>
<tbody>
<tr>
<td>MonthBegin.kwds</td>
</tr>
<tr>
<td>MonthBegin.name</td>
</tr>
<tr>
<td>MonthBegin.nanos</td>
</tr>
<tr>
<td>MonthBegin.normalize</td>
</tr>
<tr>
<td>MonthBegin.rule_code</td>
</tr>
<tr>
<td>MonthBegin.n</td>
</tr>
</tbody>
</table>

**pandas.tseries.offsets.MonthBegin.freqstr**

MonthBegin.\texttt{freqstr}

**pandas.tseries.offsets.MonthBegin.kwds**

MonthBegin.\texttt{kwds}

**pandas.tseries.offsets.MonthBegin.name**

MonthBegin.\texttt{name}

**pandas.tseries.offsets.MonthBegin.nanos**

MonthBegin.\texttt{nanos}

**pandas.tseries.offsets.MonthBegin.normalize**

MonthBegin.\texttt{normalize}
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.MonthBegin.rule_code

MonthBegin.rule_code

pandas.tseries.offsets.MonthBegin.n

MonthBegin.n

Methods

- MonthBegin.apply(other)
- MonthBegin.apply_index(other)
- MonthBegin.copy
- MonthBegin.isAnchored
- MonthBegin.onOffset
- MonthBegin.is_anchored
- MonthBegin.is_on_offset
- MonthBegin.__call__(*args, **kwargs) Call self as a function.

pandas.tseries.offsets.MonthBegin.apply

MonthBegin.apply(other)

pandas.tseries.offsets.MonthBegin.apply_index

MonthBegin.apply_index(other)

pandas.tseries.offsets.MonthBegin.copy

MonthBegin.copy()

pandas.tseries.offsets.MonthBegin.isAnchored

MonthBegin.isAnchored()

pandas.tseries.offsets.MonthBegin.onOffset

MonthBegin.onOffset()
pandas.tseries.offsets.MonthBegin.is_anchored

MonthBegin.is_anchored()

pandas.tseries.offsets.MonthBegin.is_on_offset

MonthBegin.is_on_offset()

3.8.8 BusinessMonthEnd

| BusinessMonthEnd | DateOffset increments between the last business day of the month |

pandas.tseries.offsets.BusinessMonthEnd

class pandas.tseries.offsets.BusinessMonthEnd

DateOffset increments between the last business day of the month

Examples

```python
>>> from pandas.tseries.offset import BMonthEnd
>>> ts = pd.Timestamp('2020-05-24 05:01:15')
>>> ts + BMonthEnd()
Timestamp('2020-05-29 05:01:15')
>>> ts + BMonthEnd(2)
Timestamp('2020-06-30 05:01:15')
>>> ts + BMonthEnd(-2)
Timestamp('2020-03-31 05:01:15')
```

Attributes

| base | Returns a copy of the calling offset object with n=1 and all other attributes equal. |

pandas.tseries.offsets.BusinessMonthEnd.base

BusinessMonthEnd.base

Returns a copy of the calling offset object with n=1 and all other attributes equal.

| freqstr | |
| kwds | |
| n | |
| name | |
| nanos | |
| normalize | |
| rule_code | |
Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>__call__(*args, **kwargs)</code></td>
<td>Call self as a function.</td>
</tr>
<tr>
<td><code>rollback</code></td>
<td>Roll provided date backward to next offset only if not on offset.</td>
</tr>
<tr>
<td><code>rollforward</code></td>
<td>Roll provided date forward to next offset only if not on offset.</td>
</tr>
</tbody>
</table>

**pandas.tseries.offsets.BusinessMonthEnd.__call__**

`BusinessMonthEnd.__call__(*args, **kwargs)`

Call self as a function.

**pandas.tseries.offsets.BusinessMonthEnd.rollback**

`BusinessMonthEnd.rollback()`

Roll provided date backward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

**pandas.tseries.offsets.BusinessMonthEnd.rollforward**

`BusinessMonthEnd.rollforward()`

Roll provided date forward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>Method</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>apply</td>
<td></td>
</tr>
<tr>
<td>apply_index</td>
<td></td>
</tr>
<tr>
<td>copy</td>
<td></td>
</tr>
<tr>
<td>isAnchored</td>
<td></td>
</tr>
<tr>
<td>is_anchored</td>
<td></td>
</tr>
<tr>
<td>is_on_offset</td>
<td></td>
</tr>
<tr>
<td>onOffset</td>
<td></td>
</tr>
</tbody>
</table>

Alias:

<table>
<thead>
<tr>
<th>BMonthEnd</th>
<th>alias of pandas._libs.tslibs.offsets.BusinessMonthEnd</th>
</tr>
</thead>
</table>
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.BMonthEnd

    alias of pandas._libs.tslibs.offsets.BusinessMonthEnd

Properties

<table>
<thead>
<tr>
<th>Property</th>
</tr>
</thead>
<tbody>
<tr>
<td>BusinessMonthEnd.freqstr</td>
</tr>
<tr>
<td>BusinessMonthEnd.kwds</td>
</tr>
<tr>
<td>BusinessMonthEnd.name</td>
</tr>
<tr>
<td>BusinessMonthEnd.nanos</td>
</tr>
<tr>
<td>BusinessMonthEnd.normalize</td>
</tr>
<tr>
<td>BusinessMonthEnd.rule_code</td>
</tr>
<tr>
<td>BusinessMonthEnd.n</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.BusinessMonthEnd.freqstr

BusinessMonthEnd.freqstr

pandas.tseries.offsets.BusinessMonthEnd.kwds

BusinessMonthEnd.kwds

pandas.tseries.offsets.BusinessMonthEnd.name

BusinessMonthEnd.name

pandas.tseries.offsets.BusinessMonthEnd.nanos

BusinessMonthEnd.nanos

pandas.tseries.offsets.BusinessMonthEnd.normalize

BusinessMonthEnd.normalize

pandas.tseries.offsets.BusinessMonthEnd.rule_code

BusinessMonthEnd.rule_code

3.8. Date offsets
Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>BusinessMonthEnd.apply</td>
<td>other</td>
</tr>
<tr>
<td>BusinessMonthEnd.apply_index</td>
<td>other</td>
</tr>
<tr>
<td>BusinessMonthEnd.copy</td>
<td></td>
</tr>
<tr>
<td>BusinessMonthEnd.isAnchored</td>
<td></td>
</tr>
<tr>
<td>BusinessMonthEnd.onOffset</td>
<td></td>
</tr>
<tr>
<td>BusinessMonthEnd.is_anchored</td>
<td></td>
</tr>
<tr>
<td>BusinessMonthEnd.is_on_offset</td>
<td></td>
</tr>
<tr>
<td>BusinessMonthEnd.<strong>call</strong>(*args, **kwargs)</td>
<td>Call self as a function.</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.BusinessMonthEnd.apply

BusinessMonthEnd.apply( other )

pandas.tseries.offsets.BusinessMonthEnd.apply_index

BusinessMonthEnd.apply_index( other )

pandas.tseries.offsets.BusinessMonthEnd.copy

BusinessMonthEnd.copy()

pandas.tseries.offsets.BusinessMonthEnd.isAnchored

BusinessMonthEnd.isAnchored()

pandas.tseries.offsets.BusinessMonthEnd.onOffset

BusinessMonthEnd.onOffset()

pandas.tseries.offsets.BusinessMonthEnd.is_anchored

BusinessMonthEnd.is_anchored()
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.BusinessMonthEnd.is_on_offset

BusinessMonthEnd.is_on_offset()

3.8.9 BusinessMonthBegin

BusinessMonthBegin

DateOffset of one month at the first business day.

pandas.tseries.offsets.BusinessMonthBegin

class pandas.tseries.offsets.BusinessMonthBegin

DateOffset of one month at the first business day.

Examples

```python
>>> from pandas.tseries.offset import BMonthBegin
>>> ts=pd.Timestamp('2020-05-24 05:01:15')
>>> ts + BMonthBegin()
Timestamp('2020-06-01 05:01:15')
>>> ts + BMonthBegin(2)
Timestamp('2020-07-01 05:01:15')
>>> ts + BMonthBegin(-3)
Timestamp('2020-03-02 05:01:15')
```

Attributes

<table>
<thead>
<tr>
<th>base</th>
</tr>
</thead>
<tbody>
<tr>
<td>Returns a copy of the calling offset object with n=1 and all other attributes equal.</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.BusinessMonthBegin.base

BusinessMonthBegin.base

Returns a copy of the calling offset object with n=1 and all other attributes equal.
### Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>call</strong>(*args, **kwargs)</td>
<td>Call self as a function.</td>
</tr>
<tr>
<td>rollback</td>
<td>Roll provided date backward to next offset only if not on offset.</td>
</tr>
<tr>
<td>rollforward</td>
<td>Roll provided date forward to next offset only if not on offset.</td>
</tr>
</tbody>
</table>

**pandas.tseries.offsets.BusinessMonthBegin.__call__**

```
BusinessMonthBegin.__call__(*args, **kwargs)
Call self as a function.
```

**pandas.tseries.offsets.BusinessMonthBegin.rollback**

```
BusinessMonthBegin.rollback()
Roll provided date backward to next offset only if not on offset.
```

**Returns**

- **TimeStamp**: Rolled timestamp if not on offset, otherwise unchanged timestamp.

**pandas.tseries.offsets.BusinessMonthBegin.rollforward**

```
BusinessMonthBegin.rollforward()
Roll provided date forward to next offset only if not on offset.
```

**Returns**

- **TimeStamp**: Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>apply</td>
<td></td>
</tr>
<tr>
<td>apply_index</td>
<td></td>
</tr>
<tr>
<td>copy</td>
<td></td>
</tr>
<tr>
<td>isAnchored</td>
<td></td>
</tr>
<tr>
<td>is_anchored</td>
<td></td>
</tr>
<tr>
<td>is_on_offset</td>
<td></td>
</tr>
<tr>
<td>onOffset</td>
<td></td>
</tr>
</tbody>
</table>

Alias:

- **BMonthBegin** alias of `pandas._libs.tslibs.offsets.BusinessMonthBegin`
pandas.tseries.offsets.BMonthBegin

pandas.tseries.offsets.BMonthBegin
alias of pandas._libs.tslibs.offsets.BusinessMonthBegin

Properties

BusinessMonthBegin.freqstr
BusinessMonthBegin.kwds
BusinessMonthBegin.name
BusinessMonthBegin.nanos
BusinessMonthBegin.normalize
BusinessMonthBegin.rule_code
BusinessMonthBegin.n

pandas.tseries.offsets.BusinessMonthBegin.freqstr

BusinessMonthBegin.freqstr

pandas.tseries.offsets.BusinessMonthBegin.kwds

BusinessMonthBegin.kwds

pandas.tseries.offsets.BusinessMonthBegin.name

BusinessMonthBegin.name

pandas.tseries.offsets.BusinessMonthBegin.nanos

BusinessMonthBegin.nanos

pandas.tseries.offsets.BusinessMonthBegin.normalize

BusinessMonthBegin.normalize

pandas.tseries.offsets.BusinessMonthBegin.rule_code

BusinessMonthBegin.rule_code

3.8. Date offsets
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.BusinessMonthBegin

Methods

- **BusinessMonthBegin.apply**(other)
- **BusinessMonthBegin.apply_index**(other)
- **BusinessMonthBegin.copy**
- **BusinessMonthBegin.isAnchored**
- **BusinessMonthBegin.onOffset**
- **BusinessMonthBegin.is_anchored**
- **BusinessMonthBegin.is_on_offset**

**BusinessMonthBegin.__call__**(args, **kwargs)

Call self as a function.

pandas.tseries.offsets.BusinessMonthBegin.apply

BusinessMonthBegin.**apply**(other)

pandas.tseries.offsets.BusinessMonthBegin.apply_index

BusinessMonthBegin.**apply_index**(other)

pandas.tseries.offsets.BusinessMonthBegin.copy

BusinessMonthBegin.**copy**()

pandas.tseries.offsets.BusinessMonthBegin.isAnchored

BusinessMonthBegin.isAnchored()

pandas.tseries.offsets.BusinessMonthBegin.onOffset

BusinessMonthBegin.onOffset()

pandas.tseries.offsets.BusinessMonthBegin.is_anchored

BusinessMonthBegin.is_anchored()
pandas.tseries.offsets.BusinessMonthBegin.is_on_offset

BusinessMonthBegin.is_on_offset()

### 3.8.10 CustomBusinessMonthEnd

**CustomBusinessMonthEnd**

#### Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>base</strong></td>
<td>Returns a copy of the calling offset object with n=1 and all other attributes equal.</td>
</tr>
<tr>
<td><strong>cbday_roll</strong></td>
<td>Define default roll function to be called in apply method.</td>
</tr>
<tr>
<td><strong>month_roll</strong></td>
<td>Define default roll function to be called in apply method.</td>
</tr>
<tr>
<td><strong>offset</strong></td>
<td>Alias for self._offset.</td>
</tr>
</tbody>
</table>

**pandas.tseries.offsets.CustomBusinessMonthEnd.base**

CustomBusinessMonthEnd.base

    Returns a copy of the calling offset object with n=1 and all other attributes equal.

**pandas.tseries.offsets.CustomBusinessMonthEnd.cbday_roll**

CustomBusinessMonthEnd.cbday_roll

    Define default roll function to be called in apply method.

**pandas.tseries.offsets.CustomBusinessMonthEnd.month_roll**

CustomBusinessMonthEnd.month_roll

    Define default roll function to be called in apply method.
pandas.tseries.offsets.CustomBusinessMonthEnd.offset

CustomBusinessMonthEnd.offset
Alias for self._offset.

<table>
<thead>
<tr>
<th>calendar</th>
<th>freqstr</th>
<th>holidays</th>
<th>kwds</th>
<th>m_offset</th>
<th>n</th>
<th>name</th>
<th>nanos</th>
<th>normalize</th>
<th>rule_code</th>
<th>weekmask</th>
</tr>
</thead>
</table>

Methods

__call__(*args, **kwargs)
Call self as a function.

rollback
Roll provided date backward to next offset only if not on offset.

rollforward
Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.CustomBusinessMonthEnd.__call__

CustomBusinessMonthEnd.__call__(*args, **kwargs)
Call self as a function.

pandas.tseries.offsets.CustomBusinessMonthEnd.rollback

CustomBusinessMonthEnd.rollback()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.CustomBusinessMonthEnd.rollforward

CustomBusinessMonthEnd.rollforward()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.
### 3.8. Date offsets

#### pandalas.tseries.offsets.CBMonthEnd

**pandas.tseries.offsets.CBMonthEnd**

alias of `pandas._libs.tslibs.offsets.CustomBusinessMonthEnd`

### Properties

- `CustomBusinessMonthEnd.freqstr`
- `CustomBusinessMonthEnd.kwds`
- `CustomBusinessMonthEnd.m_offset`
- `CustomBusinessMonthEnd.name`
- `CustomBusinessMonthEnd.nanos`
- `CustomBusinessMonthEnd.normalize`
- `CustomBusinessMonthEnd.rule_code`
- `CustomBusinessMonthEnd.n`
- `CustomBusinessMonthEnd.weekmask`
- `CustomBusinessMonthEnd.calendar`
- `CustomBusinessMonthEnd.holidays`

### pandas.tseries.offsets.CustomBusinessMonthEnd.freqstr

`CustomBusinessMonthEnd.freqstr`
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.CustomBusinessMonthEnd.kwds

CustomBusinessMonthEnd.kwds

pandas.tseries.offsets.CustomBusinessMonthEnd.m_offset

CustomBusinessMonthEnd.m_offset

pandas.tseries.offsets.CustomBusinessMonthEnd.name

CustomBusinessMonthEnd.name

pandas.tseries.offsets.CustomBusinessMonthEnd.nanos

CustomBusinessMonthEnd.nanos

pandas.tseries.offsets.CustomBusinessMonthEnd.normalize

CustomBusinessMonthEnd.normalize

pandas.tseries.offsets.CustomBusinessMonthEnd.rule_code

CustomBusinessMonthEnd.rule_code

pandas.tseries.offsets.CustomBusinessMonthEnd.n

CustomBusinessMonthEnd.n

pandas.tseries.offsets.CustomBusinessMonthEnd.weekmask

CustomBusinessMonthEnd.weekmask

pandas.tseries.offsets.CustomBusinessMonthEnd.calendar

CustomBusinessMonthEnd.calendar
CustomBusinessMonthEnd.holidays

Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>CustomBusinessMonthEnd.apply(other)</td>
<td>Call self as a function.</td>
</tr>
<tr>
<td>CustomBusinessMonthEnd.apply_index(other)</td>
<td></td>
</tr>
<tr>
<td>CustomBusinessMonthEnd.copy</td>
<td></td>
</tr>
<tr>
<td>CustomBusinessMonthEnd.isAnchored</td>
<td></td>
</tr>
<tr>
<td>CustomBusinessMonthEnd.onOffset</td>
<td></td>
</tr>
<tr>
<td>CustomBusinessMonthEnd.is_anchored</td>
<td></td>
</tr>
<tr>
<td>CustomBusinessMonthEnd.is_on_offset</td>
<td></td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.CustomBusinessMonthEnd.apply

CustomBusinessMonthEnd.apply(other)

pandas.tseries.offsets.CustomBusinessMonthEnd.apply_index

CustomBusinessMonthEnd.apply_index(other)

pandas.tseries.offsets.CustomBusinessMonthEnd.copy

CustomBusinessMonthEnd.copy()

pandas.tseries.offsets.CustomBusinessMonthEnd.isAnchored

CustomBusinessMonthEnd.isAnchored()

pandas.tseries.offsets.CustomBusinessMonthEnd.onOffset

CustomBusinessMonthEnd.onOffset()
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.CustomBusinessMonthEnd.is_anchored

CustomBusinessMonthEnd.is_anchored()

pandas.tseries.offsets.CustomBusinessMonthEnd.is_on_offset

CustomBusinessMonthEnd.is_on_offset()

3.8.11 CustomBusinessMonthBegin

CustomBusinessMonthBegin

<table>
<thead>
<tr>
<th>Attributes</th>
</tr>
</thead>
<tbody>
<tr>
<td>base</td>
</tr>
<tr>
<td>cbday_roll</td>
</tr>
<tr>
<td>month_roll</td>
</tr>
<tr>
<td>offset</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.CustomBusinessMonthBegin.base

CustomBusinessMonthBegin.base

Returns a copy of the calling offset object with n=1 and all other attributes equal.
pandas.tseries.offsets.CustomBusinessMonthBegin.cbday_roll

CustomBusinessMonthBegin.cbday_roll
Define default roll function to be called in apply method.

pandas.tseries.offsets.CustomBusinessMonthBegin.month_roll

CustomBusinessMonthBegin.month_roll
Define default roll function to be called in apply method.

pandas.tseries.offsets.CustomBusinessMonthBegin.offset

CustomBusinessMonthBegin.offset
Alias for self._offset.

<table>
<thead>
<tr>
<th>calendar</th>
<th>freqstr</th>
<th>holidays</th>
<th>kwds</th>
<th>m_offset</th>
<th>n</th>
<th>name</th>
<th>nanos</th>
<th>normalize</th>
<th>rule_code</th>
<th>weekmask</th>
</tr>
</thead>
</table>

Methods

__call__(*args, **kwargs) Call self as a function.

rollback
Roll provided date backward to next offset only if not on offset.

rollforward
Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.CustomBusinessMonthBegin.__call__

CustomBusinessMonthBegin.__call__(*args, **kwargs)
Call self as a function.
pandas.tseries.offsets.CustomBusinessMonthBegin.rollback

CustomBusinessMonthBegin.rollback()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp  Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.CustomBusinessMonthBegin.rollforward

CustomBusinessMonthBegin.rollforward()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp  Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>apply</th>
<th>apply_index</th>
<th>copy</th>
<th>isAnchored</th>
<th>is_anchored</th>
<th>is_on_offset</th>
<th>onOffset</th>
</tr>
</thead>
</table>

Alias:

CBMonthBegin  alias of pandas._libs.tslibs.offsets.CustomBusinessMonthBegin

pandas.tseries.offsets.CBMonthBegin

pandas.tseries.offsets.CBMonthBegin

alias of pandas._libs.tslibs.offsets.CustomBusinessMonthBegin

Properties

<table>
<thead>
<tr>
<th>CustomBusinessMonthBegin.freqstr</th>
<th>CustomBusinessMonthBegin.kwds</th>
</tr>
</thead>
<tbody>
<tr>
<td>CustomBusinessMonthBegin.m_offset</td>
<td>CustomBusinessMonthBegin.name</td>
</tr>
<tr>
<td>CustomBusinessMonthBegin.nanos</td>
<td>CustomBusinessMonthBegin.normalize</td>
</tr>
<tr>
<td>CustomBusinessMonthBegin.rule_code</td>
<td>CustomBusinessMonthBegin.n</td>
</tr>
<tr>
<td>CustomBusinessMonthBegin.weekmask</td>
<td>CustomBusinessMonthBegin.calendar</td>
</tr>
<tr>
<td>CustomBusinessMonthBegin.holidays</td>
<td></td>
</tr>
</tbody>
</table>
3.8. Date offsets

pandas.tseries.offsets.CustomBusinessMonthBegin.freqstr

CustomBusinessMonthBegin.freqstr

pandas.tseries.offsets.CustomBusinessMonthBegin.kwds

CustomBusinessMonthBegin.kwds

pandas.tseries.offsets.CustomBusinessMonthBegin.m_offset

CustomBusinessMonthBegin.m_offset

pandas.tseries.offsets.CustomBusinessMonthBegin.name

CustomBusinessMonthBegin.name

pandas.tseries.offsets.CustomBusinessMonthBegin.nanos

CustomBusinessMonthBegin.nanos

pandas.tseries.offsets.CustomBusinessMonthBegin.normalize

CustomBusinessMonthBegin.normalize

pandas.tseries.offsets.CustomBusinessMonthBegin.rule_code

CustomBusinessMonthBegin.rule_code

pandas.tseries.offsets.CustomBusinessMonthBegin.n

CustomBusinessMonthBegin.n

pandas.tseries.offsets.CustomBusinessMonthBegin.weekmask

CustomBusinessMonthBegin.weekmask
CustomBusinessMonthBegin.holidays

Methods

CustomBusinessMonthBegin.apply(other)
CustomBusinessMonthBegin.apply_index(other)
CustomBusinessMonthBegin.copy
CustomBusinessMonthBegin.isAnchored
CustomBusinessMonthBegin.onOffset
CustomBusinessMonthBegin.is_anchored
CustomBusinessMonthBegin.is_on_offset
CustomBusinessMonthBegin.__call__(*args,...) Call self as a function.

CustomBusinessMonthBegin.apply

CustomBusinessMonthBegin.apply_index

CustomBusinessMonthBegin.copy

CustomBusinessMonthBegin.isAnchored

CustomBusinessMonthBegin.isAnchored()
pandas.tseries.offsets.CustomBusinessMonthBegin.onOffset

CustomBusinessMonthBegin.onOffset()

pandas.tseries.offsets.CustomBusinessMonthBegin.is_anchored

CustomBusinessMonthBegin.is_anchored()

pandas.tseries.offsets.CustomBusinessMonthBegin.is_on_offset

CustomBusinessMonthBegin.is_on_offset()

### 3.8.12 SemiMonthEnd

<table>
<thead>
<tr>
<th>SemiMonthEnd</th>
<th>Two DateOffset’s per month repeating on the last day of the month and day_of_month.</th>
</tr>
</thead>
</table>

pandas.tseries.offsets.SemiMonthEnd

class pandas.tseries.offsets.SemiMonthEnd

Two DateOffset’s per month repeating on the last day of the month and day_of_month.

Parameters

- `n` [int]
- `normalize` [bool, default False]
- `day_of_month` [int, {1, 3,...,27}, default 15]

Attributes

<table>
<thead>
<tr>
<th>base</th>
<th>Returns a copy of the calling offset object with n=1 and all other attributes equal.</th>
</tr>
</thead>
</table>

pandas.tseries.offsets.SemiMonthEnd.base

SemiMonthEnd.base

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<table>
<thead>
<tr>
<th>day_of_month</th>
<th>freqstr</th>
<th>kwds</th>
<th>n</th>
<th>name</th>
<th>nanos</th>
<th>normalize</th>
<th>rule_code</th>
</tr>
</thead>
</table>

---

3.8. Date offsets

2093
Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>call</strong>(*args, **kwargs)</td>
<td>Call self as a function.</td>
</tr>
<tr>
<td>rollback</td>
<td>Roll provided date backward to next offset only if not on offset.</td>
</tr>
<tr>
<td>rollforward</td>
<td>Roll provided date forward to next offset only if not on offset.</td>
</tr>
</tbody>
</table>

**pandas.tseries.offsets.SemiMonthEnd.__call__**

SemiMonthEnd.__call__(*args, **kwargs)
Call self as a function.

**pandas.tseries.offsets.SemiMonthEnd.rollback**

SemiMonthEnd.rollback()
Roll provided date backward to next offset only if not on offset.

Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

**pandas.tseries.offsets.SemiMonthEnd.rollforward**

SemiMonthEnd.rollforward()
Roll provided date forward to next offset only if not on offset.

Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>Property</th>
</tr>
</thead>
<tbody>
<tr>
<td>apply</td>
</tr>
<tr>
<td>apply_index</td>
</tr>
<tr>
<td>copy</td>
</tr>
<tr>
<td>isAnchored</td>
</tr>
<tr>
<td>is_anchored</td>
</tr>
<tr>
<td>is_on_offset</td>
</tr>
<tr>
<td>onOffset</td>
</tr>
</tbody>
</table>

Properties

<table>
<thead>
<tr>
<th>Property</th>
</tr>
</thead>
<tbody>
<tr>
<td>SemiMonthEnd.freqstr</td>
</tr>
<tr>
<td>SemiMonthEnd.kwds</td>
</tr>
<tr>
<td>SemiMonthEnd.name</td>
</tr>
<tr>
<td>SemiMonthEnd.nanos</td>
</tr>
<tr>
<td>SemiMonthEnd.normalize</td>
</tr>
<tr>
<td>SemiMonthEnd.rule_code</td>
</tr>
<tr>
<td>SemiMonthEnd.n</td>
</tr>
<tr>
<td>SemiMonthEnd.day_of_month</td>
</tr>
</tbody>
</table>
Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>SemiMonthEnd.apply(other)</td>
<td>Apply function to values of this offset.</td>
</tr>
<tr>
<td>SemiMonthEnd.apply_index(other)</td>
<td>Apply function to values of this offset.</td>
</tr>
<tr>
<td>SemiMonthEnd.copy</td>
<td>Copy this offset.</td>
</tr>
<tr>
<td>SemiMonthEnd.isAnchored</td>
<td>Checks if this offset is anchored.</td>
</tr>
<tr>
<td>SemiMonthEnd.onOffset</td>
<td>Checks if this offset is on a given offset.</td>
</tr>
<tr>
<td>SemiMonthEnd.is_anchored</td>
<td>Checks if this offset is anchored.</td>
</tr>
<tr>
<td>SemiMonthEnd.is_on_offset</td>
<td>Checks if this offset is on a given offset.</td>
</tr>
<tr>
<td>SemiMonthEnd.<strong>call</strong>(*args, **kwargs)</td>
<td>Call self as a function.</td>
</tr>
</tbody>
</table>

3.8. Date offsets
3.8.13 SemiMonthBegin

SemiMonthBegin

Two DateOffset’s per month repeating on the first day of the month and day_of_month.

Parameters

- **n** [int]
- **normalize** [bool, default False]
- **day_of_month** [int, \{2, 3,…,27\}, default 15]
Attributes

```
base
Returns a copy of the calling offset object with n=1 and all other attributes equal.
```

```
pandas.tseries.offsets.SemiMonthBegin.base
SemiMonthBegin.base
Returns a copy of the calling offset object with n=1 and all other attributes equal.
```

```
+-----------------+-----------------+-----------------+-----------------+-----------------+-----------------+-----------------+-----------------+-----------------+
<table>
<thead>
<tr>
<th>day_of_month</th>
<th>freqstr</th>
<th>kwds</th>
<th>n</th>
<th>name</th>
<th>nanos</th>
<th>normalize</th>
<th>rule_code</th>
</tr>
</thead>
</table>
```

Methods

```
__call__(*args, **kwargs)
Call self as a function.
```

```
rollback
Roll provided date backward to next offset only if not on offset.
```

```
rollforward
Roll provided date forward to next offset only if not on offset.
```

3.8. Date offsets
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.SemiMonthBegin.rollforward

SemiMonthBegin.rollforward()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp  Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>apply</th>
<th>apply_index</th>
</tr>
</thead>
<tbody>
<tr>
<td>copy</td>
<td></td>
</tr>
<tr>
<td>isAnchored</td>
<td></td>
</tr>
<tr>
<td>is_anchored</td>
<td></td>
</tr>
<tr>
<td>is_on_offset</td>
<td></td>
</tr>
<tr>
<td>onOffset</td>
<td></td>
</tr>
</tbody>
</table>

Properties

SemiMonthBegin.freqstr
SemiMonthBegin.kwds
SemiMonthBegin.name
SemiMonthBegin.nanos
SemiMonthBegin.normalize
SemiMonthBegin.rule_code
SemiMonthBegin.n
SemiMonthBegin.day_of_month

pandas.tseries.offsets.SemiMonthBegin.freqstr

SemiMonthBegin.freqstr

pandas.tseries.offsets.SemiMonthBegin.kwds

SemiMonthBegin.kwds
pandas.tseries.offsets.SemiMonthBegin.name

SemiMonthBegin.name

pandas.tseries.offsets.SemiMonthBegin.nanos

SemiMonthBegin.nanos

pandas.tseries.offsets.SemiMonthBegin.normalize

SemiMonthBegin.normalize

pandas.tseries.offsets.SemiMonthBegin.rule_code

SemiMonthBegin.rule_code

pandas.tseries.offsets.SemiMonthBegin.n

SemiMonthBegin.n

pandas.tseries.offsets.SemiMonthBegin.day_of_month

SemiMonthBegin.day_of_month

Methods

SemiMonthBegin.apply(other)
SemiMonthBegin.apply_index(other)
SemiMonthBegin.copy
SemiMonthBegin.isAnchored
SemiMonthBegin.onOffset
SemiMonthBegin.is_anchored
SemiMonthBegin.is_on_offset
SemiMonthBegin.__call__("*args, **kwargs") Call self as a function.

3.8. Date offsets
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.SemiMonthBegin.apply

SemiMonthBegin.apply(other)

pandas.tseries.offsets.SemiMonthBegin.apply_index

SemiMonthBegin.apply_index(other)

pandas.tseries.offsets.SemiMonthBegin.copy

SemiMonthBegin.copy()

pandas.tseries.offsets.SemiMonthBegin.isAnchored

SemiMonthBegin.isAnchored()

pandas.tseries.offsets.SemiMonthBegin.onOffset

SemiMonthBegin.onOffset()

pandas.tseries.offsets.SemiMonthBegin.is_anchored

SemiMonthBegin.is_anchored()

pandas.tseries.offsets.SemiMonthBegin.is_on_offset

SemiMonthBegin.is_on_offset()

3.8.14 Week

<table>
<thead>
<tr>
<th>Week</th>
<th>Weekly offset.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.Week

class pandas.tseries.offsets.Week

Weekly offset.

Parameters

    weekday  [int or None, default None] Always generate specific day of week. 0 for Monday.
Attributes

\texttt{base} \hspace{1cm} \text{Returns a copy of the calling offset object with } n=1 \text{ and all other attributes equal.}

\texttt{pandas.tseries.offsets.Week.base}

\texttt{Week.base} \hspace{1cm} \text{Returns a copy of the calling offset object with } n=1 \text{ and all other attributes equal.}

<table>
<thead>
<tr>
<th>freqstr</th>
<th>kwds</th>
<th>n</th>
<th>name</th>
<th>nanos</th>
<th>normalize</th>
<th>rule_code</th>
<th>weekday</th>
</tr>
</thead>
</table>

Methods

\texttt{__call__(*args, **kwargs)} \hspace{1cm} \text{Call self as a function.}

\texttt{rollback} \hspace{1cm} \text{Roll provided date backward to next offset only if not on offset.}

\texttt{rollforward} \hspace{1cm} \text{Roll provided date forward to next offset only if not on offset.}

\texttt{pandas.tseries.offsets.Week.__call__}

\texttt{Week.__call__(*args, **kwargs)} \hspace{1cm} \text{Call self as a function.}

\texttt{pandas.tseries.offsets.Week.rollback}

\texttt{Week.rollback()} \hspace{1cm} \text{Roll provided date backward to next offset only if not on offset.}

\textbf{Returns}

\textbf{TimeStamp} \hspace{1cm} \text{Rolled timestamp if not on offset, otherwise unchanged timestamp.}
pandas.tseries.offsets.Week.rollforward

Week.rollforward()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp  Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>apply</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>apply_index</td>
<td></td>
</tr>
<tr>
<td>copy</td>
<td></td>
</tr>
<tr>
<td>isAnchored</td>
<td></td>
</tr>
<tr>
<td>is_anchored</td>
<td></td>
</tr>
<tr>
<td>is_on_offset</td>
<td></td>
</tr>
<tr>
<td>onOffset</td>
<td></td>
</tr>
</tbody>
</table>

Properties

Week.freqstr
Week.kwds
Week.name
Week.nanos
Week.normalize
Week.rule_code
Week.n
Week.weekday

pandas.tseries.offsets.Week.freqstr

Week.freqstr

pandas.tseries.offsets.Week.kwds

Week.kwds
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.Week.name

Week.name

pandas.tseries.offsets.Week.nanos

Week.nanos

pandas.tseries.offsets.Week.normalize

Week.normalize

pandas.tseries.offsets.Week.rule_code

Week.rule_code

pandas.tseries.offsets.Week.n

Week.n

pandas.tseries.offsets.Week.weekday

Week.weekday

Methods

<table>
<thead>
<tr>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Week.apply(other)</td>
</tr>
<tr>
<td>Week.apply_index(other)</td>
</tr>
<tr>
<td>Week.copy</td>
</tr>
<tr>
<td>Week.isAnchored</td>
</tr>
<tr>
<td>Week.onOffset</td>
</tr>
<tr>
<td>Week.is_anchored</td>
</tr>
<tr>
<td>Week.is_on_offset</td>
</tr>
<tr>
<td>Week.<strong>call</strong>(*args, **kwargs) Call self as a function.</td>
</tr>
</tbody>
</table>

3.8. Date offsets
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.Week.apply

\texttt{Week.apply}(\texttt{other})

pandas.tseries.offsets.Week.apply_index

\texttt{Week.apply_index}(\texttt{other})

pandas.tseries.offsets.Week.copy

\texttt{Week.copy}()

pandas.tseries.offsets.Week.isAnchored

\texttt{Week.isAnchored}()

pandas.tseries.offsets.Week.onOffset

\texttt{Week.onOffset}()

pandas.tseries.offsets.Week.is_anchored

\texttt{Week.is_anchored}()

pandas.tseries.offsets.Week.is_on_offset

\texttt{Week.is_on_offset}()

3.8.15 WeekOfMonth

<table>
<thead>
<tr>
<th>WeekOfMonth</th>
<th>Describes monthly dates like “the Tuesday of the 2nd week of each month”.</th>
</tr>
</thead>
</table>

**pandas.tseries.offsets.WeekOfMonth**

**class** pandas.tseries.offsets.WeekOfMonth

Describes monthly dates like “the Tuesday of the 2nd week of each month”.

**Parameters**

- n [int]
- week [int \{0, 1, 2, 3, \ldots\}, default 0] A specific integer for the week of the month. e.g. 0 is 1st week of month, 1 is the 2nd week, etc.
- weekday [int \{0, 1, \ldots, 6\}, default 0] A specific integer for the day of the week.
  - 0 is Monday
• 1 is Tuesday
• 2 is Wednesday
• 3 is Thursday
• 4 is Friday
• 5 is Saturday
• 6 is Sunday.

Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base</td>
<td>Returns a copy of the calling offset object with n=1 and all other attributes equal.</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.WeekOfMonth.base

WeekOfMonth.base
Returns a copy of the calling offset object with n=1 and all other attributes equal.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>freqstr</td>
<td></td>
</tr>
<tr>
<td>kwds</td>
<td></td>
</tr>
<tr>
<td>n</td>
<td></td>
</tr>
<tr>
<td>name</td>
<td></td>
</tr>
<tr>
<td>nanos</td>
<td></td>
</tr>
<tr>
<td>normalize</td>
<td></td>
</tr>
<tr>
<td>rule_code</td>
<td></td>
</tr>
<tr>
<td>week</td>
<td></td>
</tr>
<tr>
<td>weekday</td>
<td></td>
</tr>
</tbody>
</table>

Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>call</strong>(*args, **kwargs)</td>
<td>Call self as a function.</td>
</tr>
<tr>
<td>rollback</td>
<td>Roll provided date backward to next offset only if not on offset.</td>
</tr>
<tr>
<td>rollforward</td>
<td>Roll provided date forward to next offset only if not on offset.</td>
</tr>
</tbody>
</table>
pandas.tseries.offsets.WeekOfMonth.__call__

__call__(*args, **kwargs)
Call self as a function.

pandas.tseries.offsets.WeekOfMonth.rollback

rollback()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp  Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.WeekOfMonth.rollforward

rollforward()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp  Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>apply</th>
<th>apply_index</th>
<th>copy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>isAnchored</td>
<td>is_anchored</td>
<td></td>
</tr>
<tr>
<td>is_on_offset</td>
<td></td>
<td></td>
</tr>
<tr>
<td>onOffset</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Properties

<table>
<thead>
<tr>
<th>WeekOfMonth.freqstr</th>
</tr>
</thead>
<tbody>
<tr>
<td>WeekOfMonth.kwds</td>
</tr>
<tr>
<td>WeekOfMonth.name</td>
</tr>
<tr>
<td>WeekOfMonth.nanos</td>
</tr>
<tr>
<td>WeekOfMonth.normalize</td>
</tr>
<tr>
<td>WeekOfMonth.rule_code</td>
</tr>
<tr>
<td>WeekOfMonth.n</td>
</tr>
<tr>
<td>WeekOfMonth.week</td>
</tr>
</tbody>
</table>
pandas.tseries.offsets.WeekOfMonth.freqstr

WeekOfMonth.freqstr

pandas.tseries.offsets.WeekOfMonth.kwds

WeekOfMonth.kwds

pandas.tseries.offsets.WeekOfMonth.name

WeekOfMonth.name

pandas.tseries.offsets.WeekOfMonth.nanos

WeekOfMonth.nanos

pandas.tseries.offsets.WeekOfMonth.normalize

WeekOfMonth.normalize

pandas.tseries.offsets.WeekOfMonth.rule_code

WeekOfMonth.rule_code

pandas.tseries.offsets.WeekOfMonth.n

WeekOfMonth.n

pandas.tseries.offsets.WeekOfMonth.week

WeekOfMonth.week

Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>WeekOfMonth.apply( other )</td>
<td></td>
</tr>
<tr>
<td>WeekOfMonth.apply_index( other)</td>
<td></td>
</tr>
<tr>
<td>WeekOfMonth.copy</td>
<td></td>
</tr>
<tr>
<td>WeekOfMonth.isAnchored</td>
<td></td>
</tr>
<tr>
<td>WeekOfMonth.onOffset</td>
<td></td>
</tr>
<tr>
<td>WeekOfMonth.is_anchored</td>
<td></td>
</tr>
<tr>
<td>WeekOfMonth.is_on_offset</td>
<td></td>
</tr>
<tr>
<td>WeekOfMonth.<strong>call</strong>(*args, **kwargs)</td>
<td>Call self as a function.</td>
</tr>
<tr>
<td>WeekOfMonth.weekday</td>
<td></td>
</tr>
</tbody>
</table>

3.8. Date offsets
pandas: powerful Python data analysis toolkit, Release 1.1.1

```python
pandas.tseries.offsets.WeekOfMonth.apply
WeekOfMonth.apply(other)

pandas.tseries.offsets.WeekOfMonth.apply_index
WeekOfMonth.apply_index(other)

pandas.tseries.offsets.WeekOfMonth.copy
WeekOfMonth.copy()

pandas.tseries.offsets.WeekOfMonth.isAnchored
WeekOfMonth.isAnchored()

pandas.tseries.offsets.WeekOfMonth.onOffset
WeekOfMonth.onOffset()

pandas.tseries.offsets.WeekOfMonth.is_anchored
WeekOfMonth.is_anchored()

pandas.tseries.offsets.WeekOfMonth.is_on_offset
WeekOfMonth.is_on_offset()

pandas.tseries.offsets.WeekOfMonth.weekday
WeekOfMonth.weekday
```

### 3.8.16 LastWeekOfMonth

<table>
<thead>
<tr>
<th>LastWeekOfMonth</th>
<th>Describes monthly dates in last week of month like “the last Tuesday of each month”.</th>
</tr>
</thead>
</table>
pandas.tseries.offsets.LastWeekOfMonth

class pandas.tseries.offsets.LastWeekOfMonth
Describes monthly dates in last week of month like “the last Tuesday of each month”.

Parameters

- **n** [int, default 1]
- **weekday** [int \{0, 1, …, 6\}, default 0] A specific integer for the day of the week.
  - 0 is Monday
  - 1 is Tuesday
  - 2 is Wednesday
  - 3 is Thursday
  - 4 is Friday
  - 5 is Saturday
  - 6 is Sunday.

Attributes

- **base**
  Returns a copy of the calling offset object with n=1 and all other attributes equal.

pandas.tseries.offsets.LastWeekOfMonth.base

LastWeekOfMonth.base
Returns a copy of the calling offset object with n=1 and all other attributes equal.

<table>
<thead>
<tr>
<th>freqstr</th>
<th>kwds</th>
<th>n</th>
<th>name</th>
<th>nanos</th>
<th>normalize</th>
<th>rule_code</th>
<th>week</th>
<th>weekday</th>
</tr>
</thead>
</table>

Methods

- **__call__(**args, **kwargs)**
  Call self as a function.

- **rollback**
  Roll provided date backward to next offset only if not on offset.

- **rollforward**
  Roll provided date forward to next offset only if not on offset.

3.8. Date offsets
pandas.tseries.offsets.LastWeekOfMonth.__call__

```
LastWeekOfMonth.__call__(*args, **kwargs)
Call self as a function.
```

pandas.tseries.offsets.LastWeekOfMonth.rollback

```
LastWeekOfMonth.rollback()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.
```

pandas.tseries.offsets.LastWeekOfMonth.rollforward

```
LastWeekOfMonth.rollforward()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.
```

<table>
<thead>
<tr>
<th>apply</th>
<th>apply_index</th>
</tr>
</thead>
<tbody>
<tr>
<td>copy</td>
<td></td>
</tr>
<tr>
<td>isAnchored</td>
<td>is_anchored</td>
</tr>
<tr>
<td>is_on_offset</td>
<td>onOffset</td>
</tr>
</tbody>
</table>

Properties

- LastWeekOfMonth.freqstr
- LastWeekOfMonth.kwds
- LastWeekOfMonth.name
- LastWeekOfMonth.nanos
- LastWeekOfMonth.normalize
- LastWeekOfMonth.rule_code
- LastWeekOfMonth.n
- LastWeekOfMonth.weekday
- LastWeekOfMonth.week
3.8. Date offsets

pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.LastWeekOfMonth.freqstr

LastWeekOfMonth.freqstr

pandas.tseries.offsets.LastWeekOfMonth.kwds

LastWeekOfMonth.kwds

pandas.tseries.offsets.LastWeekOfMonth.name

LastWeekOfMonth.name

pandas.tseries.offsets.LastWeekOfMonth.nanos

LastWeekOfMonth.nanos

pandas.tseries.offsets.LastWeekOfMonth.normalize

LastWeekOfMonth.normalize

pandas.tseries.offsets.LastWeekOfMonth.rule_code

LastWeekOfMonth.rule_code

pandas.tseries.offsets.LastWeekOfMonth.n

LastWeekOfMonth.n

pandas.tseries.offsets.LastWeekOfMonth.weekday

LastWeekOfMonth.weekday

pandas.tseries.offsets.LastWeekOfMonth.week

LastWeekOfMonth.week
Methods

```
LastWeekOfMonth.apply(\texttt{other})
LastWeekOfMonth.apply_index(\texttt{other})
LastWeekOfMonth.copy
LastWeekOfMonth.isAnchored
LastWeekOfMonth.onOffset
LastWeekOfMonth.is_anchored
LastWeekOfMonth.is_on_offset
LastWeekOfMonth.__call__(*\texttt{args}, **\texttt{kwargs}) Call self as a function.
```

```
pandas.tseries.offsets.LastWeekOfMonth.apply

LastWeekOfMonth.\texttt{apply}(\texttt{other})

pandas.tseries.offsets.LastWeekOfMonth.apply_index

LastWeekOfMonth.\texttt{apply_index}(\texttt{other})

pandas.tseries.offsets.LastWeekOfMonth.copy

LastWeekOfMonth.\texttt{copy}()

pandas.tseries.offsets.LastWeekOfMonth.isAnchored

LastWeekOfMonth.\texttt{isAnchored}()

pandas.tseries.offsets.LastWeekOfMonth.onOffset

LastWeekOfMonth.\texttt{onOffset}()

pandas.tseries.offsets.LastWeekOfMonth.is_anchored

LastWeekOfMonth.\texttt{is_anchored}()

pandas.tseries.offsets.LastWeekOfMonth.is_on_offset

LastWeekOfMonth.\texttt{is_on_offset}()
```
3.8.17 BQuarterEnd

**BQuarterEnd**

DateOffset increments between the last business day of each Quarter.

```python
>>> from pandas.tseries.offset import BQuarterEnd
>>> ts = pd.Timestamp('2020-05-24 05:01:15')
>>> ts + BQuarterEnd()
Timestamp('2020-06-30 05:01:15')
>>> ts + BQuarterEnd(2)
Timestamp('2020-09-30 05:01:15')
>>> ts + BQuarterEnd(1, startingMonth=2)
Timestamp('2020-05-29 05:01:15')
>>> ts + BQuarterEnd(startingMonth=2)
Timestamp('2020-05-29 05:01:15')
```

**Attributes**

`BQuarterEnd.base`

Returns a copy of the calling offset object with `n=1` and all other attributes equal.
Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>call</strong>(*args, **kwargs)</td>
<td>Call self as a function.</td>
</tr>
<tr>
<td>rollback</td>
<td>Roll provided date backward to next offset only if not on offset.</td>
</tr>
<tr>
<td>rollforward</td>
<td>Roll provided date forward to next offset only if not on offset.</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.BQuarterEnd.__call__

BQuarterEnd.__call__(*args, **kwargs)
Call self as a function.

pandas.tseries.offsets.BQuarterEnd.rollback

BQuarterEnd.rollback()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.BQuarterEnd.rollforward

BQuarterEnd.rollforward()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>apply</td>
</tr>
<tr>
<td>apply_index</td>
</tr>
<tr>
<td>copy</td>
</tr>
<tr>
<td>isAnchored</td>
</tr>
<tr>
<td>is_anchored</td>
</tr>
<tr>
<td>is_on_offset</td>
</tr>
<tr>
<td>onOffset</td>
</tr>
</tbody>
</table>

Properties

<table>
<thead>
<tr>
<th>Property</th>
</tr>
</thead>
<tbody>
<tr>
<td>BQuarterEnd.freqstr</td>
</tr>
<tr>
<td>BQuarterEnd.kwds</td>
</tr>
<tr>
<td>BQuarterEnd.name</td>
</tr>
<tr>
<td>BQuarterEnd.nanos</td>
</tr>
<tr>
<td>BQuarterEnd.normalize</td>
</tr>
<tr>
<td>BQuarterEnd.rule_code</td>
</tr>
<tr>
<td>BQuarterEnd.n</td>
</tr>
<tr>
<td>BQuarterEnd.startingMonth</td>
</tr>
</tbody>
</table>
pandas.tseries.offsets.BQuarterEnd.freqstr

BQuarterEnd.freqstr

pandas.tseries.offsets.BQuarterEnd.kwds

BQuarterEnd.kwds

pandas.tseries.offsets.BQuarterEnd.name

BQuarterEnd.name

pandas.tseries.offsets.BQuarterEnd.nanos

BQuarterEnd.nanos

pandas.tseries.offsets.BQuarterEnd.normalize

BQuarterEnd.normalize

pandas.tseries.offsets.BQuarterEnd.rule_code

BQuarterEnd.rule_code

pandas.tseries.offsets.BQuarterEnd.n

BQuarterEnd.n

pandas.tseries.offsets.BQuarterEnd.startingMonth

BQuarterEnd.startingMonth

Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>BQuarterEnd.apply(other)</code></td>
<td></td>
</tr>
<tr>
<td><code>BQuarterEnd.apply_index(other)</code></td>
<td></td>
</tr>
<tr>
<td><code>BQuarterEnd.copy</code></td>
<td></td>
</tr>
<tr>
<td><code>BQuarterEnd.isAnchored</code></td>
<td></td>
</tr>
<tr>
<td><code>BQuarterEnd.isOnOffset</code></td>
<td></td>
</tr>
<tr>
<td><code>BQuarterEnd.is_anchored</code></td>
<td></td>
</tr>
<tr>
<td><code>BQuarterEnd.is_on_offset</code></td>
<td></td>
</tr>
<tr>
<td><code>BQuarterEnd.__call__(*args, **kwargs)</code></td>
<td>Call self as a function.</td>
</tr>
</tbody>
</table>

3.8. Date offsets
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.BQuarterEnd.apply

BQuarterEnd.\texttt{apply}(other)

pandas.tseries.offsets.BQuarterEnd.apply_index

BQuarterEnd.\texttt{apply\_index}(other)

pandas.tseries.offsets.BQuarterEnd.copy

BQuarterEnd.\texttt{copy}()

pandas.tseries.offsets.BQuarterEnd.isAnchored

BQuarterEnd.\texttt{isAnchored}()

pandas.tseries.offsets.BQuarterEnd.onOffset

BQuarterEnd.\texttt{onOffset}()

pandas.tseries.offsets.BQuarterEnd.is_anchored

BQuarterEnd.\texttt{is\_anchored}()

pandas.tseries.offsets.BQuarterEnd.is_on_offset

BQuarterEnd.\texttt{is\_on\_offset}()

\section*{3.8.18 BQuarterBegin}

\begin{center}
\begin{tabular}{l}
\hline
\texttt{BQuarterBegin} & DateOffset increments between the first business day of each Quarter. \\
\hline
\end{tabular}
\end{center}

pandas.tseries.offsets.BQuarterBegin

\texttt{class pandas.tseries.offsets.BQuarterBegin}

\begin{quote}
DateOffset increments between the first business day of each Quarter.

startingMonth = 1 corresponds to dates like 1/01/2007, 4/01/2007, ... startingMonth = 2 corresponds to dates like 2/01/2007, 5/01/2007, ... startingMonth = 3 corresponds to dates like 3/01/2007, 6/01/2007, ...
\end{quote}
Examples

```python
>>> from pandas.tseries.offset import BQuarterBegin
>>> ts = pd.Timestamp('2020-05-24 05:01:15')
>>> ts + BQuarterBegin()
Timestamp('2020-06-01 05:01:15')
>>> ts + BQuarterBegin(2)
Timestamp('2020-09-01 05:01:15')
>>> ts + BQuarterBegin(startingMonth=2)
Timestamp('2020-08-03 05:01:15')
>>> ts + BQuarterBegin(-1)
Timestamp('2020-03-02 05:01:15')
```

Attributes

| base | Returns a copy of the calling offset object with n=1 and all other attributes equal. |

pandas.tseries.offsets.BQuarterBegin.base

BQuarterBegin.base

Returns a copy of the calling offset object with n=1 and all other attributes equal.

| freqstr | 
| kwds | 
| n | 
| name | 
| nanos | 
| normalize | 
| rule_code | 
| startingMonth | 

Methods

<table>
<thead>
<tr>
<th><strong>call</strong> (*args, **kwargs)</th>
<th>Call self as a function.</th>
</tr>
</thead>
<tbody>
<tr>
<td>rollback</td>
<td>Roll provided date backward to next offset only if not on offset.</td>
</tr>
<tr>
<td>rollforward</td>
<td>Roll provided date forward to next offset only if not on offset.</td>
</tr>
</tbody>
</table>
pandas.tseries.offsets.BQuarterBegin.__call__

BQuarterBegin.__call__(*args, **kwargs)
Call self as a function.

pandas.tseries.offsets.BQuarterBegin.rollback

BQuarterBegin.rollback()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.BQuarterBegin.rollforward

BQuarterBegin.rollforward()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>apply</th>
<th>apply_index</th>
</tr>
</thead>
<tbody>
<tr>
<td>copy</td>
<td></td>
</tr>
<tr>
<td>isAnchored</td>
<td>is_anchored</td>
</tr>
<tr>
<td>is_on_offset</td>
<td></td>
</tr>
<tr>
<td>onOffset</td>
<td></td>
</tr>
</tbody>
</table>

Properties

BQuarterBegin.freqstr
BQuarterBegin.kwds
BQuarterBegin.name
BQuarterBegin.nanos
BQuarterBegin.normalize
BQuarterBegin.rule_code
BQuarterBegin.n
BQuarterBegin.startingMonth
Methods

- `BQuarterBegin.apply(other)`
- `BQuarterBegin.apply_index(other)`
- `BQuarterBegin.copy`
- `BQuarterBegin.isAnchored`
- `BQuarterBegin.onOffset`
- `BQuarterBegin.is_anchored`
- `BQuarterBegin.is_on_offset`
- `BQuarterBegin.__call__(*args, **kwargs)` Call self as a function.
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.BQuarterBegin.apply

BQuarterBegin.apply(other)

pandas.tseries.offsets.BQuarterBegin.apply_index

BQuarterBegin.apply_index(other)

pandas.tseries.offsets.BQuarterBegin.copy

BQuarterBegin.copy()

pandas.tseries.offsets.BQuarterBegin.isAnchored

BQuarterBegin.isAnchored()

pandas.tseries.offsets.BQuarterBegin.onOffset

BQuarterBegin.onOffset()

pandas.tseries.offsets.BQuarterBegin.is_anchored

BQuarterBegin.is_anchored()

pandas.tseries.offsets.BQuarterBegin.is_on_offset

BQuarterBegin.is_on_offset()

3.8.19 QuarterEnd

<table>
<thead>
<tr>
<th>QuarterEnd</th>
<th>DateOffset increments between Quarter end dates.</th>
</tr>
</thead>
</table>

pandas.tseries.offsets.QuarterEnd

class pandas.tseries.offsets.QuarterEnd

DateOffset increments between Quarter end dates.

startingMonth = 1 corresponds to dates like 1/31/2007, 4/30/2007, ... startingMonth = 2 corresponds to dates like 2/28/2007, 5/31/2007, ... startingMonth = 3 corresponds to dates like 3/31/2007, 6/30/2007, ...
Attributes

**base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

**pandas.tseries.offsets.QuarterEnd.base**

**QuarterEnd.base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>freqstr</td>
<td></td>
</tr>
<tr>
<td>kwds</td>
<td></td>
</tr>
<tr>
<td>n</td>
<td></td>
</tr>
<tr>
<td>name</td>
<td></td>
</tr>
<tr>
<td>nanos</td>
<td></td>
</tr>
<tr>
<td>normalize</td>
<td></td>
</tr>
<tr>
<td>rule_code</td>
<td></td>
</tr>
<tr>
<td>startingMonth</td>
<td></td>
</tr>
</tbody>
</table>

Methods

**_call_(*args, **kwargs)**

Call self as a function.

**rollback**

Roll provided date backward to next offset only if not on offset.

**rollforward**

Roll provided date forward to next offset only if not on offset.

**pandas.tseries.offsets.QuarterEnd._call_**

**QuarterEnd._call_(*args, **kwargs)**

Call self as a function.

**pandas.tseries.offsets.QuarterEnd.rollback**

**QuarterEnd.rollback()**

Roll provided date backward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.
pandas.tseries.offsets.QuarterEnd.rollforward

QuarterEnd.rollforward()

Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp  Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>apply</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>apply_index</td>
<td></td>
</tr>
<tr>
<td>copy</td>
<td></td>
</tr>
<tr>
<td>isAnchored</td>
<td></td>
</tr>
<tr>
<td>is_anchored</td>
<td></td>
</tr>
<tr>
<td>is_on_offset</td>
<td></td>
</tr>
<tr>
<td>onOffset</td>
<td></td>
</tr>
</tbody>
</table>

Properties

<table>
<thead>
<tr>
<th>QuarterEnd.freqstr</th>
</tr>
</thead>
<tbody>
<tr>
<td>QuarterEnd.kwds</td>
</tr>
<tr>
<td>QuarterEnd.name</td>
</tr>
<tr>
<td>QuarterEnd.nanos</td>
</tr>
<tr>
<td>QuarterEnd.normalize</td>
</tr>
<tr>
<td>QuarterEnd.rule_code</td>
</tr>
<tr>
<td>QuarterEnd.n</td>
</tr>
<tr>
<td>QuarterEnd.startingMonth</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.QuarterEnd.freqstr

QuarterEnd.freqstr

pandas.tseries.offsets.QuarterEnd.kwds

QuarterEnd.kwds
```python
pandas.tseries.offsets.QuarterEnd.name
QuarterEnd.name

pandas.tseries.offsets.QuarterEnd.nanos
QuarterEnd.nanos

pandas.tseries.offsets.QuarterEnd.normalize
QuarterEnd.normalize

pandas.tseries.offsets.QuarterEnd.rule_code
QuarterEnd.rule_code

pandas.tseries.offsets.QuarterEnd.startingMonth
QuarterEnd.startingMonth

Methods

QuarterEnd.apply(other)
QuarterEnd.apply_index(other)
QuarterEnd.copy
QuarterEnd.isAnchored
QuarterEnd.onOffset
QuarterEnd.is_anchored
QuarterEnd.is_on_offset
QuarterEnd.__call__(*args, **kwargs) Call self as a function.
```

3.8. Date offsets
pandas.tseries.offsets.QuarterEnd.apply
QuarterEnd.apply(\textit{other})

pandas.tseries.offsets.QuarterEnd.apply_index
QuarterEnd.apply_index(\textit{other})

pandas.tseries.offsets.QuarterEnd.copy
QuarterEnd.copy()

pandas.tseries.offsets.QuarterEnd.isAnchored
QuarterEnd.isAnchored()

pandas.tseries.offsets.QuarterEnd.onOffset
QuarterEnd.onOffset()

pandas.tseries.offsets.QuarterEnd.is_anchored
QuarterEnd.is_anchored()

pandas.tseries.offsets.QuarterEnd.is_on_offset
QuarterEnd.is_on_offset()

3.8.20 QuarterBegin

\begin{tabular}{ll}
\textit{QuarterBegin} & \\
\multicolumn{2}{c}{DateOffset increments between Quarter start dates.} \\
\end{tabular}

pandas.tseries.offsets.QuarterBegin

\texttt{class pandas.tseries.offsets.QuarterBegin} \\
\texttt{DateOffset increments between Quarter start dates.} \\
\begin{itemize}
\item startingMonth = 1 corresponds to dates like 1/01/2007, 4/01/2007, \ldots
\item startingMonth = 2 corresponds to dates like 2/01/2007, 5/01/2007, \ldots
\item startingMonth = 3 corresponds to dates like 3/01/2007, 6/01/2007, \ldots
\end{itemize}
pandas: powerful Python data analysis toolkit, Release 1.1.1

Attributes

| base | Returns a copy of the calling offset object with n=1 and all other attributes equal. |

pandas.tseries.offsets.QuarterBegin.base

QuarterBegin.base

Returns a copy of the calling offset object with n=1 and all other attributes equal.

| freqstr |
| kwds    |
| n       |
| name    |
| nanos   |
| normalize |
| rule_code |
| startingMonth |

Methods

<table>
<thead>
<tr>
<th><strong>call</strong>(*args, **kwargs)</th>
<th>Call self as a function.</th>
</tr>
</thead>
<tbody>
<tr>
<td>rollback</td>
<td>Roll provided date backward to next offset only if not on offset.</td>
</tr>
<tr>
<td>rollforward</td>
<td>Roll provided date forward to next offset only if not on offset.</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.QuarterBegin.__call__

QuarterBegin.__call__(*args, **kwargs)

Call self as a function.

pandas.tseries.offsets.QuarterBegin.rollback

QuarterBegin.rollback()

Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp  Rolled timestamp if not on offset, otherwise unchanged timestamp.

3.8. Date offsets 2125
pandas.tseries.offsets.QuarterBegin.rollforward

QuarterBegin.rollforward()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp  Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>apply</td>
</tr>
<tr>
<td>apply_index</td>
</tr>
<tr>
<td>copy</td>
</tr>
<tr>
<td>isAnchored</td>
</tr>
<tr>
<td>is_anchored</td>
</tr>
<tr>
<td>is_on_offset</td>
</tr>
<tr>
<td>onOffset</td>
</tr>
</tbody>
</table>

Properties

QuarterBegin.freqstr
QuarterBegin.kwds
QuarterBegin.name
QuarterBegin.nanos
QuarterBegin.normalize
QuarterBegin.rule_code
QuarterBegin.n
QuarterBegin.startingMonth

pandas.tseries.offsets.QuarterBegin.freqstr

QuarterBegin.freqstr

pandas.tseries.offsets.QuarterBegin.kwds

QuarterBegin.kwds
pandas.tseries.offsets.QuarterBegin.name

QuarterBegin.name

pandas.tseries.offsets.QuarterBegin.nanos

QuarterBegin.nanos

pandas.tseries.offsets.QuarterBegin.normalize

QuarterBegin.normalize

pandas.tseries.offsets.QuarterBegin.rule_code

QuarterBegin.rule_code

pandas.tseries.offsets.QuarterBegin.n

QuarterBegin.n

pandas.tseries.offsets.QuarterBegin.startingMonth

QuarterBegin.startingMonth

Methods

QuarterBegin.apply(other)

QuarterBegin.apply_index(other)

QuarterBegin.copy

QuarterBegin.isAnchored

QuarterBegin.onOffset

QuarterBegin.is_anchored

QuarterBegin.is_on_offset

QuarterBegin.__call__(*args, **kwargs) Call self as a function.

3.8. Date offsets
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.QuarterBegin.apply
QuarterBegin.apply(other)

pandas.tseries.offsets.QuarterBegin.apply_index
QuarterBegin.apply_index(other)

pandas.tseries.offsets.QuarterBegin.copy
QuarterBegin.copy()

pandas.tseries.offsets.QuarterBegin.isAnchored
QuarterBegin.isAnchored()

pandas.tseries.offsets.QuarterBegin.onOffset
QuarterBegin.onOffset()

pandas.tseries.offsets.QuarterBegin.is_anchored
QuarterBegin.is_anchored()

pandas.tseries.offsets.QuarterBegin.is_on_offset
QuarterBegin.is_on_offset()

3.8.21 BYearEnd

| BYearEnd | DateOffset increments between the last business day of the year. |

pandas.tseries.offsets.BYearEnd

class pandas.tseries.offsets.BYearEnd
    DateOffset increments between the last business day of the year.
Examples

```python
>>> from pandas.tseries.offset import BYearEnd
>>> ts = pd.Timestamp('2020-05-24 05:01:15')
>>> ts - BYearEnd()
Timestamp('2019-12-31 05:01:15')
>>> ts + BYearEnd()
Timestamp('2020-12-31 05:01:15')
>>> ts + BYearEnd(3)
Timestamp('2022-12-30 05:01:15')
>>> ts + BYearEnd(-3)
Timestamp('2017-12-29 05:01:15')
>>> ts + BYearEnd(month=11)
Timestamp('2020-11-30 05:01:15')
```

Attributes

| base | Returns a copy of the calling offset object with n=1 and all other attributes equal. |

pandas.tseries.offsets.BYearEnd.base

BYearEnd.base

Returns a copy of the calling offset object with n=1 and all other attributes equal.

| freqstr | |
| kwds | |
| month | |
| n | |
| name | |
| nanos | |
| normalize | |
| rule_code | |

Methods

| `__call__`(*args, **kwargs) | Call self as a function. |
| `rollback` | Roll provided date backward to next offset only if not on offset. |
| `rollforward` | Roll provided date forward to next offset only if not on offset. |
pandas.tseries.offsets.BYearEnd.__call__

BYearEnd.__call__(*args, **kwargs)
Call self as a function.

pandas.tseries.offsets.BYearEnd.rollback

BYearEnd.rollback()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.BYearEnd.rollforward

BYearEnd.rollforward()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>apply</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>apply_index</td>
<td></td>
</tr>
<tr>
<td>copy</td>
<td></td>
</tr>
<tr>
<td>is_Anchored</td>
<td></td>
</tr>
<tr>
<td>is_anchored</td>
<td></td>
</tr>
<tr>
<td>is_on_offset</td>
<td></td>
</tr>
<tr>
<td>onOffset</td>
<td></td>
</tr>
</tbody>
</table>

Properties

BYearEnd.freqstr
BYearEnd.kwds
BYearEnd.name
BYearEnd.nanos
BYearEnd.normalize
BYearEnd.rule_code
BYearEnd.n
BYearEnd.month
pandas.tseries.offsets.BYearEnd.freqstr

BYearEnd.freqstr

pandas.tseries.offsets.BYearEnd.kwds

BYearEnd.kwds

pandas.tseries.offsets.BYearEnd.name

BYearEnd.name

pandas.tseries.offsets.BYearEnd.nanos

BYearEnd.nanos

pandas.tseries.offsets.BYearEnd.normalize

BYearEnd.normalize

pandas.tseries.offsets.BYearEnd.rule_code

BYearEnd.rule_code

pandas.tseries.offsets.BYearEnd.n

BYearEnd.n

pandas.tseries.offsets.BYearEnd.month

BYearEnd.month

Methods

BYearEnd.apply(other)
BYearEnd.apply_index(other)
BYearEnd.copy
BYearEnd.isAnchored
BYearEnd.onOffset
BYearEnd.is_anchored
BYearEnd.is_on_offset
BYearEnd.__call__(*args, **kwargs)  Call self as a function.

3.8. Date offsets 2131
3.8.22 BYearBegin

<table>
<thead>
<tr>
<th>BYearBegin</th>
<th>DateOffset increments between the first business day of the year.</th>
</tr>
</thead>
</table>

pandas.tseries.offsets.BYearBegin

class pandas.tseries.offsets.BYearBegin

   DateOffset increments between the first business day of the year.
Examples

```python
>>> from pandas.tseries.offsets import BYearBegin
>>> ts = pd.Timestamp('2020-05-24 05:01:15')
>>> ts + BYearBegin()
Timestamp('2021-01-01 05:01:15')
>>> ts - BYearBegin()
Timestamp('2020-01-01 05:01:15')
>>> ts + BYearBegin(-1)
Timestamp('2020-01-01 05:01:15')
>>> ts + BYearBegin(2)
Timestamp('2022-01-03 05:01:15')
```

Attributes

```
base

Returns a copy of the calling offset object with n=1 and all other attributes equal.
```

pandas.tseries.offsets.BYearBegin.base

BYearBegin.base

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<table>
<thead>
<tr>
<th>freqstr</th>
<th>kwds</th>
</tr>
</thead>
<tbody>
<tr>
<td>month</td>
<td></td>
</tr>
<tr>
<td>n</td>
<td></td>
</tr>
<tr>
<td>name</td>
<td></td>
</tr>
<tr>
<td>nanos</td>
<td></td>
</tr>
<tr>
<td>normalize</td>
<td></td>
</tr>
<tr>
<td>rule_code</td>
<td></td>
</tr>
</tbody>
</table>

Methods

```
__call__(*args, **kwargs)

call self as a function.

rollback

Roll provided date backward to next offset only if not on offset.

rollforward

Roll provided date forward to next offset only if not on offset.
```

3.8. Date offsets
### pandas.tseries.offsets.BYearBegin.__call__

BYearBegin.__call__(*args, **kwargs)

Call self as a function.

### pandas.tseries.offsets.BYearBegin.rollback

BYearBegin.rollback()

Roll provided date backward to next offset only if not on offset.

**Returns**

**TimeStamp**  Rolled timestamp if not on offset, otherwise unchanged timestamp.

### pandas.tseries.offsets.BYearBegin.rollforward

BYearBegin.rollforward()

Roll provided date forward to next offset only if not on offset.

**Returns**

**TimeStamp**  Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>apply</td>
</tr>
<tr>
<td>apply_index</td>
</tr>
<tr>
<td>copy</td>
</tr>
<tr>
<td>isAnchored</td>
</tr>
<tr>
<td>is_anchored</td>
</tr>
<tr>
<td>is_on_offset</td>
</tr>
<tr>
<td>onOffset</td>
</tr>
</tbody>
</table>

### Properties

- **BYearBegin.freqstr**
- **BYearBegin.kwds**
- **BYearBegin.name**
- **BYearBegin.nanos**
- **BYearBegin.normalize**
- **BYearBegin.rule_code**
- **BYearBegin.n**
- **BYearBegin.month**
pandas.tseries.offsets.BYearBegin.freqstr

BYearBegin.freqstr

pandas.tseries.offsets.BYearBegin.kwds

BYearBegin.kwds

pandas.tseries.offsets.BYearBegin.name

BYearBegin.name

pandas.tseries.offsets.BYearBegin.nanos

BYearBegin.nanos

pandas.tseries.offsets.BYearBegin.normalize

BYearBegin.normalize

pandas.tseries.offsets.BYearBegin.rule_code

BYearBegin.rule_code

pandas.tseries.offsets.BYearBegin.n

BYearBegin.n

pandas.tseries.offsets.BYearBegin.month

BYearBegin.month

Methods

BYearBegin.apply(other)
BYearBegin.apply_index(other)
BYearBegin.copy
BYearBegin.isAnchored
BYearBegin.onOffset
BYearBegin.is_anchored
BYearBegin.is_on_offset
BYearBegin.__call__(*args, **kwargs) Call self as a function.
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.BYearBegin.apply

BYearBegin.apply(other)

pandas.tseries.offsets.BYearBegin.apply_index

BYearBegin.apply_index(other)

pandas.tseries.offsets.BYearBegin.copy

BYearBegin.copy()

pandas.tseries.offsets.BYearBegin.isAnchored

BYearBegin.isAnchored()

pandas.tseries.offsets.BYearBegin.onOffset

BYearBegin.onOffset()

pandas.tseries.offsets.BYearBegin.is_anchored

BYearBegin.is_anchored()

pandas.tseries.offsets.BYearBegin.is_on_offset

BYearBegin.is_on_offset()

3.8.23 YearEnd

| YearEnd | DateOffset increments between calendar year ends. |

pandas.tseries.offsets.YearEnd

class pandas.tseries.offsets.YearEnd
    DateOffset increments between calendar year ends.
**Attributes**

| base | Returns a copy of the calling offset object with n=1 and all other attributes equal. |

**pandas.tseries.offsets.YearEnd.base**

YearEnd.base

Returns a copy of the calling offset object with n=1 and all other attributes equal.

| freqstr | | | |
| kwds | | | |
| month | | | |
| n | | | |
| name | | | |
| nanos | | | |
| normalize | | | |
| rule_code | | | |

**Methods**

<table>
<thead>
<tr>
<th><strong>call</strong>(*args, **kwargs)</th>
<th>Call self as a function.</th>
</tr>
</thead>
<tbody>
<tr>
<td>rollback</td>
<td>Roll provided date backward to next offset only if not on offset.</td>
</tr>
<tr>
<td>rollforward</td>
<td>Roll provided date forward to next offset only if not on offset.</td>
</tr>
</tbody>
</table>

**pandas.tseries.offsets.YearEnd.__call__**

YearEnd.__call__(*args, **kwargs)

Call self as a function.

**pandas.tseries.offsets.YearEnd.rollback**

YearEnd.rollback()

Roll provided date backward to next offset only if not on offset.

**Returns**

TimeStamp  Rolled timestamp if not on offset, otherwise unchanged timestamp.
pandas.tseries.offsets.YearEnd.rollforward

`YearEnd.rollforward()`
Roll provided date forward to next offset only if not on offset.

**Returns**

*TimeStamp*  Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>apply</th>
<th>apply_index</th>
</tr>
</thead>
<tbody>
<tr>
<td>copy</td>
<td></td>
</tr>
<tr>
<td>isAnchored</td>
<td></td>
</tr>
<tr>
<td>is_anchored</td>
<td></td>
</tr>
<tr>
<td>is_on_offset</td>
<td></td>
</tr>
<tr>
<td>onOffset</td>
<td></td>
</tr>
</tbody>
</table>

**Properties**

- `YearEnd.freqstr`
- `YearEnd.kwds`
- `YearEnd.name`
- `YearEnd.nanos`
- `YearEnd.normalize`
- `YearEnd.rule_code`
- `YearEnd.n`
- `YearEnd.month`

**pandas.tseries.offsets.YearEnd.freqstr**

`YearEnd.freqstr`

**pandas.tseries.offsets.YearEnd.kwds**

`YearEnd.kwds`
pandas.tseries.offsets.YearEnd.name

YearEnd.name

pandas.tseries.offsets.YearEnd.nanos

YearEnd.nanos

pandas.tseries.offsets.YearEnd.normalize

YearEnd.normalize

pandas.tseries.offsets.YearEnd.rule_code

YearEnd.rule_code

pandas.tseries.offsets.YearEnd.n

YearEnd.n

pandas.tseries.offsets.YearEnd.month

YearEnd.month

Methods

<table>
<thead>
<tr>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>YearEnd.apply(other)</td>
</tr>
<tr>
<td>YearEnd.apply_index(other)</td>
</tr>
<tr>
<td>YearEnd.copy</td>
</tr>
<tr>
<td>YearEnd.isAnchored</td>
</tr>
<tr>
<td>YearEnd.onOffset</td>
</tr>
<tr>
<td>YearEnd.is_anchored</td>
</tr>
<tr>
<td>YearEnd.is_on_offset</td>
</tr>
<tr>
<td>YearEnd.<strong>call</strong>(*args, **kwargs) Call self as a function.</td>
</tr>
</tbody>
</table>

3.8. Date offsets
pandas.tseries.offsets.YearEnd.apply

YearEnd.apply(other)

pandas.tseries.offsets.YearEnd.apply_index

YearEnd.apply_index(other)

pandas.tseries.offsets.YearEnd.copy

YearEnd.copy()

pandas.tseries.offsets.YearEnd.isAnchored

YearEnd.isAnchored()

pandas.tseries.offsets.YearEnd.onOffset

YearEnd.onOffset()

pandas.tseries.offsets.YearEnd.is_anchored

YearEnd.is_anchored()

pandas.tseries.offsets.YearEnd.is_on_offset

YearEnd.is_on_offset()

3.8.24 YearBegin

<table>
<thead>
<tr>
<th>YearBegin</th>
<th>DateOffset increments between calendar year begin dates.</th>
</tr>
</thead>
</table>

pandas.tseries.offsets.YearBegin

class pandas.tseries.offsets.YearBegin

DateOffset increments between calendar year begin dates.
pandas: powerful Python data analysis toolkit, Release 1.1.1

Attributes

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base</td>
<td>Returns a copy of the calling offset object with n=1 and all other attributes equal.</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.YearBegin.base

YearBegin.base
Returns a copy of the calling offset object with n=1 and all other attributes equal.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>freqstr</td>
<td></td>
</tr>
<tr>
<td>kwds</td>
<td></td>
</tr>
<tr>
<td>month</td>
<td></td>
</tr>
<tr>
<td>n</td>
<td></td>
</tr>
<tr>
<td>name</td>
<td></td>
</tr>
<tr>
<td>nanos</td>
<td></td>
</tr>
<tr>
<td>normalize</td>
<td></td>
</tr>
<tr>
<td>rule_code</td>
<td></td>
</tr>
</tbody>
</table>

Methods

<table>
<thead>
<tr>
<th>Methods</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>call</strong>(*args, **kwargs)</td>
<td>Call self as a function.</td>
</tr>
<tr>
<td>rollback</td>
<td>Roll provided date backward to next offset only if not on offset.</td>
</tr>
<tr>
<td>rollforward</td>
<td>Roll provided date forward to next offset only if not on offset.</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.YearBegin.__call__

YearBegin.__call__(*args, **kwargs)
Call self as a function.

pandas.tseries.offsets.YearBegin.rollback

YearBegin.rollback()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.
**pandas.tseries.offsets.YearBegin.rollforward**

*YearBegin.rollforward()*

Roll provided date forward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>apply</td>
<td></td>
</tr>
<tr>
<td>apply_index</td>
<td></td>
</tr>
<tr>
<td>copy</td>
<td></td>
</tr>
<tr>
<td>isAnchored</td>
<td></td>
</tr>
<tr>
<td>is_anchored</td>
<td></td>
</tr>
<tr>
<td>is_on_offset</td>
<td></td>
</tr>
<tr>
<td>onOffset</td>
<td></td>
</tr>
</tbody>
</table>

**Properties**

- **pandas.tseries.offsets.YearBegin.freqstr**
- **pandas.tseries.offsets.YearBegin.kwds**
- **pandas.tseries.offsets.YearBegin.name**
- **pandas.tseries.offsets.YearBegin.nanos**
- **pandas.tseries.offsets.YearBegin.normalize**
- **pandas.tseries.offsets.YearBegin.rule_code**
- **pandas.tseries.offsets.YearBegin.n**
- **pandas.tseries.offsets.YearBegin.month**

**pandas.tseries.offsets.YearBegin.freqstr**

*YearBegin.freqstr*

**pandas.tseries.offsets.YearBegin.kwds**

*YearBegin.kwds*
pandas.tseries.offsets.YearBegin.name

YearBegin.name

pandas.tseries.offsets.YearBegin.nanos

YearBegin.nanos

pandas.tseries.offsets.YearBegin.normalize

YearBegin.normalize

pandas.tseries.offsets.YearBegin.rule_code

YearBegin.rule_code

pandas.tseries.offsets.YearBegin.n

YearBegin.n

pandas.tseries.offsets.YearBegin.month

YearBegin.month

Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>YearBegin.apply(other)</td>
<td></td>
</tr>
<tr>
<td>YearBegin.apply_index(other)</td>
<td></td>
</tr>
<tr>
<td>YearBegin.copy</td>
<td></td>
</tr>
<tr>
<td>YearBegin.isAnchored</td>
<td></td>
</tr>
<tr>
<td>YearBegin.onOffset</td>
<td></td>
</tr>
<tr>
<td>YearBegin.is_anchored</td>
<td></td>
</tr>
<tr>
<td>YearBegin.is_on_offset</td>
<td></td>
</tr>
<tr>
<td>YearBegin.<strong>call</strong>(*args, *<em>kwargs)</em></td>
<td>Call self as a function.</td>
</tr>
</tbody>
</table>
pandas.tseries.offsets.YearBegin.apply

YearBegin.apply(other)

pandas.tseries.offsets.YearBegin.apply_index

YearBegin.apply_index(other)

pandas.tseries.offsets.YearBegin.copy

YearBegin.copy()

pandas.tseries.offsets.YearBegin.isAnchored

YearBegin.isAnchored()

pandas.tseries.offsets.YearBegin.onOffset

YearBegin.onOffset()

pandas.tseries.offsets.YearBegin.is_anchored

YearBegin.is_anchored()

pandas.tseries.offsets.YearBegin.is_on_offset

YearBegin.is_on_offset()

3.8.25 FY5253

<table>
<thead>
<tr>
<th>FY5253</th>
<th>Describes 52-53 week fiscal year.</th>
</tr>
</thead>
</table>

pandas.tseries.offsets.FY5253

class pandas.tseries.offsets.FY5253

Describes 52-53 week fiscal year. This is also known as a 4-4-5 calendar.

It is used by companies that desire that their fiscal year always end on the same day of the week.

It is a method of managing accounting periods. It is a common calendar structure for some industries, such as retail, manufacturing and parking industry.

For more information see: https://en.wikipedia.org/wiki/4-4-5_calendar

The year may either:
  • end on the last X day of the Y month.
  • end on the last X day closest to the last day of the Y month.
X is a specific day of the week. Y is a certain month of the year

**Parameters**

- **n** [int] 
  - weekday [int \{0, 1, . . . , 6\}, default 0] A specific integer for the day of the week.
  - 0 is Monday
  - 1 is Tuesday
  - 2 is Wednesday
  - 3 is Thursday
  - 4 is Friday
  - 5 is Saturday
  - 6 is Sunday.
- **startingMonth** [int \{1, 2, . . . 12\}, default 1] The month in which the fiscal year ends.
- **variation** [str, default “nearest”] Method of employing 4-4-5 calendar.
  - There are two options:
  - “nearest” means year end is weekday closest to last day of month in year.
  - “last” means year end is final weekday of the final month in fiscal year.

**Attributes**

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base</td>
<td>Returns a copy of the calling offset object with n=1 and all other attributes equal.</td>
</tr>
</tbody>
</table>

**pandas.tseries.offsets.FY5253.base**

FY5253 . base

Returns a copy of the calling offset object with n=1 and all other attributes equal.
Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>call</strong>(*args, **kwargs)</td>
<td>Call self as a function.</td>
</tr>
<tr>
<td>rollback</td>
<td>Roll provided date backward to next offset only if not on offset.</td>
</tr>
<tr>
<td>rollforward</td>
<td>Roll provided date forward to next offset only if not on offset.</td>
</tr>
</tbody>
</table>

```python
pandas.tseries.offsets.FY5253.__call__
```

FY5253.__call__(*args, **kwargs)
Call self as a function.

```python
pandas.tseries.offsets.FY5253.rollback
```

FY5253.rollback()
Roll provided date backward to next offset only if not on offset.

Returns

**TimeStamfp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

```python
pandas.tseries.offsets.FY5253.rollforward
```

FY5253.rollforward()
Roll provided date forward to next offset only if not on offset.

Returns

**TimeStamfp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

```python
<table>
<thead>
<tr>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>apply</td>
</tr>
<tr>
<td>apply_index</td>
</tr>
<tr>
<td>copy</td>
</tr>
<tr>
<td>get_rule_code_suffix</td>
</tr>
<tr>
<td>get_year_end</td>
</tr>
<tr>
<td>isAnchored</td>
</tr>
<tr>
<td>is_anchored</td>
</tr>
<tr>
<td>is_on_offset</td>
</tr>
<tr>
<td>onOffset</td>
</tr>
</tbody>
</table>
```
Properties

FY5253.freqstr
FY5253.kwds
FY5253.name
FY5253.nanos
FY5253.normalize
FY5253.rule_code
FY5253.n
FY5253.startingMonth
FY5253.variation
FY5253.weekday

pandas.tseries.offsets.FY5253.freqstr

FY5253.freqstr

pandas.tseries.offsets.FY5253.kwds

FY5253.kwds

pandas.tseries.offsets.FY5253.name

FY5253.name

pandas.tseries.offsets.FY5253.nanos

FY5253.nanos

pandas.tseries.offsets.FY5253.normalize

FY5253.normalize

pandas.tseries.offsets.FY5253.rule_code

FY5253.rule_code
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.FY5253.n

FY5253.n

pandas.tseries.offsets.FY5253.startingMonth

FY5253.startingMonth

pandas.tseries.offsets.FY5253.variation

FY5253.variation

pandas.tseries.offsets.FY5253.weekday

FY5253.weekday

Methods

FY5253.apply(other)
FY5253.apply_index(other)
FY5253.copy
FY5253.get_rule_code_suffix
FY5253.get_year_end
FY5253.isAnchored
FY5253.onOffset
FY5253.is_anchored
FY5253.is_on_offset
FY5253.__call__(*args, **kwargs) Call self as a function.

pandas.tseries.offsets.FY5253.apply

FY5253.apply(other)
3.8.26 FY5253Quarter

FY5253Quarter

DateOffset increments between business quarter dates for 52-53 week fiscal year (also known as a 4-4-5 calendar).
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.FY5253Quarter

class pandas.tseries.offsets.FY5253Quarter
DateOffset increments between business quarter dates for 52-53 week fiscal year (also known as a 4-4-5 calen-
dar).

It is used by companies that desire that their fiscal year always end on the same day of the week.

It is a method of managing accounting periods. It is a common calendar structure for some industries, such as
retail, manufacturing and parking industry.

For more information see: https://en.wikipedia.org/wiki/4-4-5_calendar

The year may either:
• end on the last X day of the Y month.
• end on the last X day closest to the last day of the Y month.
X is a specific day of the week. Y is a certain month of the year

startingMonth = 1 corresponds to dates like 1/31/2007, 4/30/2007, … startingMonth = 2 corresponds to dates

Parameters

n [int]

weekday [int {0, 1, …, 6}, default 0] A specific integer for the day of the week.
• 0 is Monday
• 1 is Tuesday
• 2 is Wednesday
• 3 is Thursday
• 4 is Friday
• 5 is Saturday
• 6 is Sunday.

startingMonth [int {1, 2, …, 12}, default 1] The month in which fiscal years end.

qtr_with_extra_week [int {1, 2, 3, 4}, default 1] The quarter number that has the leap or 14
week when needed.

variation [str, default “nearest”] Method of employing 4-4-5 calendar.

There are two options:
• “nearest” means year end is weekday closest to last day of month in year.
• “last” means year end is final weekday of the final month in fiscal year.

Attributes

<table>
<thead>
<tr>
<th>base</th>
<th>Returns a copy of the calling offset object with n=1 and all other attributes equal.</th>
</tr>
</thead>
</table>
pandas.tseries.offsets.FY5253Quarter.base

FY5253Quarter.base

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<table>
<thead>
<tr>
<th>freqstr</th>
<th>kwds</th>
<th>n</th>
<th>name</th>
<th>nanos</th>
<th>normalize</th>
<th>qtr_with_extra_week</th>
<th>rule_code</th>
<th>startingMonth</th>
<th>variation</th>
<th>weekday</th>
</tr>
</thead>
</table>

Methods

FY5253Quarter.__call__(*args, **kwargs)

Call self as a function.

FY5253Quarter.rollback()

Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

FY5253Quarter.rollforward()

Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

3.8. Date offsets
Properties

FY5253Quarter.freqstr
FY5253Quarter.kwds
FY5253Quarter.name
FY5253Quarter.nanos
FY5253Quarter.normalize
FY5253Quarter.rule_code
FY5253Quarter.n
FY5253Quarter.qtr_with_extra_week
FY5253Quarter.startingMonth
FY5253Quarter.variation
FY5253Quarter.weekday

pandas.tseries.offsets.FY5253Quarter.freqstr

FY5253Quarter.freqstr

pandas.tseries.offsets.FY5253Quarter.kwds

FY5253Quarter.kwds

pandas.tseries.offsets.FY5253Quarter.name

FY5253Quarter.name

pandas.tseries.offsets.FY5253Quarter.nanos

FY5253Quarter.nanos
pandas.tseries.offsets.FY253Quarter.normalize

FY253Quarter.normalize

pandas.tseries.offsets.FY253Quarter.rule_code

FY253Quarter.rule_code

pandas.tseries.offsets.FY253Quarter.n

FY253Quarter.n

pandas.tseries.offsets.FY253Quarter.qtr_with_extra_week

FY253Quarter.qtr_with_extra_week

pandas.tseries.offsets.FY253Quarter.startingMonth

FY253Quarter.startingMonth

pandas.tseries.offsets.FY253Quarter.variation

FY253Quarter.variation

pandas.tseries.offsets.FY253Quarter.weekday

FY253Quarter.weekday

Methods

FY253Quarter.apply(other)
FY253Quarter.apply_index(other)
FY253Quarter.copy
FY253Quarter.get_rule_code_suffix
FY253Quarter.get_weeks
FY253Quarter.isAnchored
FY253Quarter.onOffset
FY253Quarter.is_anchored
FY253Quarter.is_on_offset
FY253Quarter.year_has_extra_week
FY253Quarter.__call__(*args, **kwargs) Call self as a function.
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.FY5253Quarter.apply
FY5253Quarter.apply(other)

pandas.tseries.offsets.FY5253Quarter.apply_index
FY5253Quarter.apply_index(other)

pandas.tseries.offsets.FY5253Quarter.copy
FY5253Quarter.copy()

pandas.tseries.offsets.FY5253Quarter.get_rule_code_suffix
FY5253Quarter.get_rule_code_suffix()

pandas.tseries.offsets.FY5253Quarter.get_weeks
FY5253Quarter.get_weeks()

pandas.tseries.offsets.FY5253Quarter.isAnchored
FY5253Quarter.isAnchored()

pandas.tseries.offsets.FY5253Quarter.onOffset
FY5253Quarter.onOffset()

pandas.tseries.offsets.FY5253Quarter.is_anchored
FY5253Quarter.is_anchored()

pandas.tseries.offsets.FY5253Quarter.is_on_offset
FY5253Quarter.is_on_offset()
**3.8.27 Easter**

*Easter* DateOffset for the Easter holiday using logic defined in dateutil.

**pandas.tseries.offsets.Easter**

```python
class pandas.tseries.offsets.Easter
    DateOffset for the Easter holiday using logic defined in dateutil.
    Right now uses the revised method which is valid in years 1583-4099.
```

**Attributes**

<table>
<thead>
<tr>
<th><strong>base</strong></th>
<th>Returns a copy of the calling offset object with n=1 and all other attributes equal.</th>
</tr>
</thead>
</table>

**pandas.tseries.offsets.Easter.base**

*Easter.base* Returns a copy of the calling offset object with n=1 and all other attributes equal.

<table>
<thead>
<tr>
<th>freqstr</th>
<th>kwds</th>
<th>n</th>
<th>name</th>
<th>nanos</th>
<th>normalize</th>
<th>rule_code</th>
</tr>
</thead>
</table>

**Methods**

<table>
<thead>
<tr>
<th><code>__call__</code>(*args, **kwargs)</th>
<th>Call self as a function.</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>rollback</code></td>
<td>Roll provided date backward to next offset only if not on offset.</td>
</tr>
<tr>
<td><code>rollforward</code></td>
<td>Roll provided date forward to next offset only if not on offset.</td>
</tr>
</tbody>
</table>
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.Easter.__call__

Easter.__call__(*args, **kwargs)
Call self as a function.

pandas.tseries.offsets.Easter.rollback

Easter.rollback()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp  Rolled timestamp if not on offset, otherwise unchanged timestamp.

pandas.tseries.offsets.Easter.rollforward

Easter.rollforward()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp  Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>apply</th>
<th>apply_index</th>
<th>copy</th>
</tr>
</thead>
<tbody>
<tr>
<td>isAnchored</td>
<td>is_anchored</td>
<td>is_on_offset</td>
</tr>
<tr>
<td>onOffset</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Properties

Easter.freqstr
Easter.kwds
Easter.name
Easter.nanos
Easter.normalize
Easter.rule_code
Easter.n
pandas.tseries.offsets.Easter.freqstr

Easter.freqstr

pandas.tseries.offsets.Easter.kwds

Easter.kwds

pandas.tseries.offsets.Easter.name

Easter.name

pandas.tseries.offsets.Easter.nanos

Easter.nanos

pandas.tseries.offsets.Easter.normalize

Easter.normalize

pandas.tseries.offsets.Easter.rule_code

Easter.rule_code

pandas.tseries.offsets.Easter.n

Easter.n

Methods

Easter.apply(other)
Easter.apply_index(other)
Easter.copy
Easter.isAnchored
Easter.onOffset
Easter.is_anchored
Easter.is_on_offset
Easter.__call__(*args, **kwargs)  Call self as a function.

3.8. Date offsets
pandas: powerful Python data analysis toolkit, Release 1.1.1

**pandas.tseries.offsets.Easter.apply**

Easter.apply(other)

**pandas.tseries.offsets.Easter.apply_index**

Easter.apply_index(other)

**pandas.tseries.offsets.Easter.copy**

Easter.copy()

**pandas.tseries.offsets.Easter.isAnchored**

Easter.isAnchored()

**pandas.tseries.offsets.Easter.onOffset**

Easter.onOffset()

**pandas.tseries.offsets.Easter.is_anchored**

Easter.is_anchored()

**pandas.tseries.offsets.Easter.is_on_offset**

Easter.is_on_offset()

### 3.8.28 Tick

Tick

<table>
<thead>
<tr>
<th>Attributes</th>
</tr>
</thead>
</table>
class pandas.tseries.offsets.Tick

Attributes

| base | Returns a copy of the calling offset object with n=1 and all other attributes equal. |

pandas.tseries.offsets.Tick.base

Tick.base

Returns a copy of the calling offset object with n=1 and all other attributes equal.

Methods

<table>
<thead>
<tr>
<th><strong>call</strong>(*args, **kwargs)</th>
<th>Call self as a function.</th>
</tr>
</thead>
<tbody>
<tr>
<td>rollback</td>
<td>Roll provided date backward to next offset only if not on offset.</td>
</tr>
<tr>
<td>rollforward</td>
<td>Roll provided date forward to next offset only if not on offset.</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.Tick.__call__

Tick.__call__(*args, **kwargs)

Call self as a function.

pandas.tseries.offsets.Tick.rollback

Tick.rollback()

Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.
pandas.tseries.offsets.Tick.rollforward

**Tick.rollforward()**
Roll provided date forward to next offset only if not on offset.

**Returns**

**TimeStamp**  Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>apply</td>
</tr>
<tr>
<td>apply_index</td>
</tr>
<tr>
<td>copy</td>
</tr>
<tr>
<td>isAnchored</td>
</tr>
<tr>
<td>is_anchored</td>
</tr>
<tr>
<td>is_on_offset</td>
</tr>
<tr>
<td>onOffset</td>
</tr>
</tbody>
</table>

**Properties**

<table>
<thead>
<tr>
<th>Property</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tick.delta</td>
</tr>
<tr>
<td>Tick.freqstr</td>
</tr>
<tr>
<td>Tick.kwds</td>
</tr>
<tr>
<td>Tick.name</td>
</tr>
<tr>
<td>Tick.nanos</td>
</tr>
<tr>
<td>Tick.normalize</td>
</tr>
<tr>
<td>Tick.rule_code</td>
</tr>
<tr>
<td>Tick.n</td>
</tr>
</tbody>
</table>

**pandas.tseries.offsets.Tick.delta**

**Tick.delta**

**pandas.tseries.offsets.Tick.freqstr**

**Tick.freqstr**
pandas.tseries.offsets.Tick.kwds

Tick.kwds

pandas.tseries.offsets.Tick.name

Tick.name

pandas.tseries.offsets.Tick.nanos

Tick.nanos

pandas.tseries.offsets.Tick.normalize

Tick.normalize

pandas.tseries.offsets.Tick.rule_code

Tick.rule_code

pandas.tseries.offsets.Tick.n

Tick.n

Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tick.copy</td>
<td></td>
</tr>
<tr>
<td>Tick.isAnchored</td>
<td></td>
</tr>
<tr>
<td>Tick.onOffset</td>
<td></td>
</tr>
<tr>
<td>Tick.is_anchored</td>
<td></td>
</tr>
<tr>
<td>Tick.is_on_offset</td>
<td></td>
</tr>
<tr>
<td>Tick.<strong>call</strong></td>
<td>Call self as a function.</td>
</tr>
<tr>
<td>Tick.apply</td>
<td></td>
</tr>
<tr>
<td>Tick.apply_index</td>
<td>other</td>
</tr>
</tbody>
</table>

3.8. Date offsets
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.Tick.copy

Tick.copy()

pandas.tseries.offsets.Tick.isAnchored

Tick.isAnchored()

pandas.tseries.offsets.Tick.onOffset

Tick.onOffset()

pandas.tseries.offsets.Tick.is_anchored

Tick.is_anchored()

pandas.tseries.offsets.Tick.is_on_offset

Tick.is_on_offset()

pandas.tseries.offsets.Tick.apply

Tick.apply()

pandas.tseries.offsets.Tick.apply_index

Tick.apply_index(other)

3.8.29 Day

Day

Attributes
pandas.tseries.offsets.Day

```python
class pandas.tseries.offsets.Day

Attributes

| base | Returns a copy of the calling offset object with n=1 and all other attributes equal. |

pandas.tseries.offsets.Day.base

Day.base
Returns a copy of the calling offset object with n=1 and all other attributes equal.

<table>
<thead>
<tr>
<th>delta</th>
<th>freqstr</th>
<th>kwds</th>
<th>n</th>
<th>name</th>
<th>nanos</th>
<th>normalize</th>
<th>rule_code</th>
</tr>
</thead>
</table>

Methods

<table>
<thead>
<tr>
<th><strong>call</strong>(*args, **kwargs)</th>
<th>Call self as a function.</th>
</tr>
</thead>
<tbody>
<tr>
<td>rollback</td>
<td>Roll provided date backward to next offset only if not on offset.</td>
</tr>
<tr>
<td>rollforward</td>
<td>Roll provided date forward to next offset only if not on offset.</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.Day.__call__

Day.__call__(*args, **kwargs)
Call self as a function.

pandas.tseries.offsets.Day.rollback

Day.rollback()
Roll provided date backward to next offset only if not on offset.

Returns

TimeSpan  Rolled timestamp if not on offset, otherwise unchanged timestamp.
pandas.tseries.offsets.Day.rollforward

Day.rollforward()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

apply
apply_index
copy
isAnchored
is_anchored
is_on_offset
onOffset

Properties

Day.delta
Day.freqstr
Day.kwds
Day.name
Day.nanos
Day.normalize
Day.rule_code
Day.n

pandas.tseries.offsets.Day.delta

Day.delta

pandas.tseries.offsets.Day.freqstr

Day.freqstr
pandas.tseries.offsets.Day.kwds

Day.kwds

pandas.tseries.offsets.Day.name

Day.name

pandas.tseries.offsets.Day.nanos

Day.nanos

pandas.tseries.offsets.Day.normalize

Day.normalize

pandas.tseries.offsets.Day.rule_code

Day.rule_code

pandas.tseries.offsets.Day.n

Day.n

**Methods**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Day.copy</td>
<td></td>
</tr>
<tr>
<td>Day.isAnchored</td>
<td></td>
</tr>
<tr>
<td>Day.onOffset</td>
<td></td>
</tr>
<tr>
<td>Day.is_anchored</td>
<td></td>
</tr>
<tr>
<td>Day.is_on_offset</td>
<td></td>
</tr>
<tr>
<td>Day.<strong>call</strong>(*args, *<em>kwargs</em>)</td>
<td>Call self as a function.</td>
</tr>
<tr>
<td>Day.apply</td>
<td></td>
</tr>
<tr>
<td>Day.apply_index(other)</td>
<td></td>
</tr>
</tbody>
</table>

3.8. Date offsets
pandas: powerful Python data analysis toolkit, Release 1.1.1

```
pandas.tseries.offsets.Day.copy

Day.copy()

pandas.tseries.offsets.Day.isAnchored

Day.isAnchored()

pandas.tseries.offsets.Day.onOffset

Day.onOffset()

pandas.tseries.offsets.Day.is_anchored

Day.is_anchored()

pandas.tseries.offsets.Day.is_on_offset

Day.is_on_offset()

pandas.tseries.offsets.Day.apply

Day.apply()

pandas.tseries.offsets.Day.apply_index

Day.apply_index(other)

3.8.30 Hour

Hour

Attributes
```
pandas.tseries.offsets.Hour

class pandas.tseries.offsets.Hour

Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base</td>
<td>Returns a copy of the calling offset object with n=1 and all other attributes equal.</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.Hour.base

Hour.base

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>delta</td>
<td></td>
</tr>
<tr>
<td>freqstr</td>
<td></td>
</tr>
<tr>
<td>kwds</td>
<td></td>
</tr>
<tr>
<td>n</td>
<td></td>
</tr>
<tr>
<td>name</td>
<td></td>
</tr>
<tr>
<td>nanos</td>
<td></td>
</tr>
<tr>
<td>normalize</td>
<td></td>
</tr>
<tr>
<td>rule_code</td>
<td></td>
</tr>
</tbody>
</table>

Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>call</strong>(*args, **kwargs)</td>
<td>Call self as a function.</td>
</tr>
<tr>
<td>rollback</td>
<td>Roll provided date backward to next offset only if not on offset.</td>
</tr>
<tr>
<td>rollforward</td>
<td>Roll provided date forward to next offset only if not on offset.</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.Hour.__call__

Hour.__call__(*args, **kwargs)

Call self as a function.

docs
docs

pandas.tseries.offsets.Hour.rollback

Hour.rollback()

Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp  Rolled timestamp if not on offset, otherwise unchanged timestamp.
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.Hour.rollforward

Hour.rollforward()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp  Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>apply</th>
<th>apply_index</th>
<th>copy</th>
<th>isAnchored</th>
<th>is_anchored</th>
<th>is_on_offset</th>
<th>onOffset</th>
</tr>
</thead>
</table>

Properties

Hour.delta
Hour.freqstr
Hour.kwds
Hour.name
Hour.nanos
Hour.normalize
Hour.rule_code
Hour.n

pandas.tseries.offsets.Hour.delta

Hour.delta

pandas.tseries.offsets.Hour.freqstr

Hour.freqstr
pandas.tseries.offsets.Hour.kwds

\texttt{Hour.kwds}

pandas.tseries.offsets.Hour.name

\texttt{Hour.name}

pandas.tseries.offsets.Hour.nanos

\texttt{Hour.nanos}

pandas.tseries.offsets.Hour.normalize

\texttt{Hour.normalize}

pandas.tseries.offsets.Hour.rule_code

\texttt{Hour.rule_code}

pandas.tseries.offsets.Hour.n

\texttt{Hour.n}

**Methods**

- \texttt{Hour.copy}
- \texttt{Hour.isAnchored}
- \texttt{Hour.onOffset}
- \texttt{Hour.is_anchored}
- \texttt{Hour.is_on_offset}
- \texttt{Hour.__call__(*args, **kwargs)} Call self as a function.
- \texttt{Hour.apply}
- \texttt{Hour.apply_index(other)}

---

3.8. Date offsets

2169
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.Hour.copy

Hour.copy()

pandas.tseries.offsets.Hour.isAnchored

Hour.isAnchored()

pandas.tseries.offsets.Hour.onOffset

Hour.onOffset()

pandas.tseries.offsets.Hour.is_anchored

Hour.is_anchored()

pandas.tseries.offsets.Hour.is_on_offset

Hour.is_on_offset()

pandas.tseries.offsets.Hour.apply

Hour.apply()

pandas.tseries.offsets.Hour.apply_index

Hour.apply_index(other)

3.8.31 Minute

Minute

Attributes
pandas.tseries.offsets.Minute

class pandas.tseries.offsets.Minute

Attributes

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base</td>
<td>Returns a copy of the calling offset object with n=1 and all other attributes equal.</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.Minute.base

Minute.base
Returns a copy of the calling offset object with n=1 and all other attributes equal.

Methods

<table>
<thead>
<tr>
<th>Methods</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>call</strong>(*args, **kwargs)</td>
<td>Call self as a function.</td>
</tr>
<tr>
<td>rollback</td>
<td>Roll provided date backward to next offset only if not on offset.</td>
</tr>
<tr>
<td>rollforward</td>
<td>Roll provided date forward to next offset only if not on offset.</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.Minute.__call__

Minute.__call__(*args, **kwargs)
Call self as a function.

pandas.tseries.offsets.Minute.rollback

Minute.rollback()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.
pandas.tseries.offsets.Minute.rollforward

```
Minute.rollforward()
```

Roll provided date forward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>apply</td>
</tr>
<tr>
<td>apply_index</td>
</tr>
<tr>
<td>copy</td>
</tr>
<tr>
<td>isAnchored</td>
</tr>
<tr>
<td>is_anchored</td>
</tr>
<tr>
<td>is_on_offset</td>
</tr>
<tr>
<td>onOffset</td>
</tr>
</tbody>
</table>

**Properties**

- `Minute.delta`
- `Minute.freqstr`
- `Minute.kwds`
- `Minute.name`
- `Minute.nanos`
- `Minute.normalize`
- `Minute.rule_code`
- `Minute.n`

**pandas.tseries.offsets.Minute.delta**

`Minute.delta`

**pandas.tseries.offsets.Minute.freqstr**

`Minute.freqstr`
pandas.tseries.offsets.Minute.kwds

Minute.kwds

pandas.tseries.offsets.Minute.name

Minute.name

pandas.tseries.offsets.Minute.nanos

Minute.nanos

pandas.tseries.offsets.Minute.normalize

Minute.normalize

pandas.tseries.offsets.Minute.rule_code

Minute.rule_code

pandas.tseries.offsets.Minute.n

Minute.n

Methods

- Minute.copy
- Minute.isAnchored
- Minute.onOffset
- Minute.is_anchored
- Minute.is_on_offset
- Minute.__call__(*args, **kwargs) Call self as a function.
- Minute.apply
- Minute.apply_index(other)
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.Minute.copy

Minute.copy()

pandas.tseries.offsets.Minute.isAnchored

Minute.isAnchored()

pandas.tseries.offsets.Minute.onOffset

Minute.onOffset()

pandas.tseries.offsets.Minute.is_anchored

Minute.is_anchored()

pandas.tseries.offsets.Minute.is_on_offset

Minute.is_on_offset()

pandas.tseries.offsets.Minute.apply

Minute.apply()

pandas.tseries.offsets.Minute.apply_index

Minute.apply_index(other)

3.8.32 Second

Second

Attributes
pandas.tseries.offsets.Second

class pandas.tseries.offsets.Second

Attributes

| base | Returns a copy of the calling offset object with n=1 and all other attributes equal. |

pandas.tseries.offsets.Second.base

Second.base
Returns a copy of the calling offset object with n=1 and all other attributes equal.

<table>
<thead>
<tr>
<th>delta</th>
<th>freqstr</th>
</tr>
</thead>
<tbody>
<tr>
<td>kwds</td>
<td></td>
</tr>
<tr>
<td>n</td>
<td>name</td>
</tr>
<tr>
<td>nanos</td>
<td>normalize</td>
</tr>
<tr>
<td></td>
<td>rule_code</td>
</tr>
</tbody>
</table>

Methods

<table>
<thead>
<tr>
<th><strong>call</strong></th>
<th>(*args, **kwargs)</th>
<th>Call self as a function.</th>
</tr>
</thead>
<tbody>
<tr>
<td>rollback</td>
<td></td>
<td>Roll provided date backward to next offset only if not on offset.</td>
</tr>
<tr>
<td>rollforward</td>
<td></td>
<td>Roll provided date forward to next offset only if not on offset.</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.Second.__call__

Second.__call__(*args, **kwargs)
Call self as a function.

pandas.tseries.offsets.Second.rollback

Second.rollback()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp  Rolled timestamp if not on offset, otherwise unchanged timestamp.
pandas: powerful Python data analysis toolkit, Release 1.1.1

**pandas.tseries.offsets.Second.rollforward**

Second.rollforward()  
Roll provided date forward to next offset only if not on offset.

**Returns**

*TimeStamp*  Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>apply</th>
<th>apply_index</th>
</tr>
</thead>
<tbody>
<tr>
<td>copy</td>
<td></td>
</tr>
<tr>
<td>isAnchored</td>
<td>is_anchored</td>
</tr>
<tr>
<td>is_on_offset</td>
<td></td>
</tr>
<tr>
<td>onOffset</td>
<td></td>
</tr>
</tbody>
</table>

**Properties**

<table>
<thead>
<tr>
<th>Second.delta</th>
</tr>
</thead>
<tbody>
<tr>
<td>Second.freqstr</td>
</tr>
<tr>
<td>Second.kwds</td>
</tr>
<tr>
<td>Second.name</td>
</tr>
<tr>
<td>Second.nanos</td>
</tr>
<tr>
<td>Second.normalize</td>
</tr>
<tr>
<td>Second.rule_code</td>
</tr>
<tr>
<td>Second.n</td>
</tr>
</tbody>
</table>

**pandas.tseries.offsets.Second.delta**

Second.delta

**pandas.tseries.offsets.Second.freqstr**

Second.freqstr
pandas.tseries.offsets.Second.kwds
Second.kwds

pandas.tseries.offsets.Second.name
Second.name

pandas.tseries.offsets.Second.nanos
Second.nanos

pandas.tseries.offsets.Second.normalize
Second.normalize

pandas.tseries.offsets.Second.rule_code
Second.rule_code

pandas.tseries.offsets.Second.n
Second.n

Methods

Second.copy
Second.isAnchored
Second.onOffset
Second.is_anchored
Second.is_on_offset
Second.__call__(*args, **kwargs) Call self as a function.
Second.apply
Second.apply_index(other)

3.8. Date offsets
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.Second.copy

Second.copy()

pandas.tseries.offsets.Second.isAnchored

Second.isAnchored()

pandas.tseries.offsets.Second.onOffset

Second.onOffset()

pandas.tseries.offsets.Second.is_anchored

Second.is_anchored()

pandas.tseries.offsets.Second.is_on_offset

Second.is_on_offset()

pandas.tseries.offsets.Second.apply

Second.apply()

pandas.tseries.offsets.Second.apply_index

Second.apply_index(other)

3.8.33 Milli

Milli

Attributes
pandas.tseries.offsets.Milli

```python
class pandas.tseries.offsets.Milli

Attributes

base

Returns a copy of the calling offset object with n=1 and all other attributes equal.
```

pandas.tseries.offsets.Milli.base

```python
Milli.base

Returns a copy of the calling offset object with n=1 and all other attributes equal.
```

<table>
<thead>
<tr>
<th>delta</th>
</tr>
</thead>
<tbody>
<tr>
<td>freqstr</td>
</tr>
<tr>
<td>kwds</td>
</tr>
<tr>
<td>n</td>
</tr>
<tr>
<td>name</td>
</tr>
<tr>
<td>nanos</td>
</tr>
<tr>
<td>normalize</td>
</tr>
<tr>
<td>rule_code</td>
</tr>
</tbody>
</table>

Methods

```python
__call__(*args, **kwargs)

Call self as a function.
```

```python
rollback

Roll provided date backward to next offset only if not on offset.
```

```python
rollforward

Roll provided date forward to next offset only if not on offset.
```

```
pandas.tseries.offsets.Milli.__call__

Milli.__call__(*args, **kwargs)

Call self as a function.
```

```
pandas.tseries.offsets.Milli.rollback

Milli.rollback()

Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp  Rolled timestamp if not on offset, otherwise unchanged timestamp.
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.Milli.rollforward

Milli.rollforward()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp  Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>apply</th>
<th>apply_index</th>
</tr>
</thead>
<tbody>
<tr>
<td>copy</td>
<td>isAnchored</td>
</tr>
<tr>
<td>is_anchored</td>
<td>is_on_offset</td>
</tr>
<tr>
<td>is_on_offset</td>
<td></td>
</tr>
<tr>
<td>onOffset</td>
<td></td>
</tr>
</tbody>
</table>

Properties

Milli.delta
Milli.freqstr
Milli.kwds
Milli.name
Milli.nanos
Milli.normalize
Milli.rule_code
Milli.n

pandas.tseries.offsets.Milli.delta

Milli.delta

pandas.tseries.offsets.Milli.freqstr

Milli.freqstr
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.Milli.kwds

Milli.kwds

pandas.tseries.offsets.Milli.name

Milli.name

pandas.tseries.offsets.Milli.nanos

Milli.nanos

pandas.tseries.offsets.Milli.normalize

Milli.normalize

pandas.tseries.offsets.Milli.rule_code

Milli.rule_code

pandas.tseries.offsets.Milli.n

Milli.n

Methods

Milli.copy
Milli.isAnchored
Milli.onOffset
Milli.is_anchored
Milli.is_on_offset
Milli.__call__(*args, **kwargs) Call self as a function.
Milli.apply
Milli.apply_index(other)

3.8. Date offsets
pandas.tseries.offsets.Milli.copy

Milli.copy()

pandas.tseries.offsets.Milli.isAnchored

Milli.isAnchored()

pandas.tseries.offsets.Milli.onOffset

Milli.onOffset()

pandas.tseries.offsets.Milli.is_anchored

Milli.is_anchored()

pandas.tseries.offsets.Milli.is_on_offset

Milli.is_on_offset()

pandas.tseries.offsets.Milli.apply

Milli.apply()

pandas.tseries.offsets.Milli.apply_index

Milli.apply_index(other)

### 3.8.34 Micro

<table>
<thead>
<tr>
<th>Micro</th>
<th>Attributes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>
pandas.tseries.offsets.Micro

```python
class pandas.tseries.offsets.Micro

Attributes
```

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base</td>
<td>Returns a copy of the calling offset object with n=1 and all other attributes equal.</td>
</tr>
</tbody>
</table>

```
pandas.tseries.offsets.Micro.base

Micro.base
Returns a copy of the calling offset object with n=1 and all other attributes equal.
```

```python
<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>call</strong>(*args,**kwargs)</td>
<td>Call self as a function.</td>
</tr>
<tr>
<td>rollback</td>
<td>Roll provided date backward to next offset only if not on offset.</td>
</tr>
<tr>
<td>rollforward</td>
<td>Roll provided date forward to next offset only if not on offset.</td>
</tr>
</tbody>
</table>

pandas.tseries.offsets.Micro.__call__

Micro.__call__(*args,**kwargs)
Call self as a function.

pandas.tseries.offsets.Micro.rollback

Micro.rollback()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.

3.8. Date offsets 2183
pandas.tseries.offsets.Micro.rollforward

Micro.rollforward()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp  Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>apply</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>apply_index</td>
<td></td>
</tr>
<tr>
<td>copy</td>
<td></td>
</tr>
<tr>
<td>isAnchored</td>
<td></td>
</tr>
<tr>
<td>is_anchored</td>
<td></td>
</tr>
<tr>
<td>is_on_offset</td>
<td></td>
</tr>
<tr>
<td>onOffset</td>
<td></td>
</tr>
</tbody>
</table>

Properties

| Micro.delta |  |
| Micro.freqstr |  |
| Micro.kwds |  |
| Micro.name |  |
| Micro.nanos |  |
| Micro.normalize |  |
| Micro.rule_code |  |
| Micro.n |  |

pandas.tseries.offsets.Micro.delta

Micro.delta

pandas.tseries.offsets.Micro.freqstr

Micro.freqstr
pandas.tseries.offsets.Micro.kwds

Micro.kwds

pandas.tseries.offsets.Micro.name

Micro.name

pandas.tseries.offsets.Micro.nanos

Micro.nanos

pandas.tseries.offsets.Micro.normalize

Micro.normalize

pandas.tseries.offsets.Micro.rule_code

Micro.rule_code

Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Micro.copy</td>
<td></td>
</tr>
<tr>
<td>Micro.isAnchored</td>
<td></td>
</tr>
<tr>
<td>Micro.onOffset</td>
<td></td>
</tr>
<tr>
<td>Micro.is_anchored</td>
<td></td>
</tr>
<tr>
<td>Micro.is_on_offset</td>
<td></td>
</tr>
<tr>
<td>Micro.<strong>call</strong>(*args, **kwargs)</td>
<td>Call self as a function.</td>
</tr>
<tr>
<td>Micro.apply</td>
<td></td>
</tr>
<tr>
<td>Micro.apply_index(other)</td>
<td></td>
</tr>
</tbody>
</table>

3.8. Date offsets
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.Micro.copy

Micro.copy()

pandas.tseries.offsets.Micro.isAnchored

Micro.isAnchored()

pandas.tseries.offsets.Micro.onOffset

Micro.onOffset()

pandas.tseries.offsets.Micro.is_anchored

Micro.is_anchored()

pandas.tseries.offsets.Micro.is_on_offset

Micro.is_on_offset()

pandas.tseries.offsets.Micro.apply

Micro.apply()

pandas.tseries.offsets.Micro.apply_index

Micro.apply_index(other)

3.8.35 Nano

Nano

Attributes
pandas.tseries.offsets.Nano

class pandas.tseries.offsets.Nano

Attributes

| base | Returns a copy of the calling offset object with n=1 and all other attributes equal. |

pandas.tseries.offsets.Nano.base

Nano.base
Returns a copy of the calling offset object with n=1 and all other attributes equal.

<table>
<thead>
<tr>
<th>delta</th>
<th>freqstr</th>
<th>kwds</th>
<th>n</th>
<th>name</th>
<th>nanos</th>
<th>normalize</th>
<th>rule_code</th>
</tr>
</thead>
</table>

Methods

__call__(*args, **kwargs) Call self as a function.

rollback
Roll provided date backward to next offset only if not on offset.

rollforward
Roll provided date forward to next offset only if not on offset.

pandas.tseries.offsets.Nano.__call__

Nano.__call__(*args, **kwargs)
Call self as a function.

pandas.tseries.offsets.Nano.rollback

Nano.rollback()
Roll provided date backward to next offset only if not on offset.

Returns

TimeStamp Rolled timestamp if not on offset, otherwise unchanged timestamp.
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.tseries.offsets.Nano.rollforward

Nano.rollforward()
Roll provided date forward to next offset only if not on offset.

Returns

TimeStamp  Rolled timestamp if not on offset, otherwise unchanged timestamp.

<table>
<thead>
<tr>
<th>apply</th>
<th>apply_index</th>
<th>copy</th>
<th>isAnchored</th>
<th>is_anchored</th>
<th>is_on_offset</th>
<th>onOffset</th>
</tr>
</thead>
</table>

Properties

Nano.delta
Nano.freqstr
Nano.kwds
Nano.name
Nano.nanos
Nano.normalize
Nano.rule_code
Nano.n

pandas.tseries.offsets.Nano.delta

Nano.delta

pandas.tseries.offsets.Nano.freqstr

Nano.freqstr
**pandas.tseries.offsets.Nano.kwds**

Nano.kwds

**pandas.tseries.offsets.Nano.name**

Nano.name

**pandas.tseries.offsets.Nano.nanos**

Nano.nanos

**pandas.tseries.offsets.Nano.normalize**

Nano.normalize

**pandas.tseries.offsets.Nano.rule_code**

Nano.rule_code

**pandas.tseries.offsets.Nano.n**

Nano.n

**Methods**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nano.copy</td>
<td></td>
</tr>
<tr>
<td>Nano.isAnchored</td>
<td></td>
</tr>
<tr>
<td>Nano.onOffset</td>
<td></td>
</tr>
<tr>
<td>Nano.is_anchored</td>
<td></td>
</tr>
<tr>
<td>Nano.is_on_offset</td>
<td></td>
</tr>
<tr>
<td>Nano.<strong>call</strong>(*args, **kwargs)</td>
<td>Call self as a function.</td>
</tr>
<tr>
<td>Nano.apply</td>
<td></td>
</tr>
<tr>
<td>Nano.apply_index</td>
<td>(other)</td>
</tr>
</tbody>
</table>

### 3.8. Date offsets
3.9 Frequencies

| to_offset | Return DateOffset object from string or tuple representation or datetime.timedelta object.

3.9.1 pandas.tseries.frequencies.to_offset

pandas.tseries.frequencies.to_offset()

Return DateOffset object from string or tuple representation or datetime.timedelta object.

Parameters

- freq [str, tuple, datetime.timedelta, DateOffset or None]

Returns

- DateOffset or None

Raises
ValueError  If freq is an invalid frequency

See also:

DateOffset  Standard kind of date increment used for a date range.

Examples

```python
>>> to_offset("5min")
<5 * Minutes>
```

```python
>>> to_offset("1D1H")
<25 * Hours>
```

```python
>>> to_offset("2W")
<2 * Weeks: weekday=6>
```

```python
>>> to_offset("2B")
<2 * BusinessDays>
```

```python
>>> to_offset(pd.Timedelta(days=1))
<Day>
```

```python
>>> to_offset(Hour())
<Hour>
```

3.10 Window

Rolling objects are returned by .rolling calls: `pandas.DataFrame.rolling()`, `pandas.Series.rolling()`, etc. Expanding objects are returned by .expanding calls: `pandas.DataFrame.expanding()`, `pandas.Series.expanding()`, etc. ExponentialMovingWindow objects are returned by .ewm calls: `pandas.DataFrame.ewm()`, `pandas.Series.ewm()`, etc.

3.10.1 Standard moving window functions

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Rolling.count()</code></td>
<td>The rolling count of any non-NaN observations inside the window.</td>
</tr>
<tr>
<td><code>Rolling.sum(*args, **kwargs)</code></td>
<td>Calculate rolling sum of given DataFrame or Series.</td>
</tr>
<tr>
<td><code>Rolling.mean(*args, **kwargs)</code></td>
<td>Calculate the rolling mean of the values.</td>
</tr>
<tr>
<td><code>Rolling.median(**kwargs)</code></td>
<td>Calculate the rolling median.</td>
</tr>
<tr>
<td><code>Rolling.var(ddof)</code></td>
<td>Calculate unbiased rolling variance.</td>
</tr>
<tr>
<td><code>Rolling.std(ddof)</code></td>
<td>Calculate rolling standard deviation.</td>
</tr>
<tr>
<td><code>Rolling.min(*args, **kwargs)</code></td>
<td>Calculate the rolling minimum.</td>
</tr>
<tr>
<td><code>Rolling.max(*args, **kwargs)</code></td>
<td>Calculate the rolling maximum.</td>
</tr>
<tr>
<td><code>Rolling.corr(other, pairwise)</code></td>
<td>Calculate rolling correlation.</td>
</tr>
<tr>
<td><code>Rolling.cov(other, pairwise, ddof)</code></td>
<td>Calculate the rolling sample covariance.</td>
</tr>
<tr>
<td><code>Rolling.skew(**kwargs)</code></td>
<td>Unbiased rolling skewness.</td>
</tr>
<tr>
<td><code>Rolling.kurt(**kwargs)</code></td>
<td>Calculate unbiased rolling kurtosis.</td>
</tr>
<tr>
<td><code>Rolling.apply(func[, raw, engine, ...])</code></td>
<td>Apply an arbitrary function to each rolling window.</td>
</tr>
</tbody>
</table>

continues on next page
Table 362 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Rolling.aggregate(func, *args, **kwargs)</code></td>
<td>Aggregate using one or more operations over the specified axis.</td>
</tr>
<tr>
<td><code>Rolling.quantile(quantile[, interpolation])</code></td>
<td>Calculate the rolling quantile.</td>
</tr>
<tr>
<td><code>Window.mean(*args, **kwargs)</code></td>
<td>Calculate the window mean of the values.</td>
</tr>
<tr>
<td><code>Window.sum(*args, **kwargs)</code></td>
<td>Calculate window sum of given DataFrame or Series.</td>
</tr>
<tr>
<td><code>Window.var([ddof])</code></td>
<td>Calculate unbiased window variance.</td>
</tr>
<tr>
<td><code>Window.std([ddof])</code></td>
<td>Calculate window standard deviation.</td>
</tr>
</tbody>
</table>

**pandas.core.window.rolling.Rolling.count**

`Rolling.count()`

The rolling count of any non-NaN observations inside the window.

**Returns**

- **Series or DataFrame**: Returned object type is determined by the caller of the rolling calculation.

**See also:**
- `pandas.Series.rolling` Calling object with Series data.
- `pandas.DataFrame.rolling` Calling object with DataFrames.
- `pandas.DataFrame.count` Count of the full DataFrame.

**Examples**

```python
>>> s = pd.Series([2, 3, np.nan, 10])
>>> s.rolling(2).count()
0    1.0
1    2.0
2    1.0
3    1.0
dtype: float64
>>> s.rolling(3).count()
0    1.0
1    2.0
2    2.0
3    2.0
dtype: float64
>>> s.rolling(4).count()
0    1.0
1    2.0
2    2.0
3    3.0
dtype: float64
```
pandas.core.window.rolling.Rolling.sum

Rolling.sum(*args, **kwargs)
Calculate rolling sum of given DataFrame or Series.

Parameters
*args, **kwargs For compatibility with other rolling methods. Has no effect on the computed value.

Returns
Series or DataFrame Same type as the input, with the same index, containing the rolling sum.

See also:
pandas.Series.sum Reducing sum for Series.
pandas.DataFrame.sum Reducing sum for DataFrame.

Examples

```python
>>> s = pd.Series([1, 2, 3, 4, 5])
>>> s
0    1
1    2
2    3
3    4
4    5
dtype: int64

>>> s.rolling(3).sum()
0   NaN
1   NaN
2    6.0
3    9.0
4   12.0
dtype: float64

>>> s.expanding(3).sum()
0   NaN
1   NaN
2    6.0
3    9.0
4   15.0
dtype: float64

>>> s.rolling(3, center=True).sum()
0   NaN
1    6.0
2    9.0
3   12.0
4   NaN
dtype: float64
```

For DataFrame, each rolling sum is computed column-wise.
```python
>>> df = pd.DataFrame({"A": s, "B": s ** 2})
>>> df
   A   B
0  1   1
1  2   4
2  3   9
3  4  16
4  5  25

>>> df.rolling(3).sum()
    A   B
0  NaN NaN
1  NaN NaN
2  6.0 14.0
3  9.0 29.0
4 12.0 50.0

**pandas.core.window.rolling.Rolling.mean**

Rolling.mean(*args, **kwargs)
Calculate the rolling mean of the values.

Parameters

*args Under Review.

**kwargs Under Review.

Returns

Series or DataFrame Returned object type is determined by the caller of the rolling calculation.

See also:

pandas.Series.rolling Calling object with Series data.
pandas.DataFrame.rolling Calling object with DataFrames.
pandas.Series.mean Equivalent method for Series.
pandas.DataFrame.mean Equivalent method for DataFrame.

Examples

The below examples will show rolling mean calculations with window sizes of two and three, respectively.

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s.rolling(2).mean()
0   NaN
1  1.5
2  2.5
3  3.5
dtype: float64

>>> s.rolling(3).mean()
0   NaN
1   NaN
2   2.0
3   3.0
dtype: float64
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.core.window.rolling.Rolling.median

Rolling.median(**kwargs)
Calculate the rolling median.

Parameters

**kwargs For compatibility with other rolling methods. Has no effect on the computed median.

Returns

Series or DataFrame Returned type is the same as the original object.

See also:
pandas.Series.rolling Calling object with Series data.
pandas.DataFrame.rolling Calling object with DataFrames.
pandas.Series.median Equivalent method for Series.
pandas.DataFrame.median Equivalent method for DataFrame.

Examples

Compute the rolling median of a series with a window size of 3.

```python
>>> s = pd.Series([0, 1, 2, 3, 4])
>>> s.rolling(3).median()
0    NaN
1    NaN
2    1.0
3    2.0
4    3.0
dtype: float64
```

pandas.core.window.rolling.Rolling.var

Rolling.var(ddof=1, *args, **kwargs)
Calculate unbiased rolling variance.

Normalized by N-1 by default. This can be changed using the ddof argument.

Parameters

ddof [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is N – ddof, where N represents the number of elements.

*args, **kwargs For NumPy compatibility. No additional arguments are used.

Returns

Series or DataFrame Returns the same object type as the caller of the rolling calculation.

See also:
pandas.Series.rolling Calling object with Series data.
pandas.DataFrame.rolling Calling object with DataFrames.
pandas.Series.var Equivalent method for Series.
pandas.DataFrame.var Equivalent method for DataFrame.
numpy.var Equivalent method for Numpy array.
Notes

The default $ddof$ of 1 used in `Series.var()` is different than the default $ddof$ of 0 in `numpy.var()`.
A minimum of 1 period is required for the rolling calculation.

Examples

```python
>>> s = pd.Series([5, 5, 6, 7, 5, 5, 5])
>>> s.rolling(3).var()
0    NaN
1    NaN
2    0.333333
3   1.000000
4   1.000000
5   1.333333
6   0.000000
dtype: float64

>>> s.expanding(3).var()
0    NaN
1    NaN
2    0.333333
3    0.916667
4    0.800000
5    0.700000
6    0.619048
dtype: float64
```

```
pandas.core.window.rolling.Rolling.std

Rolling.std($ddof=1$, *args, **kwargs)
Calculate rolling standard deviation.
Normalized by N-1 by default. This can be changed using the $ddof$ argument.

Parameters

$ddof$ [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is $N - ddof$, where $N$ represents the number of elements.

*args, **kwargs For NumPy compatibility. No additional arguments are used.

Returns

Series or DataFrame Returns the same object type as the caller of the rolling calculation.

See also:
pandas.Series.rolling Calling object with Series data.
pandas.DataFrame.rolling Calling object with DataFrames.
pandas.Series.std Equivalent method for Series.
pandas.DataFrame.std Equivalent method for DataFrame.
numpy.std Equivalent method for Numpy array.
```
Notes

The default $ddof$ of 1 used in Series.std is different than the default $ddof$ of 0 in numpy.std.

A minimum of one period is required for the rolling calculation.

Examples

```python
>>> s = pd.Series([5, 5, 6, 7, 5, 5, 5])
>>> s.rolling(3).std()
0   NaN
1   NaN
2   0.577350
3   1.000000
4   1.000000
5   1.154701
6   0.000000
```

```python
dtype: float64
```
Examples

Performing a rolling minimum with a window size of 3.

```python
>>> s = pd.Series([4, 3, 5, 2, 6])
>>> s.rolling(3).min()
0   NaN
1   NaN
2   3.0
3   2.0
4   2.0
dtype: float64
```

pandas.core.window.rolling.Rolling.max

Rolling.max(*args, **kwargs)
Calculate the rolling maximum.

Parameters

*args, **kwargs
Arguments and keyword arguments to be passed into func.

Returns

Series or DataFrame
Return type is determined by the caller.

See also:

pandas.Series.rolling
Calling object with Series data.
pandas.DataFrame.rolling
Calling object with DataFrame data.
pandas.Series.max
Similar method for Series.
pandas.DataFrame.max
Similar method for DataFrame.

pandas.core.window.rolling.Rolling.corr

Rolling.corr(other=None, pairwise=None, **kwargs)
Calculate rolling correlation.

Parameters

other [Series, DataFrame, or ndarray, optional] If not supplied then will default to self.

pairwise [bool, default None] Calculate pairwise combinations of columns within a DataFrame. If other is not specified, defaults to True, otherwise defaults to False. Not relevant for Series.

**kwargs
Unused.

Returns

Series or DataFrame
Returned object type is determined by the caller of the rolling calculation.

See also:

pandas.Series.rolling
Calling object with Series data.
pandas.DataFrame.rolling
Calling object with DataFrames.
pandas.Series.corr
Equivalent method for Series.
pandas.DataFrame.corr
Equivalent method for DataFrame.
cov
Similar method to calculate covariance.
numpy.corrcoef
NumPy Pearson’s correlation calculation.
Notes

This function uses Pearson’s definition of correlation (https://en.wikipedia.org/wiki/Pearson_correlation_coefficient).

When other is not specified, the output will be self correlation (e.g. all 1’s), except for DataFrame inputs with pairwise set to True.

Function will return NaN for correlations of equal valued sequences; this is the result of a 0/0 division error.

When pairwise is set to False, only matching columns between self and other will be used.

When pairwise is set to True, the output will be a MultiIndex DataFrame with the original index on the first level, and the other DataFrame columns on the second level.

In the case of missing elements, only complete pairwise observations will be used.

Examples

The below example shows a rolling calculation with a window size of four matching the equivalent function call using numpy.corrcoef().

```python
>>> v1 = [3, 3, 3, 5, 8]
>>> v2 = [3, 4, 4, 4, 8]
>>> # numpy returns a 2X2 array, the correlation coefficient
>>> # is the number at entry [0][1]
>>> print(f"{np.corrcoef(v1[:-1], v2[:-1])[0][1]:.6f}"")
0.333333
>>> print(f"{np.corrcoef(v1[1:], v2[1:])[0][1]:.6f}"")
0.916949
>>> s1 = pd.Series(v1)
>>> s2 = pd.Series(v2)
>>> s1.rolling(4).corr(s2)
0    NaN
1    NaN
2    NaN
3  0.333333
4  0.916949
dtype: float64
```

The below example shows a similar rolling calculation on a DataFrame using the pairwise option.

```python
>>> print(np.corrcoef(matrix[:-1,0], matrix[:-1,1]).round(7))
[[ 1.00000000  0.62630014]
 [ 0.62630014  1.00000000]]
>>> print(np.corrcoef(matrix[1:,0], matrix[1:,1]).round(7))
[[ 1.00000000  0.55536810]
 [ 0.55536810  1.00000000]]
>>> df = pd.DataFrame(matrix, columns=['X','Y'])
>>> df
     X   Y
0  51.0  35.0
1  49.0  30.0
2  47.0  32.0
3  46.0  31.0
4  50.0  36.0
```
(continues on next page)
>>> df.rolling(4).corr(pairwise=True)
   X    Y
0 X  NaN  NaN
  Y  NaN  NaN
1 X  NaN  NaN
  Y  NaN  NaN
2 X  NaN  NaN
  Y  NaN  NaN
3 X  1.000000  0.626300
  Y  0.626300  1.000000
4 X  1.000000  0.555368
  Y  0.555368  1.000000

pandas.core.window.rolling.Rolling.cov

Rolling.cov(\texttt{other=None, pairwise=None, ddof=1, **kwargs})

Calculate the rolling sample covariance.

Parameters

\texttt{other} [Series, DataFrame, or ndarray, optional] If not supplied then will default to self and produce pairwise output.

\texttt{pairwise} [bool, default None] If False then only matching columns between self and other will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a MultiIndexed DataFrame in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

\texttt{ddof} [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is \( N - \text{ddof} \), where \( N \) represents the number of elements.

\texttt{**kwargs} Keyword arguments to be passed into func.

Returns

Series or DataFrame Return type is determined by the caller.

See also:

\texttt{pandas.Series.rolling} Calling object with Series data.
\texttt{pandas.DataFrame.rolling} Calling object with DataFrame data.
\texttt{pandas.Series.cov} Similar method for Series.
\texttt{pandas.DataFrame.cov} Similar method for DataFrame.

pandas.core.window.rolling.Rolling.skew

Rolling.skew(\texttt{**kwargs})

Unbiased rolling skewness.

Parameters

\texttt{**kwargs} Keyword arguments to be passed into func.

Returns

Series or DataFrame Return type is determined by the caller.

See also:

\texttt{pandas.Series.rolling} Calling object with Series data.
pandas.DataFrame.rolling Calling object with DataFrame data.
pandas.Series.skew Similar method for Series.
pandas.DataFrame.skew Similar method for DataFrame.

pandas.core.window.rolling.Rolling.kurt

Rolling.kurt(**kwargs)
Calculate unbiased rolling kurtosis.

This function uses Fisher’s definition of kurtosis without bias.

Parameters

**kwargs Under Review.

Returns

Series or DataFrame Returned object type is determined by the caller of the rolling calculation.

See also:
pandas.Series.rolling Calling object with Series data.
pandas.DataFrame.rolling Calling object with DataFrames.
pandas.Series.kurt Equivalent method for Series.
pandas.DataFrame.kurt Equivalent method for DataFrame.
skpy.stats.skew Third moment of a probability density.

Notes

A minimum of 4 periods is required for the rolling calculation.

Examples

The example below will show a rolling calculation with a window size of four matching the equivalent function call using *scipy.stats*.

```python
>>> arr = [1, 2, 3, 4, 999]
>>> import scipy.stats
>>> print(f"{scipy.stats.kurtosis(arr[:-1], bias=False):.6f}")
-1.200000
>>> print(f"{scipy.stats.kurtosis(arr[1:], bias=False):.6f}")
3.999946
>>> s = pd.Series(arr)
>>> s.rolling(4).kurt()
0    NaN
1    NaN
2    NaN
3  -1.200000
4  3.999946
dtype: float64
```
Rolling.apply (func, raw=False, engine=None, engine_kwars=None, args=None, kwars=None)

Apply an arbitrary function to each rolling window.

Parameters

func [function] Must produce a single value from an ndarray input if raw=True or a single value from a Series if raw=False. Can also accept a Numba JIT function with engine='numba' specified.

Changed in version 1.0.0.

raw [bool, default None]

- False: passes each row or column as a Series to the function.
- True: the passed function will receive ndarray objects instead. If you are just applying a NumPy reduction function this will achieve much better performance.

engine [str, default None]

- 'cython': Runs rolling apply through C-extensions from cython.
- 'numba': Runs rolling apply through JIT compiled code from numba. Only available when raw is set to True.
- None: Defaults to 'cython' or globally setting compute.use_numba

New in version 1.0.0.

engine_kwars [dict, default None]

- For 'cython' engine, there are no accepted engine_kwars
- For 'numba' engine, the engine can accept nopython, nogil and parallel dictionary keys. The values must either be True or False. The default engine_kwars for the 'numba' engine is {'nopython': True, 'nogil': False, 'parallel': False} and will be applied to both the func and the apply rolling aggregation.

New in version 1.0.0.

args [tuple, default None] Positional arguments to be passed into func.

kwars [dict, default None] Keyword arguments to be passed into func.

Returns

Series or DataFrame Return type is determined by the caller.

See also:

pandas.Series.rolling Calling object with Series data.
pandas.DataFrame.rolling Calling object with DataFrame data.
pandas.Series.apply Similar method for Series.
pandas.DataFrame.apply Similar method for DataFrame.
Notes

See *Rolling apply* for extended documentation and performance considerations for the Numba engine.

**pandas.core.window.rolling.Rolling.aggregate**

Rolling.**aggregate**(func, *args, **kwargs)

Aggregate using one or more operations over the specified axis.

**Parameters**

- **func** [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a Series/Dataframe or when passed to Series/Dataframe.apply.
  
  Accepted combinations are:
  
  - function
  - string function name
  - list of functions and/or function names, e.g. [np.sum, 'mean']
  - dict of axis labels -> functions, function names or list of such.

- **args** Positional arguments to pass to func.

- **kwargs** Keyword arguments to pass to func.

**Returns**

- scalar, Series or DataFrame The return can be:
  
  - scalar : when Series.agg is called with single function
  - Series : when DataFrame.agg is called with a single function
  - DataFrame : when DataFrame.agg is called with several functions

Return scalar, Series or DataFrame.

See also:

- **pandas.Series.rolling** Calling object with Series data.
- **pandas.DataFrame.rolling** Calling object with DataFrame data.

Notes

*agg* is an alias for *aggregate*. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

Examples

```python
>>> df = pd.DataFrame({'A': [1, 2, 3], 'B': [4, 5, 6], 'C': [7, 8, 9]})
>>> df
   A  B  C
0  1  4  7
1  2  5  8
2  3  6  9
```
```python
>>> df.rolling(2).sum()
  A  B  C
0  NaN NaN NaN
1  3.0 9.0 15.0
2  5.0 11.0 17.0

>>> df.rolling(2).agg({'A': 'sum', 'B': 'min'})
   A  B
0  NaN NaN
1  3.0 4.0
2  5.0 5.0
```

**pandas.core.window.rolling.Rolling.quantile**

Rolling.quantile(quantile, interpolation='linear', **kwargs)

Calculate the rolling quantile.

**Parameters**

- **quantile** [float] Quantile to compute. 0 <= quantile <= 1.
- **interpolation** [{'linear', 'lower', 'higher', 'midpoint', 'nearest'}] New in version 0.23.0.

This optional parameter specifies the interpolation method to use, when the desired quantile lies between two data points \( i \) and \( j \):

- linear: \( i + (j - i) \times \text{fraction} \), where \( \text{fraction} \) is the fractional part of the index surrounded by \( i \) and \( j \).
- lower: \( i \).
- higher: \( j \).
- nearest: \( i \) or \( j \) whichever is nearest.
- midpoint: \( (i + j) / 2 \).

**kwargs** For compatibility with other rolling methods. Has no effect on the result.

**Returns**

- Series or DataFrame Returned object type is determined by the caller of the rolling calculation.

**See also:**

- **pandas.Series.quantile** Computes value at the given quantile over all data in Series.
- **pandas.DataFrame.quantile** Computes values at the given quantile over requested axis in DataFrame.

**Examples**

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s.rolling(2).quantile(.4, interpolation='lower')
0    NaN
1    1.0
2    2.0
3    3.0
dtype: float64
```
>>> s.rolling(2).quantile(.4, interpolation='midpoint')
0   NaN
1   1.5
2   2.5
3   3.5
dtype: float64

pandas.core.window.rolling.Window.mean

Window.mean(*args, **kwargs)
Calculate the window mean of the values.
Parameters
  *args  Under Review.
  **kwargs  Under Review.

Returns
  Series or DataFrame  Returned object type is determined by the caller of the window calculation.

See also:
  pandas.Series.window  Calling object with Series data.
  pandas.DataFrame.window  Calling object with DataFrames.
  pandas.Series.mean  Equivalent method for Series.
  pandas.DataFrame.mean  Equivalent method for DataFrame.

Examples

The below examples will show rolling mean calculations with window sizes of two and three, respectively.

>>> s = pd.Series([1, 2, 3, 4])
>>> s.rolling(2).mean()
0   NaN
1   1.5
2   2.5
3   3.5
dtype: float64

>>> s.rolling(3).mean()
0   NaN
1   NaN
2   2.0
3   3.0
dtype: float64
**pandas.core.window.rolling.Window.sum**

Window.sum(*args, **kwargs)

Calculate window sum of given DataFrame or Series.

**Parameters**

*args, **kwargs For compatibility with other window methods. Has no effect on the computed value.

**Returns**

Series or DataFrame Same type as the input, with the same index, containing the window sum.

**See also:**

pandas.Series.sum Reducing sum for Series.

pandas.DataFrame.sum Reducing sum for DataFrame.

**Examples**

```python
>>> s = pd.Series([1, 2, 3, 4, 5])
>>> s
0    1
1    2
2    3
3    4
4    5
dtype: int64

>>> s.rolling(3).sum()
0    NaN
1    NaN
2     6.0
3     9.0
4    12.0
dtype: float64

>>> s.expanding(3).sum()
0    NaN
1    NaN
2     6.0
3    10.0
4    15.0
dtype: float64

>>> s.rolling(3, center=True).sum()
0    NaN
1     6.0
2     9.0
3    12.0
4    NaN
dtype: float64
```

For DataFrame, each window sum is computed column-wise.

---

2206 Chapter 3. API reference
```python
>>> df = pd.DataFrame({"A": s, "B": s ** 2})
>>> df
        A  B
0       1  1
1       2  4
2       3  9
3       4 16
4       5 25

>>> df.rolling(3).sum()
        A  B
0       NaN  NaN
1       NaN  NaN
2       6.0 14.0
3       9.0 29.0
4      12.0 50.0
```

**pandas.core.window.rolling.Window.var**

Window.var(ddof=1, *args, **kwargs)

Calculate unbiased window variance.

New in version 1.0.0.

Normalized by N-1 by default. This can be changed using the ddof argument.

**Parameters**

- **ddof** [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.
- ***args, **kwargs** For NumPy compatibility. No additional arguments are used.

**Returns**

Series or DataFrame Returns the same object type as the caller of the window calculation.

**See also:**

- pandas.Series.window Calling object with Series data.
- pandas.DataFrame.window Calling object with DataFrames.
- pandas.Series.var Equivalent method for Series.
- pandas.DataFrame.var Equivalent method for DataFrame.
- numpy.var Equivalent method for Numpy array.

**Notes**

The default ddof of 1 used in Series.var() is different than the default ddof of 0 in numpy.var().

A minimum of 1 period is required for the rolling calculation.
Examples

```python
>>> s = pd.Series([5, 5, 6, 7, 5, 5, 5])
>>> s.rolling(3).var()
0    NaN
1    NaN
2    0.333333
3    1.000000
4    1.000000
5    1.333333
6    0.000000
dtype: float64

>>> s.expanding(3).var()
0    NaN
1    NaN
2    0.333333
3    0.916667
4    0.800000
5    0.700000
6    0.619048
dtype: float64
```

**pandas.core.window.rolling.Window.std**

`Window.std(ddof=1, *args, **kwargs)`

Calculate window standard deviation.

New in version 1.0.0.

Normalized by N-1 by default. This can be changed using the `ddof` argument.

- **Parameters**
  - `ddof` [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is \( N - ddof \), where \( N \) represents the number of elements.

  - `*args, **kwargs` For NumPy compatibility. No additional arguments are used.

- **Returns**
  - `Series or DataFrame` Returns the same object type as the caller of the window calculation.

See also:

- `pandas.Series.window` Calling object with Series data.
- `pandas.DataFrame.window` Calling object with DataFrames.
- `pandas.Series.std` Equivalent method for Series.
- `pandas.DataFrame.std` Equivalent method for DataFrame.
- `numpy.std` Equivalent method for Numpy array.
Notes

The default `ddof` of 1 used in Series.std is different than the default `ddof` of 0 in numpy.std.

A minimum of one period is required for the rolling calculation.

Examples

```python
>>> s = pd.Series([5, 5, 6, 7, 5, 5, 5])
>>> s.rolling(3).std()
0    NaN
1    NaN
2  0.577350
3  1.000000
4  1.000000
5  1.154701
6  0.000000
dtype: float64

>>> s.expanding(3).std()
0    NaN
1    NaN
2  0.577350
3  0.957427
4  0.894427
5  0.836660
6  0.786796
dtype: float64
```

### 3.10.2 Standard expanding window functions

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Expanding.count(**kwargs)</code></td>
<td>The expanding count of any non-NaN observations inside the window.</td>
</tr>
<tr>
<td><code>Expanding.sum(*args, **kwargs)</code></td>
<td>Calculate expanding sum of given DataFrame or Series.</td>
</tr>
<tr>
<td><code>Expanding.mean(*args, **kwargs)</code></td>
<td>Calculate the expanding mean of the values.</td>
</tr>
<tr>
<td><code>Expanding.median(**kwargs)</code></td>
<td>Calculate the expanding median.</td>
</tr>
<tr>
<td><code>Expanding.var([ddof])</code></td>
<td>Calculate unbiased expanding variance.</td>
</tr>
<tr>
<td><code>Expanding.std([ddof])</code></td>
<td>Calculate expanding standard deviation.</td>
</tr>
<tr>
<td><code>Expanding.min(*args, **kwargs)</code></td>
<td>Calculate the expanding minimum.</td>
</tr>
<tr>
<td><code>Expanding.max(*args, **kwargs)</code></td>
<td>Calculate the expanding maximum.</td>
</tr>
<tr>
<td><code>Expanding.corr([other, pairwise])</code></td>
<td>Calculate expanding correlation.</td>
</tr>
<tr>
<td><code>Expanding.cov([other, pairwise, ddof])</code></td>
<td>Calculate the expanding sample covariance.</td>
</tr>
<tr>
<td><code>Expanding.skew(**kwargs)</code></td>
<td>Unbiased expanding skewness.</td>
</tr>
<tr>
<td><code>Expanding.kurt(**kwargs)</code></td>
<td>Calculate unbiased expanding kurtosis.</td>
</tr>
<tr>
<td><code>Expanding.apply(func[, raw, engine, ...])</code></td>
<td>Apply an arbitrary function to each expanding window.</td>
</tr>
<tr>
<td><code>Expanding.aggregate(func, *args, **kwargs)</code></td>
<td>Aggregate using one or more operations over the specified axis.</td>
</tr>
<tr>
<td><code>Expanding.quantile(quantile[, interpolation])</code></td>
<td>Calculate the expanding quantile.</td>
</tr>
</tbody>
</table>
pandas.core.window.expanding.Expanding.count

Expanding.count(**kwargs)

The expanding count of any non-NaN observations inside the window.

Returns

Series or DataFrame Returned object type is determined by the caller of the expanding calculation.

See also:

pandas.Series.expanding Calling object with Series data.
pandas.DataFrame.expanding Calling object with DataFrames.
pandas.DataFrame.count Count of the full DataFrame.

Examples

```python
>>> s = pd.Series([2, 3, np.nan, 10])
>>> s.rolling(2).count()
0    1.0
1    2.0
2    1.0
3    1.0
dtype: float64
>>> s.rolling(3).count()
0    1.0
1    2.0
2    2.0
3    2.0
dtype: float64
>>> s.rolling(4).count()
0    1.0
1    2.0
2    2.0
3    3.0
dtype: float64
```

pandas.core.window.expanding.Expanding.sum

Expanding.sum(*args, **kwargs)

Calculate expanding sum of given DataFrame or Series.

Parameters

*args, **kwargs For compatibility with other expanding methods. Has no effect on the computed value.

Returns

Series or DataFrame Same type as the input, with the same index, containing the expanding sum.

See also:

pandas.Series.sum Reducing sum for Series.
pandas.DataFrame.sum Reducing sum for DataFrame.
Examples

```python
>>> s = pd.Series([1, 2, 3, 4, 5])
>>> s
0    1
1    2
2    3
3    4
4    5
dtype: int64
```

```python
>>> s.rolling(3).sum()
0    NaN
1    NaN
2    6.0
3    9.0
4    12.0
dtype: float64
```

```python
>>> s.expanding(3).sum()
0    NaN
1    NaN
2    6.0
3    10.0
4    15.0
dtype: float64
```

```python
>>> s.rolling(3, center=True).sum()
0    NaN
1    6.0
2    9.0
3    12.0
4    NaN
dtype: float64
```

For DataFrame, each expanding sum is computed column-wise.

```python
>>> df = pd.DataFrame({"A": s, "B": s ** 2})
>>> df
   A   B
0  1   1
1  2   4
2  3   9
3  4  16
4  5  25
```

```python
>>> df.rolling(3).sum()
   A   B
0  NaN NaN
1  NaN NaN
2  6.0 14.0
3  9.0 29.0
4 12.0 50.0
```
**pandas.core.window.expanding.Expanding.mean**

```python
Expanding.mean(*args, **kwargs)
```

Calculate the expanding mean of the values.

**Parameters**

- *args: Under Review.
- **kwargs: Under Review.

**Returns**

- **Series or DataFrame**: Returned object type is determined by the caller of the expanding calculation.

**See also:**

- `pandas.Series.expanding`: Calling object with Series data.
- `pandas.DataFrame.expanding`: Calling object with DataFrames.
- `pandas.DataFrame.mean`: Equivalent method for DataFrame.

**Examples**

The below examples will show rolling mean calculations with window sizes of two and three, respectively.

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s.rolling(2).mean()
0   NaN
1   1.5
2   2.5
3   3.5
dtype: float64
```

```python
>>> s.rolling(3).mean()
0   NaN
1   NaN
2   2.0
3   3.0
dtype: float64
```

**pandas.core.window.expanding.Expanding.median**

```python
Expanding.median(**kwargs)
```

Calculate the expanding median.

**Parameters**

- **kwargs: For compatibility with other expanding methods. Has no effect on the computed median.

**Returns**

- **Series or DataFrame**: Returned type is the same as the original object.

**See also:**

- `pandas.Series.expanding`: Calling object with Series data.
- `pandas.DataFrame.expanding`: Calling object with DataFrames.
Examples

Compute the rolling median of a series with a window size of 3.

```python
>>> s = pd.Series([0, 1, 2, 3, 4])
>>> s.rolling(3).median()
0   NaN
1   NaN
2   1.0
3   2.0
4   3.0
dtype: float64
```

`pandas.core.window.expanding.Expanding.var`

`Expanding.var(ddof=1, *args, **kwargs)`

Calculate unbiased expanding variance.

Normalized by N-1 by default. This can be changed using the `ddof` argument.

**Parameters**

- `ddof` [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is \( N - ddof \), where \( N \) represents the number of elements.
- `*args, **kwargs` For NumPy compatibility. No additional arguments are used.

**Returns**

- `Series` or `DataFrame` Returns the same object type as the caller of the expanding calculation.

**See also:**

- `pandas.Series.expanding` Calling object with Series data.
- `pandas.DataFrame.expanding` Calling object with DataFrames.
- `pandas.Series.var` Equivalent method for Series.
- `pandas.DataFrame.var` Equivalent method for DataFrame.
- `numpy.var` Equivalent method for Numpy array.

**Notes**

The default `ddof` of 1 used in `Series.var()` is different than the default `ddof` of 0 in `numpy.var()`.

A minimum of 1 period is required for the rolling calculation.

**Examples**

```python
>>> s = pd.Series([5, 5, 6, 7, 5, 5, 5])
>>> s.rolling(3).var()
0   NaN
1   NaN
2   0.333333
3   1.000000
4   1.000000
5   1.333333
6   0.000000
dtype: float64
```
>>> s.expanding(3).var()
0   NaN
1   NaN
2   0.333333
3   0.916667
4   0.800000
5   0.700000
6   0.619048
dtype: float64

pandas.core.window.expanding.Expanding.std

Expanding.std(ddof=1, *args, **kwargs)
Calculate expanding standard deviation.

Normalized by N-1 by default. This can be changed using the ddof argument.

Parameters

- **ddof** [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.

- **args, **kwargs For NumPy compatibility. No additional arguments are used.

Returns

Series or DataFrame Returns the same object type as the caller of the expanding calculation.

See also:

- pandas.Series.expanding Calling object with Series data.
- pandas.DataFrame.expanding Calling object with DataFrames.
- pandas.Series.std Equivalent method for Series.
- pandas.DataFrame.std Equivalent method for DataFrame.
- numpy.std Equivalent method for Numpy array.

Notes

The default ddof of 1 used in Series.std is different than the default ddof of 0 in numpy.std.

A minimum of one period is required for the rolling calculation.

Examples

>>> s = pd.Series([5, 5, 6, 7, 5, 5, 5])
>>> s.rolling(3).std()
0   NaN
1   NaN
2   0.577350
3   1.000000
4   1.000000
5   1.154701
6   0.000000
dtype: float64
```python
>>> s.expanding(3).std()
0    NaN
1    NaN
2  0.577350
3  0.957427
4  0.894427
5  0.836660
6  0.786796
dtype: float64
```

**pandas.core.window.expanding.Expanding.min**

`Expanding.min(*args, **kwargs)`

Calculate the expanding minimum.

**Parameters**

**kwargs  Under Review.

**Returns**

*Series or DataFrame*  Returned object type is determined by the caller of the expanding calculation.

**Examples**

Performing a rolling minimum with a window size of 3.

```python
>>> s = pd.Series([4, 3, 5, 2, 6])
>>> s.rolling(3).min()
0    NaN
1    NaN
2    3.0
3    2.0
4    2.0
dtype: float64
```

**pandas.core.window.expanding.Expanding.max**

`Expanding.max(*args, **kwargs)`

Calculate the expanding maximum.

**Parameters**

*:args, **kwargs*  Arguments and keyword arguments to be passed into func.

**Returns**

*Series or DataFrame*  Return type is determined by the caller.

**See also:**

*pandas.Series.expanding*  Calling object with a Series.
*pandas.DataFrame.expanding*  Calling object with a DataFrame.
*pandas.Series.min*  Similar method for Series.
*pandas.DataFrame.min*  Similar method for DataFrame.
Expanding.corr (other=None, pairwise=None, **kwargs)
Calculate expanding correlation.

Parameters

other [Series, DataFrame, or ndarray, optional] If not supplied then will default to self.

pairwise [bool, default None] Calculate pairwise combinations of columns within a DataFrame. If other is not specified, defaults to True, otherwise defaults to False. Not relevant for Series.

**kwargs Unused.

Returns

Series or DataFrame Returned object type is determined by the caller of the expanding calculation.

See also:
pandas.Series.expanding Calling object with Series data.
pandas.DataFrame.expanding Calling object with DataFrames.
pandas.Series.corr Equivalent method for Series.
pandas.DataFrame.corr Equivalent method for DataFrame.
cov Similar method to calculate covariance.
numpy.corrcoef NumPy Pearson’s correlation calculation.

Notes

This function uses Pearson’s definition of correlation (https://en.wikipedia.org/wiki/Pearson_correlation_coefficient).

When other is not specified, the output will be self correlation (e.g. all 1’s), except for DataFrame inputs with pairwise set to True.

Function will return NaN for correlations of equal valued sequences; this is the result of a 0/0 division error.

When pairwise is set to False, only matching columns between self and other will be used.

When pairwise is set to True, the output will be a MultiIndex DataFrame with the original index on the first level, and the other DataFrame columns on the second level.

In the case of missing elements, only complete pairwise observations will be used.
Examples

The below example shows a rolling calculation with a window size of four matching the equivalent function call using `numpy.corrcoef()`.

```python
>>> v1 = [3, 3, 3, 5, 8]
>>> v2 = [3, 4, 4, 4, 8]
>>> # numpy returns a 2x2 array, the correlation coefficient
>>> # is the number at entry [0][1]
>>> print(f"{np.corrcoef(v1[:-1], v2[:-1])[0][1]:.6f}")
0.333333
>>> print(f"{np.corrcoef(v1[1:], v2[1:])[0][1]:.6f}")
0.916949
>>> s1 = pd.Series(v1)
>>> s2 = pd.Series(v2)
>>> s1.rolling(4).corr(s2)
0 NaN
1 NaN
2 NaN
3 0.333333
4 0.916949
dtype: float64
```

The below example shows a similar rolling calculation on a DataFrame using the pairwise option.

```python
>>> print(np.corrcoef(matrix[:-1,0], matrix[:-1,1]).round(7))
[[1.0000000 0.6263001]
 [0.6263001 1.0000000]]
>>> print(np.corrcoef(matrix[1:,0], matrix[1:,1]).round(7))
[[1.0000000 0.5553681]
 [0.5553681 1.0000000]]
>>> df = pd.DataFrame(matrix, columns=['X','Y'])
>>> df.
0 51.0 35.0
1 49.0 30.0
2 47.0 32.0
3 46.0 31.0
4 50.0 36.0
>>> df.rolling(4).corr(pairwise=True)
```

```
x       y
0 NaN   NaN
1 NaN   NaN
2 NaN   NaN
3 x 1.000000 0.626300
y 0.626300 1.000000
2 x 1.000000 0.555368
y 0.555368 1.000000
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.core.window.expanding.Expanding.cov

Expanding.cov(other=None, pairwise=None, ddof=1, **kwargs)

Calculate the expanding sample covariance.

Parameters

other [Series, DataFrame, or ndarray, optional] If not supplied then will default to self and produce pairwise output.

pairwise [bool, default None] If False then only matching columns between self and other will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a MultiIndexed DataFrame in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

ddof [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is N – ddof, where N represents the number of elements.

**kwargs Keyword arguments to be passed into func.

Returns

Series or DataFrame Return type is determined by the caller.

See also:

pandas.Series.expanding Calling object with Series data.
pandas.DataFrame.expanding Calling object with DataFrame data.
pandas.Series.cov Similar method for Series.
pandas.DataFrame.cov Similar method for DataFrame.

pandas.core.window.expanding.Expanding.skew

Expanding.skew(**kwargs)

Unbiased expanding skewness.

Parameters

**kwargs Keyword arguments to be passed into func.

Returns

Series or DataFrame Return type is determined by the caller.

See also:

pandas.Series.expanding Calling object with Series data.
pandas.DataFrame.expanding Calling object with DataFrame data.
pandas.Series.skew Similar method for Series.
pandas.DataFrame.skew Similar method for DataFrame.

pandas.core.window.expanding.Expanding.kurt

Expanding.kurt(**kwargs)

Calculate unbiased expanding kurtosis.

This function uses Fisher’s definition of kurtosis without bias.

Parameters

**kwargs Under Review.

Returns
Series or DataFrame  Returned object type is determined by the caller of the expanding calculation.

See also:

pandas.Series.expanding  Calling object with Series data.
pandas.DataFrame.expanding  Calling object with DataFrames.
pandas.Series.kurt  Equivalent method for Series.
pandas.DataFrame.kurt  Equivalent method for DataFrame.
scipy.stats.skew  Third moment of a probability density.

Notes

A minimum of 4 periods is required for the expanding calculation.

Examples

The example below will show an expanding calculation with a window size of four matching the equivalent function call using scipy.stats.

```python
>>> arr = [1, 2, 3, 4, 999]
>>> import scipy.stats
>>> print(f"scipy.stats.kurtosis(arr[:-1], bias=\n:bias=False):.6f")
-1.200000
>>> print(f"scipy.stats.kurtosis(arr, bias=\n:bias=False):.6f")
4.999874
>>> s = pd.Series(arr)
>>> s.expanding(4).kurt()
0    NaN
1    NaN
2    NaN
3   -1.200000
4    4.999874
dtype: float64
```

pandas.core.window.expanding.Expanding.apply

Expanding .apply (func, raw=False, engine=None, engine_kwargs=None, args=None, kwargs=None)  
Apply an arbitrary function to each expanding window.

Parameters

- **func** [function] Must produce a single value from an ndarray input if raw=True or a single value from a Series if raw=False. Can also accept a Numba JIT function with engine='numba' specified.

  Changed in version 1.0.0.

- **raw** [bool, default None]

  - False: passes each row or column as a Series to the function.
  - True: the passed function will receive ndarray objects instead. If you are just applying a NumPy reduction function this will achieve much better performance.

- **engine** [str, default None]

  - 'cython': Runs rolling apply through C-extensions from cython.
• 'numba': Runs rolling apply through JIT compiled code from numba. Only available when raw is set to True.
• None: Defaults to 'cython' or globally setting compute.use_numba

New in version 1.0.0.

engine_kwargs [dict, default None]

• For 'cython' engine, there are no accepted engine_kwargs
• For 'numba' engine, the engine can accept nopython, nogil and parallel dictionary keys. The values must either be True or False. The default engine_kwargs for the 'numba' engine is {'nopython': True, 'nogil': False, 'parallel': False} and will be applied to both the func and the apply rolling aggregation.

New in version 1.0.0.

args [tuple, default None] Positional arguments to be passed into func.

kwargs [dict, default None] Keyword arguments to be passed into func.

Returns

Series or DataFrame Return type is determined by the caller.

See also:

pandas.Series.expanding Calling object with Series data.
pandas.DataFrame.expanding Calling object with DataFrame data.
pandas.Series.aggregate Similar method for Series.
pandas.DataFrame.aggregate Similar method for DataFrame.

Notes

See Rolling apply for extended documentation and performance considerations for the Numba engine.

pandas.core.window.expanding.Expanding.aggregate

Expanding.aggregate (func, *args, **kwargs)

Aggregates using one or more operations over the specified axis.

Parameters

func [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a Series/Dataframe or when passed to Series/Dataframe.apply.

Accepted combinations are:

• function
• string function name
• list of functions and/or function names, e.g. [np.sum, 'mean']
• dict of axis labels -> functions, function names or list of such.

*args Positional arguments to pass to func.

**kwargs Keyword arguments to pass to func.

Returns

scalar, Series or DataFrame The return can be:
• scalar: when Series.agg is called with single function
• Series: when DataFrame.agg is called with a single function
• DataFrame: when DataFrame.agg is called with several functions

Return scalar, Series or DataFrame.

See also:
pandas.DataFrame.aggregate Similar DataFrame method.
pandas.Series.aggregate Similar Series method.

Notes

agg is an alias for aggregate. Use the alias.
A passed user-defined-function will be passed a Series for evaluation.

Examples

```python
>>> df = pd.DataFrame({"A": [1, 2, 3], "B": [4, 5, 6], "C": [7, 8, 9]})
```

```plaintext
A  B  C
0 1 4 7
1 2 5 8
2 3 6 9
```

```python
>>> df.ewm(alpha=0.5).mean()
```

```plaintext
A  B  C
0 1.000000 4.000000 7.000000
1 1.666667 4.666667 7.666667
2 2.428571 5.428571 8.428571
```

pandas.core.window.expanding.Expanding.quantile

Expanding. **quantile**(quantile, interpolation='linear', **kwargs)
Calculate the expanding quantile.

**Parameters**

quantile [float] Quantile to compute. 0 <= quantile <= 1.

This optional parameter specifies the interpolation method to use, when the desired
quantile lies between two data points i and j:
• linear: \( i + (j - i) \times fraction \), where fraction is the fractional part of the index sur-
rounded by i and j.
• lower: i.
• higher: j.
• nearest: i or j whichever is nearest.
• midpoint: \( (i + j) / 2 \).

**kwargs For compatibility with other expanding methods. Has no effect on the result.
Returns

Series or DataFrame Returned object type is determined by the caller of the expanding calculation.

See also:

pandas.Series.quantile Computes value at the given quantile over all data in Series.
pandas.DataFrame.quantile Computes values at the given quantile over requested axis in DataFrame.

Examples

```python
>>> s = pd.Series([1, 2, 3, 4])
>>> s.rolling(2).quantile(.4, interpolation='lower')
0  NaN
1  1.0
2  2.0
3  3.0
dtype: float64

>>> s.rolling(2).quantile(.4, interpolation='midpoint')
0  NaN
1  1.5
2  2.5
3  3.5
dtype: float64
```

3.10.3 Exponentially-weighted moving window functions

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>pandas.core.window.ewm.ExponentialMovingWindow.mean(*args, **kwargs)</td>
<td>Exponential weighted moving average.</td>
</tr>
<tr>
<td>pandas.core.window.ewm.ExponentialMovingWindow.std([bias])</td>
<td>Exponential weighted moving stddev.</td>
</tr>
<tr>
<td>pandas.core.window.ewm.ExponentialMovingWindow.var([bias])</td>
<td>Exponential weighted moving variance.</td>
</tr>
<tr>
<td>pandas.core.window.ewm.ExponentialMovingWindow.corr([other, pairwise])</td>
<td>Exponential weighted sample correlation.</td>
</tr>
<tr>
<td>pandas.core.window.ewm.ExponentialMovingWindow.cov([other, ...])</td>
<td>Exponential weighted sample covariance.</td>
</tr>
</tbody>
</table>

pandas.core.window.ewm.ExponentialMovingWindow.mean

ExponentialMovingWindow.mean(*args, **kwargs)

Exponential weighted moving average.

Parameters

*args, **kwargs Arguments and keyword arguments to be passed into func.

Returns

Series or DataFrame Return type is determined by the caller.

See also:

pandas.Series.ewm Calling object with Series data.
pandas.DataFrame.ewm Calling object with DataFrame data.
pandas.Series.mean Similar method for Series.
pandas.DataFrame.mean Similar method for DataFrame.
**pandas.core.window.ewm.ExponentialMovingWindow.std**

```python
ExponentialMovingWindow.std(bias=False, *args, **kwargs)
```

Exponential weighted moving stddev.

**Parameters**

- `bias` [bool, default False] Use a standard estimation bias correction.
- `*args, **kwargs` Arguments and keyword arguments to be passed into func.

**Returns**

- `Series or DataFrame` Return type is determined by the caller.

**See also:**

- `pandas.Series.ewm` Calling object with Series data.
- `pandas.DataFrame.ewm` Calling object with DataFrame data.
- `pandas.Series.std` Similar method for Series.
- `pandas.DataFrame.std` Similar method for DataFrame.

**pandas.core.window.ewm.ExponentialMovingWindow.var**

```python
ExponentialMovingWindow.var(bias=False, *args, **kwargs)
```

Exponential weighted moving variance.

**Parameters**

- `bias` [bool, default False] Use a standard estimation bias correction.
- `*args, **kwargs` Arguments and keyword arguments to be passed into func.

**Returns**

- `Series or DataFrame` Return type is determined by the caller.

**See also:**

- `pandas.Series.ewm` Calling object with Series data.
- `pandas.DataFrame.ewm` Calling object with DataFrame data.
- `pandas.Series.var` Similar method for Series.
- `pandas.DataFrame.var` Similar method for DataFrame.

**pandas.core.window.ewm.ExponentialMovingWindow.corr**

```python
ExponentialMovingWindow.corr(other=None, pairwise=None, **kwargs)
```

Exponential weighted sample correlation.

**Parameters**

- `other` [Series, DataFrame, or ndarray, optional] If not supplied then will default to self and produce pairwise output.
- `pairwise` [bool, default None] If False then only matching columns between self and other will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a MultiIndex DataFrame in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.
- `**kwargs` Keyword arguments to be passed into func.

**Returns**

- `Series or DataFrame` Return type is determined by the caller.
pandas: powerful Python data analysis toolkit, Release 1.1.1

See also:

- **pandas.Series.ewm** Calling object with Series data.
- **pandas.DataFrame.ewm** Calling object with DataFrame data.
- **pandas.Series.corr** Similar method for Series.
- **pandas.DataFrame.corr** Similar method for DataFrame.

**pandas.core.window.ewm.ExponentialMovingWindow.cov**

ExponentialMovingWindow.cov (other=None, pairwise=None, bias=False, **kwargs)

Exponential weighted sample covariance.

**Parameters**

- **other** [Series, DataFrame, or ndarray, optional] If not supplied then will default to self and produce pairwise output.
- **pairwise** [bool, default None] If False then only matching columns between self and other will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a MultiIndex DataFrame in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.
- **bias** [bool, default False] Use a standard estimation bias correction.
- **kwargs** Keyword arguments to be passed into func.

**Returns**

- **Series or DataFrame** Return type is determined by the caller.

See also:

- **pandas.Series.ewm** Calling object with Series data.
- **pandas.DataFrame.ewm** Calling object with DataFrame data.
- **pandas.Series.cov** Similar method for Series.
- **pandas.DataFrame.cov** Similar method for DataFrame.

### 3.10.4 Window indexer

Base class for defining custom window boundaries.

- **api.indexers.BaseIndexer**([index_array, ...]) Base class for window bounds calculations.
- **api.indexers.FixedForwardWindowIndexer**([create window boundaries for fixed-length windows that include the current row.
- **api.indexers.VariableOffsetWindowIndexer**([create window boundaries based on a non-fixed offset such as a BusinessDay])
pandas.api.indexers.BaseIndexer

class pandas.api.indexers.BaseIndexer(index_array=None, window_size=0, **kwargs)
   Base class for window bounds calculations.

   Methods

   get_window_bounds([num_values, min_periods,...])
      Computes the bounds of a window.

pandas.api.indexers.BaseIndexer.get_window_bounds

BaseIndexer.get_window_bounds (num_values=0, min_periods=None, center=None, closed=None)
   Computes the bounds of a window.

   Parameters

   num_values [int, default 0] number of values that will be aggregated over
   window_size [int, default 0] the number of rows in a window
   min_periods [int, default None] min_periods passed from the top level rolling API
   center [bool, default None] center passed from the top level rolling API
   closed [str, default None] closed passed from the top level rolling API
   win_type [str, default None] win_type passed from the top level rolling API

   Returns

   A tuple of ndarray[int64], indicating the boundaries of each window

pandas.api.indexers.FixedForwardWindowIndexer

class pandas.api.indexers.FixedForwardWindowIndexer(index_array=None, window_size=0, **kwargs)
   Creates window boundaries for fixed-length windows that include the current row.

Examples

>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]})
>>> df
   B
0  0.0
1  1.0
2  2.0
3  NaN
4  4.0

3.10. Window
```python
>>> indexer = pd.api.indexers.FixedForwardWindowIndexer(window_size=2)
>>> df.rolling(window=indexer, min_periods=1).sum()
B
0 1.0
1 3.0
2 2.0
3 4.0
4 4.0
```

**Methods**

```python
get_window_bounds([num_values, min_periods, ...])
```

Computes the bounds of a window.

**pandas.api.indexers.FixedForwardWindowIndexer.get_window_bounds**

FixedForwardWindowIndexer.get_window_bounds(num_values=0, min_periods=None, center=None, closed=None)

Computes the bounds of a window.

**Parameters**

- **num_values** [int, default 0] number of values that will be aggregated over
- **window_size** [int, default 0] the number of rows in a window
- **min_periods** [int, default None] min_periods passed from the top level rolling API
- **center** [bool, default None] center passed from the top level rolling API
- **closed** [str, default None] closed passed from the top level rolling API
- **win_type** [str, default None] win_type passed from the top level rolling API

**Returns**

A tuple of ndarray[int64], indicating the boundaries of each window

**pandas.api.indexers.VariableOffsetWindowIndexer**

class pandas.api.indexers.VariableOffsetWindowIndexer(index_array=None, window_size=0, index=None, offset=None, **kwargs)

Calculate window boundaries based on a non-fixed offset such as a BusinessDay
Methods

```python
get_window_bounds([num_values, min_periods, ...])
```

Computes the bounds of a window.

```python
pandas.api.indexers.VariableOffsetWindowIndexer.get_window_bounds
```

VariableOffsetWindowIndexer.get_window_bounds(num_values=0, min_periods=None, center=None, closed=None)

Computes the bounds of a window.

Parameters

- **num_values** [int, default 0] number of values that will be aggregated over
- **window_size** [int, default 0] the number of rows in a window
- **min_periods** [int, default None] min_periods passed from the top level rolling API
- **center** [bool, default None] center passed from the top level rolling API
- **closed** [str, default None] closed passed from the top level rolling API
- **win_type** [str, default None] win_type passed from the top level rolling API

Returns

A tuple of ndarray[int64], indicating the boundaries of each window

### 3.11 GroupBy

GroupBy objects are returned by groupby calls: `pandas.DataFrame.groupby()`, `pandas.Series.groupby()`, etc.

#### 3.11.1 Indexing, iteration

```python
GroupBy.__iter__()  Groupby iterator.
GroupBy.groups       Dict {group name -> group labels}.
GroupBy.indices      Dict {group name -> group indices}.
GroupBy.get_group(name[, obj]) Construct DataFrame from group with provided name.
```
pandas.core.groupby.GroupBy.__iter__

GroupBy.__iter__()

Groupby iterator.

Returns

Generator yielding sequence of (name, subsetted object)
for each group

pandas.core.groupby.GroupBy.groups

property GroupBy.groups

Dict {group name -> group labels}.

pandas.core.groupby.GroupBy.indices

property GroupBy.indices

Dict {group name -> group indices}.

pandas.core.groupby.GroupBy.get_group

GroupBy.get_group(name, obj=None)

Construct DataFrame from group with provided name.

Parameters

name [object] The name of the group to get as a DataFrame.

obj [DataFrame, default None] The DataFrame to take the DataFrame out of. If it is None, the object groupby was called on will be used.

Returns

group [same type as obj]

Grouper(*args, **kwargs)

A Grouper allows the user to specify a groupby instruction for an object.

class pandas.Grouper(*args, **kwargs)

A Grouper allows the user to specify a groupby instruction for an object.

This specification will select a column via the key parameter, or if the level and/or axis parameters are given, a level of the index of the target object.

If axis and/or level are passed as keywords to both Grouper and groupby, the values passed to Grouper take precedence.

Parameters

key [str, defaults to None] Groupby key, which selects the grouping column of the target.

level [name/number, defaults to None] The level for the target index.

freq [str / frequency object, defaults to None] This will groupby the specified frequency if the target selection (via key or level) is a datetime-like object. For full specification of
available frequencies, please see here.

**axis** [str, int, defaults to 0] Number/name of the axis.

**sort** [bool, default to False] Whether to sort the resulting labels.

**closed** ['left' or 'right']) Closed end of interval. Only when *freq* parameter is passed.

**label** ['left' or 'right']) Interval boundary to use for labeling. Only when *freq* parameter is passed.

**convention** ['start', 'end', 'e', 's'] If grouper is PeriodIndex and *freq* parameter is passed.

**base** [int, default 0] Only when *freq* parameter is passed. For frequencies that evenly subdivide 1 day, the “origin” of the aggregated intervals. For example, for ‘5min’ frequency, base could range from 0 through 4. Defaults to 0.

Deprecation: Since version 1.1.0: The new arguments that you should use are ‘offset’ or ‘origin’.

**loffset** [str, DateOffset, timedelta object] Only when *freq* parameter is passed.

Deprecation: Since version 1.1.0: loffset is only working for .resample(...) and not for Grouper (GH28302). However, loffset is also deprecated for .resample(...)

See: DataFrame.resample

**origin** [‘epoch’, ‘start’, ‘start_day’] The timestamp on which to adjust the grouping. The timezone of origin must match the timezone of the index. If a timestamp is not used, these values are also supported:

  * ‘epoch’: *origin* is 1970-01-01
  * ‘start’: *origin* is the first value of the timeseries
  * ‘start_day’: *origin* is the first day at midnight of the timeseries

New in version 1.1.0.

**offset** [Timedelta or str, default is None] An offset timedelta added to the origin.

New in version 1.1.0.

**Returns**

A specification for a groupby instruction

**Examples**

Syntactic sugar for df.groupby('A')

```python
>>> df = pd.DataFrame(
    ... {  
    ...     "Animal": ["Falcon", "Parrot", "Falcon", "Falcon", "Parrot"],  
    ...     "Speed": [100, 5, 200, 300, 15],  
    ... }  
    ...
>>> df
   Animal  Speed
0   Falcon    100
1    Parrot     5
2   Falcon    200
3   Falcon    300
4    Parrot     5
```

(continues on next page)
Specify a resample operation on the column ‘Publish date’

```python
>>> df = pd.DataFrame(
...     {
...         "Publish date": [pd.Timestamp("2000-01-02"),
...                         pd.Timestamp("2000-01-02"),
...                         pd.Timestamp("2000-01-09"),
...                         pd.Timestamp("2000-01-16")),
...         "ID": [0, 1, 2, 3],
...         "Price": [10, 20, 30, 40]
...     }
... )
```

```python
>>> df
df
```

<table>
<thead>
<tr>
<th>Publish date</th>
<th>ID</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-02</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>1</td>
<td>20</td>
</tr>
<tr>
<td>2000-01-09</td>
<td>2</td>
<td>30</td>
</tr>
<tr>
<td>2000-01-16</td>
<td>3</td>
<td>40</td>
</tr>
</tbody>
</table>

```python
>>> df.groupby(pd.Grouper(key="Publish date", freq="1W")).mean()
```

<table>
<thead>
<tr>
<th>Publish date</th>
<th>ID</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-02</td>
<td>0.5</td>
<td>15.0</td>
</tr>
<tr>
<td>2000-01-09</td>
<td>2</td>
<td>30.0</td>
</tr>
<tr>
<td>2000-01-16</td>
<td>3</td>
<td>40.0</td>
</tr>
</tbody>
</table>

If you want to adjust the start of the bins based on a fixed timestamp:

```python
>>> start, end = '2000-10-01 23:30:00', '2000-10-02 00:30:00'
>>> rng = pd.date_range(start, end, freq='7min')
>>> ts = pd.Series(np.arange(len(rng)) * 3, index=rng)
>>> ts
```

| 2000-10-01 23:30:00 | 0  |
| 2000-10-01 23:37:00 | 3  |
| 2000-10-01 23:44:00 | 6  |
| 2000-10-01 23:51:00 | 9  |
| 2000-10-01 23:58:00 | 12 |
| 2000-10-02 00:05:00 | 15 |
| 2000-10-02 00:12:00 | 18 |
| 2000-10-02 00:19:00 | 21 |
| 2000-10-02 00:26:00 | 24 |

Freq: 7T, dtype: int64

```python
>>> ts.groupby(pd.Grouper(freq='17min')).sum()
```

| 2000-10-01 23:14:00 | 0  |
| 2000-10-01 23:31:00 | 9  |
| 2000-10-01 23:48:00 | 21 |
| 2000-10-02 00:05:00 | 54 |
| 2000-10-02 00:22:00 | 24 |

Freq: 17T, dtype: int64
>>> ts.groupby(pd.Grouper(freq='17min', origin='epoch')).sum()
2000-10-01 23:18:00 0
2000-10-01 23:35:00 18
2000-10-01 23:52:00 27
2000-10-02 00:09:00 39
2000-10-02 00:26:00 24
Freq: 17T, dtype: int64

>>> ts.groupby(pd.Grouper(freq='17min', origin='2000-01-01')).sum()
2000-10-01 23:24:00 3
2000-10-01 23:41:00 15
2000-10-01 23:58:00 45
2000-10-02 00:15:00 45
Freq: 17T, dtype: int64

If you want to adjust the start of the bins with an offset Timedelta, the two following lines are equivalent:

>>> ts.groupby(pd.Grouper(freq='17min', origin='start')).sum()
2000-10-01 23:30:00 9
2000-10-01 23:47:00 21
2000-10-02 00:04:00 54
2000-10-02 00:21:00 24
Freq: 17T, dtype: int64

>>> ts.groupby(pd.Grouper(freq='17min', offset='23h30min')).sum()
2000-10-01 23:30:00 9
2000-10-01 23:47:00 21
2000-10-02 00:04:00 54
2000-10-02 00:21:00 24
Freq: 17T, dtype: int64

To replace the use of the deprecated base argument, you can now use offset, in this example it is equivalent to have base=2:

>>> ts.groupby(pd.Grouper(freq='17min', offset='2min')).sum()
2000-10-01 23:16:00 0
2000-10-01 23:33:00 9
2000-10-01 23:50:00 36
2000-10-02 00:07:00 39
2000-10-02 00:24:00 24
Freq: 17T, dtype: int64
3.11.2 Function application

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>GroupBy.apply(func, *args, **kwargs)</code></td>
<td>Apply function <code>func</code> group-wise and combine the results together.</td>
</tr>
<tr>
<td><code>GroupBy.agg(func, *args, **kwargs)</code></td>
<td>Aggregate using one or more operations over the specified axis.</td>
</tr>
<tr>
<td><code>SeriesGroupBy.aggregate(func, engine, . . .)</code></td>
<td>Aggregate using one or more operations over the specified axis.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.aggregate(func, engine, . . .)</code></td>
<td>Aggregate using one or more operations over the specified axis.</td>
</tr>
<tr>
<td><code>SeriesGroupBy.transform(func, *args[, . . .])</code></td>
<td>Call function producing a like-indexed Series on each group and return a Series having the same indexes as the original object filled with the transformed values.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.transform(func, *args[ , . . .])</code></td>
<td>Call function producing a like-indexed DataFrame on each group and return a DataFrame having the same indexes as the original object filled with the transformed values.</td>
</tr>
<tr>
<td><code>GroupBy.pipe(func, *args, **kwargs)</code></td>
<td>Apply a function <code>func</code> with arguments to this GroupBy object and return the function’s result.</td>
</tr>
</tbody>
</table>

**pandas.core.groupby.GroupBy.apply**

`GroupBy.apply(func, *args, **kwargs)`

Apply function `func` group-wise and combine the results together.

The function passed to `apply` must take a dataframe as its first argument and return a DataFrame, Series or scalar. `apply` will then take care of combining the results back together into a single dataframe or series. `apply` is therefore a highly flexible grouping method.

While `apply` is a very flexible method, its downside is that using it can be quite a bit slower than using more specific methods like `agg` or `transform`. Pandas offers a wide range of method that will be much faster than using `apply` for their specific purposes, so try to use them before reaching for `apply`.

**Parameters**

- `func` [callable] A callable that takes a dataframe as its first argument, and returns a dataframe, a series or a scalar. In addition the callable may take positional and keyword arguments.
- `args, kwargs` [tuple and dict] Optional positional and keyword arguments to pass to `func`.

**Returns**

- `applied` [Series or DataFrame]

**See also:**

- `pipe` Apply function to the full GroupBy object instead of to each group.
- `aggregate` Apply aggregate function to the GroupBy object.
- `transform` Apply function column-by-column to the GroupBy object.
- `Series.apply` Apply a function to a Series.
- `DataFrame.apply` Apply a function to each row or column of a DataFrame.
pandas.core.groupby.GroupBy.agg

GroupBy.**agg**(func, *args, **kwargs)

pandas.core.groupby.SeriesGroupBy.aggregate

SeriesGroupBy.**aggregate**(func=None, *args, engine=None, engine_kwargs=None, **kwargs)

Aggregate using one or more operations over the specified axis.

**Parameters**

- `func` [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a Series or when passed to Series.apply.
  
  Accepted combinations are:
  
  - function
  - string function name
  - list of functions and/or function names, e.g. [np.sum, 'mean']
  - dict of axis labels -> functions, function names or list of such.

  Can also accept a Numba JIT function with `engine='numba'` specified.

  If the `numba` engine is chosen, the function must be a user defined function with `values` and `index` as the first and second arguments respectively in the function signature. Each group’s index will be passed to the user defined function and optionally available for use.

  Changed in version 1.1.0.

- `*args` Positional arguments to pass to func

- `engine` [str, default None]
  
  - `cython`: Runs the function through C-extensions from cython.
  - `numba`: Runs the function through JIT compiled code from numba.
  - `None`: Defaults to `cython` or globally setting `compute.use_numba`

  New in version 1.1.0.

- `engine_kwargs` [dict, default None]
  
  - For `cython` engine, there are no accepted engine_kwargs
  - For `numba` engine, the engine can accept `nopython`, `nogil` and `parallel` dictionary keys. The values must either be `True` or `False`. The default `engine_kwargs` for the `numba` engine is `{ 'nopython': True, 'nogil': False, 'parallel': False }` and will be applied to the function

  New in version 1.1.0.

- `**kwargs` Keyword arguments to be passed into func.

**Returns**

Series

See also:

- `Series.groupby.apply`
- `Series.groupby.transform`

3.11. GroupBy 2233
**Series.aggregate**

**Notes**

When using `engine='numba'`, there will be no “fall back” behavior internally. The group data and group index will be passed as numpy arrays to the JITed user defined function, and no alternative execution attempts will be tried.

**Examples**

```python
>>> s = pd.Series([1, 2, 3, 4])
```

```text
0 1
1 2
2 3
3 4
dtype: int64
```

```python
>>> s.groupby([1, 1, 2, 2]).min()
```

```text
1 1
2 3
dtype: int64
```

```python
>>> s.groupby([1, 1, 2, 2]).agg('min')
```

```text
1 1
2 3
dtype: int64
```

```python
>>> s.groupby([1, 1, 2, 2]).agg(['min', 'max'])
```

```text
min max
1 1 2
2 3 4
```

The output column names can be controlled by passing the desired column names and aggregations as keyword arguments.

```python
>>> s.groupby([1, 1, 2, 2]).agg(
...     minimum='min',
...     maximum='max',
... )
```

```text
minimum maximum
1 1 2
2 3 4
```
DataFrameGroupBy.aggregate (func=None, *args, engine=None, engine_kwars=0, **kwargs)

Aggregate using one or more operations over the specified axis.

Parameters

- **func** [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a DataFrame or when passed to DataFrame.apply.

  Accepted combinations are:

  - function
  - string function name
  - list of functions and/or function names, e.g. [np.sum, 'mean']
  - dict of axis labels -> functions, function names or list of such.

  Can also accept a Numba JIT function with engine='numba' specified.

  If the 'numba' engine is chosen, the function must be a user defined function with values and index as the first and second arguments respectively in the function signature. Each group’s index will be passed to the user defined function and optionally available for use.

  Changed in version 1.1.0.

- **args** Positional arguments to pass to func

- **engine** [str, default None]

  - 'cython': Runs the function through C-extensions from cython.
  - 'numba': Runs the function through JIT compiled code from numba.
  - None: Defaults to 'cython' or globally setting compute.use_numba.

  New in version 1.1.0.

- **engine_kwars** [dict, default None]

  - For 'cython' engine, there are no accepted engine_kwars.
  - For 'numba' engine, the engine can accept nopython, nogil and parallel dictionary keys. The values must either be True or False. The default engine_kwars for the 'numba' engine is {'nopython': True, 'nogil': False, 'parallel': False} and will be applied to the function.

  New in version 1.1.0.

- **kwargs** Keyword arguments to be passed into func.

Returns

DataFrame

See also:

DataFrame.groupby.apply
DataFrame.groupby.transform
DataFrame.aggregate
Notes

When using engine='numba', there will be no “fall back” behavior internally. The group data and group index will be passed as numpy arrays to the JITed user defined function, and no alternative execution attempts will be tried.

Examples

```python
>>> df = pd.DataFrame(
...     {
...         "A": [1, 1, 2, 2],
...         "B": [1, 2, 3, 4],
...         "C": [0.362838, 0.227877, 1.267767, -0.562860],
...     }
... )

>>> df
  A  B     C
0  1  1  0.362838
1  1  2  0.227877
2  2  3  1.267767
3  2  4 -0.562860

The aggregation is for each column.

>>> df.groupby('A').agg('min')
     B     C
A
1  1  0.227877
2  3 -0.562860

Multiple aggregations

>>> df.groupby('A').agg(['min', 'max'])
        B     C
A  min max  min max
1  1  2  0.227877  0.362838
2  3  4 -0.562860  1.267767

Select a column for aggregation

>>> df.groupby('A').B.agg(['min', 'max'])
    min  max
A
1  1  2
2  3  4

Different aggregations per column

>>> df.groupby('A').agg({'B': ['min', 'max'], 'C': 'sum'})
     B     C
A  min max   sum
1  1  2  0.590715
2  3  4  0.704907
```
To control the output names with different aggregations per column, pandas supports “named aggregation”

```python
>>> df.groupby("A").agg(
...     b_min=pd.NamedAgg(column="B", aggfunc="min"),
...     c_sum=pd.NamedAgg(column="C", aggfunc="sum"))
```

```
b_min  c_sum
   A
1  1  0.590715
2  3  0.704907
```

- The keywords are the output column names
- The values are tuples whose first element is the column to select and the second element is the aggregation to apply to that column. Pandas provides the `pd.NamedAgg` namedtuple with the fields ['column', 'aggfunc'] to make it clearer what the arguments are. As usual, the aggregation can be a callable or a string alias.

See [Named aggregation](#) for more.

---

**pandas.core.groupby.SeriesGroupBy.transform**

`SeriesGroupBy.transform(func, *args, engine=None, engine_kwargs=None, **kwargs)`

Call function producing a like-indexed Series on each group and return a Series having the same indexes as the original object filled with the transformed values

**Parameters**

- `f` [function] Function to apply to each group.
  
  Can also accept a Numba JIT function with `engine='numba'` specified.

  If the 'numba' engine is chosen, the function must be a user defined function with `values` and `index` as the first and second arguments respectively in the function signature. Each group’s index will be passed to the user defined function and optionally available for use.

  Changed in version 1.1.0.

- `*args` Positional arguments to pass to func

- `engine` [str, default None]

  - 'cython': Runs the function through C-extensions from cython.
  
  - 'numba': Runs the function through JIT compiled code from numba.
  
  - None: Defaults to 'cython' or globally setting `compute.use_numba` New in version 1.1.0.

  `engine_kwargs` [dict, default None]

  - For 'cython' engine, there are no accepted `engine_kwargs`

  - For 'numba' engine, the engine can accept `nopython`, `nogil` and `parallel` dictionary keys. The values must either be `True` or `False`. The default `engine_kwargs` for the 'numba' engine is `{'nopython': True, 'nogil': False, 'parallel': False}` and will be applied to the function

    New in version 1.1.0.

- `**kwargs` Keyword arguments to be passed into func.
Returns

Series

See also:

Series.groupby.apply
Series.groupby.aggregate
Series.transform

Notes

Each group is endowed the attribute ‘name’ in case you need to know which group you are working on.

The current implementation imposes three requirements on f:

• f must return a value that either has the same shape as the input subframe or can be broadcast to the shape of the input subframe. For example, if f returns a scalar it will be broadcast to have the same shape as the input subframe.

• if this is a DataFrame, f must support application column-by-column in the subframe. If f also supports application to the entire subframe, then a fast path is used starting from the second chunk.

• f must not mutate groups. Mutation is not supported and may produce unexpected results.

When using engine='numba', there will be no “fall back” behavior internally. The group data and group index will be passed as numpy arrays to the JITed user defined function, and no alternative execution attempts will be tried.

Examples

```python
>>> df = pd.DataFrame({'A' : ['foo', 'bar', 'foo', 'bar',
... 'foo', 'bar'],
... 'B' : ['one', 'one', 'two', 'three',
... 'two', 'two'],
... 'C' : [1, 5, 5, 2, 5, 5],
... 'D' : [2.0, 5., 8., 1., 2., 9.]})
>>> grouped = df.groupby('A')
>>> grouped.transform(lambda x: (x - x.mean()) / x.std())
          C         D
0  0.115470  -0.577350
1  0.577350   0.000000
2  0.577350   1.154701
3 -0.115470  -1.000000
4  0.577350  -0.577350
5  0.577350   1.000000

Broadcast result of the transformation
```

```python
>>> grouped.transform(lambda x: x.max() - x.min())
          C         D
0   4.00000   6.00000
1   3.00000   8.00000
2   4.00000   6.00000
3   3.00000   8.00000
4   4.00000   6.00000
5   3.00000   8.00000
```
pandas.core.groupby.DataFrameGroupBy.transform

DataFrameGroupBy.transform(func, *args, engine=None, engine_kwars=None, **kwargs)

Call function producing a like-indexed DataFrame on each group and return a DataFrame having the same indexes as the original object filled with the transformed values.

Parameters

f [function] Function to apply to each group.

Can also accept a Numba JIT function with engine='numba' specified.

If the 'numba' engine is chosen, the function must be a user defined function with values and index as the first and second arguments respectively in the function signature. Each group’s index will be passed to the user defined function and optionally available for use.

Changed in version 1.1.0.

*args Positional arguments to pass to func

engine [str, default None]

- 'cython': Runs the function through C-extensions from cython.
- 'numba': Runs the function through JIT compiled code from numba.
- None: Defaults to 'cython' or globally setting compute.use_numba

New in version 1.1.0.

engine_kwars [dict, default None]

- For 'cython' engine, there are no accepted engine_kwars
- For 'numba' engine, the engine can accept nopython, nogil and parallel dictionary keys. The values must either be True or False. The default engine_kwars for the 'numba' engine is {'nopython': True, 'nogil': False, 'parallel': False} and will be applied to the function

New in version 1.1.0.

**kwargs Keyword arguments to be passed into func.

Returns

DataFrame

See also:

DataFrame.groupby.apply
DataFrame.groupby.aggregate
DataFrame.transform
Notes

Each group is endowed the attribute ‘name’ in case you need to know which group you are working on.

The current implementation imposes three requirements on f:

- f must return a value that either has the same shape as the input subframe or can be broadcast to the shape of the input subframe. For example, if f returns a scalar it will be broadcast to have the same shape as the input subframe.
- if this is a DataFrame, f must support application column-by-column in the subframe. If f also supports application to the entire subframe, then a fast path is used starting from the second chunk.
- f must not mutate groups. Mutation is not supported and may produce unexpected results.

When using engine='numba', there will be no “fall back” behavior internally. The group data and group index will be passed as numpy arrays to the JITed user defined function, and no alternative execution attempts will be tried.

Examples

```python
>>> df = pd.DataFrame({'A' : ['foo', 'bar', 'foo', 'bar', 'foo', 'bar'],
            'B' : ['one', 'one', 'two', 'three', 'two', 'two'],
            'C' : [1, 5, 5, 2, 5, 5],
            'D' : [2.0, 5., 8., 1., 2., 9.]})
```
```bash
>>> grouped = df.groupby('A')
>>> grouped.transform(lambda x: (x - x.mean()) / x.std())
```
```
   C       D
0 -1.154701 -0.577350
1  0.577350  0.000000
2  0.577350  1.154701
3 -1.154701 -1.000000
4  0.577350 -0.577350
5  0.577350  1.000000
```
Broadcast result of the transformation

```python
>>> grouped.transform(lambda x: x.max() - x.min())
```
```
   C  D
0  4  6.0
1  3  8.0
2  4  6.0
3  3  8.0
4  4  6.0
5  3  8.0
```

pandas.core.groupby.GroupBy.pipe

GroupBy.pipe(func, *args, **kwargs)

Apply a function `func` with arguments to this GroupBy object and return the function’s result.

New in version 0.21.0.

Use .pipe when you want to improve readability by chaining together functions that expect Series, DataFrames, GroupBy or Resampler objects. Instead of writing
You can write

```python
>>> (df.groupby('group')
... .pipe(f)
... .pipe(g, arg1=a)
... .pipe(h, arg2=b, arg3=c))
```

which is much more readable.

**Parameters**

- **func** [callable or tuple of (callable, str)] Function to apply to this GroupBy object or, alternatively, a (callable, data_keyword) tuple where data_keyword is a string indicating the keyword of callable that expects the GroupBy object.

- **args** [iterable, optional] Positional arguments passed into `func`.

- **kwargs** [dict, optional] A dictionary of keyword arguments passed into `func`.

**Returns**

- **object** [the return type of `func`]

**See also:**

- `Series.pipe` Apply a function with arguments to a series.
- `DataFrame.pipe` Apply a function with arguments to a dataframe.
- `apply` Apply function to each group instead of to the full GroupBy object.

**Notes**

See more here

**Examples**

```python
>>> df = pd.DataFrame({'A': 'a b a b'.split(), 'B': [1, 2, 3, 4]})
>>> df
   A  B
0  a  1
1  b  2
2  a  3
3  b  4
```

To get the difference between each groups maximum and minimum value in one pass, you can do

```python
>>> df.groupby('A').pipe(lambda x: x.max() - x.min())
```

```python
   B
A
a 2
b 2
```
### 3.11.3 Computations / descriptive stats

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>GroupBy.all([skipna])</code></td>
<td>Return True if all values in the group are truthful, else False.</td>
</tr>
<tr>
<td><code>GroupBy.any([skipna])</code></td>
<td>Return True if any value in the group is truthful, else False.</td>
</tr>
<tr>
<td><code>GroupBy.bfill([limit])</code></td>
<td>Backward fill the values.</td>
</tr>
<tr>
<td><code>GroupBy.backfill([limit])</code></td>
<td>Backward fill the values.</td>
</tr>
<tr>
<td><code>GroupBy.count()</code></td>
<td>Compute count of group, excluding missing values.</td>
</tr>
<tr>
<td><code>GroupBy.cumcount([ascending])</code></td>
<td>Number each item in each group from 0 to the length of that group - 1.</td>
</tr>
<tr>
<td><code>GroupBy.cummax([axis])</code></td>
<td>Cumulative max for each group.</td>
</tr>
<tr>
<td><code>GroupBy.cummin([axis])</code></td>
<td>Cumulative min for each group.</td>
</tr>
<tr>
<td><code>GroupBy.cumprod([axis])</code></td>
<td>Cumulative product for each group.</td>
</tr>
<tr>
<td><code>GroupBy.cumsum([axis])</code></td>
<td>Cumulative sum for each group.</td>
</tr>
<tr>
<td><code>GroupBy.ffill([limit])</code></td>
<td>Forward fill the values.</td>
</tr>
<tr>
<td><code>GroupBy.first([numeric_only, min_count])</code></td>
<td>Compute first of group values.</td>
</tr>
<tr>
<td><code>GroupBy.head([n])</code></td>
<td>Return first n rows of each group.</td>
</tr>
<tr>
<td><code>GroupBy.last([numeric_only, min_count])</code></td>
<td>Compute last of group values.</td>
</tr>
<tr>
<td><code>GroupBy.max([numeric_only, min_count])</code></td>
<td>Compute max of group values.</td>
</tr>
<tr>
<td><code>GroupBy.mean([numeric_only, min_count])</code></td>
<td>Compute mean of groups, excluding missing values.</td>
</tr>
<tr>
<td><code>GroupBy.median([numeric_only])</code></td>
<td>Compute median of groups, excluding missing values.</td>
</tr>
<tr>
<td><code>GroupBy.min([numeric_only, min_count])</code></td>
<td>Compute min of group values.</td>
</tr>
<tr>
<td><code>GroupBy.ngroup([ascending])</code></td>
<td>Number each group from 0 to the number of groups - 1.</td>
</tr>
<tr>
<td><code>GroupBy.nth(n, [dropna])</code></td>
<td>Take the nth row from each group if n is an int, or a subset of rows if n is a list of ints.</td>
</tr>
<tr>
<td><code>GroupBy.ohlc()</code></td>
<td>Compute open, high, low and close values of a group, excluding missing values.</td>
</tr>
<tr>
<td><code>GroupBy.pad([limit])</code></td>
<td>Forward fill the values.</td>
</tr>
<tr>
<td><code>GroupBy.prod([numeric_only, min_count])</code></td>
<td>Compute prod of group values.</td>
</tr>
<tr>
<td><code>GroupBy.rank([method, ascending, na_option, ...])</code></td>
<td>Provide the rank of values within each group.</td>
</tr>
<tr>
<td><code>GroupBy.pct_change([periods, fill_method, ...])</code></td>
<td>Calculate pct_change of each value to previous entry in group.</td>
</tr>
<tr>
<td><code>GroupBy.size()</code></td>
<td>Compute group sizes.</td>
</tr>
<tr>
<td><code>GroupBy.sem([ddof])</code></td>
<td>Compute standard error of the mean of groups, excluding missing values.</td>
</tr>
<tr>
<td><code>GroupBy.std([ddof])</code></td>
<td>Compute standard deviation of groups, excluding missing values.</td>
</tr>
<tr>
<td><code>GroupBy.sum([numeric_only, min_count])</code></td>
<td>Compute sum of group values.</td>
</tr>
<tr>
<td><code>GroupBy.var([ddof])</code></td>
<td>Compute variance of groups, excluding missing values.</td>
</tr>
<tr>
<td><code>GroupBy.tail([n])</code></td>
<td>Return last n rows of each group.</td>
</tr>
</tbody>
</table>
pandas.core.groupby.GroupBy.all

GroupBy.all (skipna=True)
Return True if all values in the group are truthful, else False.
Parameters
    skipna   [bool, default True] Flag to ignore nan values during truth testing.
Returns
    bool
See also:
    Series.groupby
    DataFrame.groupby

pandas.core.groupby.GroupBy.any

GroupBy.any (skipna=True)
Return True if any value in the group is truthful, else False.
Parameters
    skipna   [bool, default True] Flag to ignore nan values during truth testing.
Returns
    bool
See also:
    Series.groupby
    DataFrame.groupby

pandas.core.groupby.GroupBy.bfill

GroupBy.bfill (limit=None)
Backward fill the values.
Parameters
    limit   [int, optional] Limit of how many values to fill.
Returns
    Series or DataFrame Object with missing values filled.
See also:
    Series.backfill
    DataFrame.backfill
    Series.fillna
    DataFrame.fillna
pandas.core.groupby.GroupBy.backfill

GroupBy.backfill(limit=None)

Backward fill the values.

Parameters

limit [int, optional] Limit of how many values to fill.

Returns

Series or DataFrame Object with missing values filled.

See also:

Series.backfill
DataFrame.backfill
Series.fillna
DataFrame.fillna

pandas.core.groupby.GroupBy.count

GroupBy.count()

Compute count of group, excluding missing values.

Returns

Series or DataFrame Count of values within each group.

See also:

Series.groupby
DataFrame.groupby

pandas.core.groupby.GroupBy.cumcount

GroupBy.cumcount(ascending=True)

Number each item in each group from 0 to the length of that group - 1.

Essentially this is equivalent to

```python
self.apply(lambda x: pd.Series(np.arange(len(x)), x.index))
```

Parameters

ascending [bool, default True] If False, number in reverse, from length of group - 1 to 0.

Returns

Series Sequence number of each element within each group.

See also:

ngroup Number the groups themselves.
Examples

```python
>>> df = pd.DataFrame([['a'], ['a'], ['a'], ['b'], ['b'], ['a']],
                   columns=['A'])
>>> df
   A
0  a
1  a
2  a
3  b
4  b
5  a
>>> df.groupby('A').cumcount()
   0  1  2  3  4  5
0  0  1  2  3  4  5
1  0  0  1  2  3  4
2  1  2  3  0  1  0
3  0  1  0  1  4  3
dtype: int64
>>> df.groupby('A').cumcount(ascending=False)
   0  1  2  3  4  5
0  3  2  1  1  0  0
1  0  1  2  3  0  4
2  0  1  3  1  2  1
3  0  0  3  4  5  5
dtype: int64
```

`pandas.core.groupby.GroupBy.cummax`

GroupBy.cummax(axis=0, **kwargs)
Cumulative max for each group.

Returns
Series or DataFrame

See also:
Series.groupby
DataFrame.groupby

`pandas.core.groupby.GroupBy.cummin`

GroupBy.cummin(axis=0, **kwargs)
Cumulative min for each group.

Returns
Series or DataFrame

See also:
Series.groupby
DataFrame.groupby
pandas.core.groupby.GroupBy.cumprod

GroupBy.cumprod(axis=0, *args, **kwargs)
Cumulative product for each group.

Returns
Series or DataFrame

See also:
Series.groupby
DataFrame.groupby

pandas.core.groupby.GroupBy.cumsum

GroupBy.cumsum(axis=0, *args, **kwargs)
Cumulative sum for each group.

Returns
Series or DataFrame

See also:
Series.groupby
DataFrame.groupby

pandas.core.groupby.GroupBy.ffill

GroupBy.ffill(limit=None)
Forward fill the values.

Parameters

limit [int, optional] Limit of how many values to fill.

Returns
Series or DataFrame Object with missing values filled.

See also:
Series.pad
DataFrame.pad
Series.fillna
DataFrame.fillna

pandas.core.groupby.GroupBy.first

GroupBy.first(numeric_only=False, min_count=-1)
Compute first of group values.

Parameters

numeric_only [bool, default False] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

min_count [int, default -1] The required number of valid values to perform the operation. If fewer than min_count non-NA values are present the result will be NA.

Returns
Series or DataFrame Computed first of values within each group.
**pandas.core.groupby.GroupBy.head**

GroupBy.**head**(n=5)

Return first n rows of each group.

Similar to .apply(lambda x: x.head(n)), but it returns a subset of rows from the original DataFrame with original index and order preserved (as_index flag is ignored).

Does not work for negative values of n.

**Returns**

Series or DataFrame

See also:

*Series.groupby*
*DataFrame.groupby*

**Examples**

```python
def = pd.DataFrame([[1, 2], [1, 4], [5, 6]],
                   columns=['A', 'B'])
def.groupby('A').head(1)
A  B
0 1 2
2 5 6
def.groupby('A').head(-1)
Empty DataFrame
Columns: [A, B]
Index: []
```

**pandas.core.groupby.GroupBy.last**

GroupBy.**last**(numeric_only=False, min_count=-1)

Compute last of group values.

**Parameters**

- **numeric_only** [bool, default False] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

- **min_count** [int, default -1] The required number of valid values to perform the operation. If fewer than min_count non-NA values are present the result will be NA.

**Returns**

Series or DataFrame  Computed last of values within each group.

**pandas.core.groupby.GroupBy.max**

GroupBy.**max**(numeric_only=False, min_count=-1)

Compute max of group values.

**Parameters**

- **numeric_only** [bool, default False] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

- **min_count** [int, default -1] The required number of valid values to perform the operation. If fewer than min_count non-NA values are present the result will be NA.
**pandas: powerful Python data analysis toolkit, Release 1.1.1**

**Returns**

**Series or DataFrame** Computed max of values within each group.

**pandas.core.groupby.GroupBy.mean**

```python
groupby.mean(numeric_only=True)
```

Compute mean of groups, excluding missing values.

**Parameters**

- **numeric_only** [bool, default True] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

**Returns**

**pandas.Series or pandas.DataFrame**

**See also:**

- **Series.groupby**
- **DataFrame.groupby**

**Examples**

```python
def pd.DataFrame({'A': [1, 1, 2, 1, 2],
                 'B': [np.nan, 2, 3, 4, 5],
                 'C': [1, 2, 1, 1, 2]}, columns=['A', 'B', 'C'])
```

Groupby one column and return the mean of the remaining columns in each group.

```python
def.groupby('A').mean()
```

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3.0</td>
<td>1.333333</td>
</tr>
<tr>
<td>2</td>
<td>4.0</td>
<td>1.500000</td>
</tr>
</tbody>
</table>

Groupby two columns and return the mean of the remaining column.

```python
def.groupby(['A', 'B']).mean()
```

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2.0</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>4.0</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>3.0</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>5.0</td>
<td>2</td>
</tr>
</tbody>
</table>

Groupby one column and return the mean of only particular column in the group.

```python
def.groupby('A')['B'].mean()
```

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3.0</td>
</tr>
<tr>
<td>2</td>
<td>4.0</td>
</tr>
</tbody>
</table>

Name: B, dtype: float64
pandas.core.groupby.GroupBy.median

GroupBy.median(numeric_only=True)
Compute median of groups, excluding missing values.

For multiple groupings, the result index will be a MultiIndex

Parameters

numeric_only [bool, default True] Include only float, int, boolean columns. If None, will
attempt to use everything, then use only numeric data.

Returns

Series or DataFrame Median of values within each group.

See also:
Series.groupby
DataFrame.groupby

pandas.core.groupby.GroupBy.min

GroupBy.min(numeric_only=False, min_count=-1)
Compute min of group values.

Parameters

numeric_only [bool, default False] Include only float, int, boolean columns. If None, will
attempt to use everything, then use only numeric data.

min_count [int, default -1] The required number of valid values to perform the operation. If
fewer than min_count non-NA values are present the result will be NA.

Returns

Series or DataFrame Computed min of values within each group.

pandas.core.groupby.GroupBy.ngroup

GroupBy.ngroup(ascending=True)
Number each group from 0 to the number of groups - 1.

This is the enumerative complement of cumcount. Note that the numbers given to the groups match the order in
which the groups would be seen when iterating over the groupby object, not the order they are first observed.

Parameters

ascending [bool, default True] If False, number in reverse, from number of group - 1 to 0.

Returns

Series Unique numbers for each group.

See also:
cumcount Number the rows in each group.
Examples

```python
>>> df = pd.DataFrame({'A': list('aaabba'))
>>> df
   A
0  a  0
1  a  0
2  a  0
3  b  1
4  b  1
5  a  0
>>> df.groupby('A').ngroup()
0 0
1 0
2 0
3 1
4 1
5 0
dtype: int64
>>> df.groupby('A').ngroup(ascending=False)
0 1
1 1
2 1
3 0
4 0
5 1
dtype: int64
>>> df.groupby(["A", [1,1,2,3,2,1]]).ngroup()
0 0
1 0
2 1
3 3
4 2
5 0
dtype: int64
```

**pandas.core.groupby.GroupBy.nth**

`GroupBy.nth(n, dropna=None)`

Take the nth row from each group if n is an int, or a subset of rows if n is a list of ints.

If dropna, will take the nth non-null row, dropna is either `all` or `any`; this is equivalent to calling `dropna(how=dropna)` before the groupby.

**Parameters**

- **n** [int or list of ints] A single nth value for the row or a list of nth values.
- **dropna** [None or str, optional] Apply the specified dropna operation before counting which row is the nth row. Needs to be None, ‘any’ or ‘all’.

**Returns**

- `Series or DataFrame` N-th value within each group.

**See also**:

- `Series.groupby`
- `DataFrame.groupby`
Examples

```python
>>> df = pd.DataFrame({'A': [1, 1, 2, 1, 2],
                     'B': [np.nan, 2, 3, 4, 5]}, columns=['A', 'B'])
>>> g = df.groupby('A')
>>> g.nth(0)
   B
A
1  NaN
2  3.0
>>> g.nth(1)
   B
A
1  2.0
2  5.0
>>> g.nth(-1)
   B
A
1  4.0
2  5.0
>>> g.nth([0, 1])
   B
A
1  NaN
1  2.0
2  3.0
2  5.0
```

Specifying `dropna` allows count ignoring NaN

```python
>>> g.nth(0, dropna='any')
   B
A
1  2.0
2  3.0
```

NaNs denote group exhausted when using dropna

```python
>>> g.nth(3, dropna='any')
   B
A
1  NaN
1  NaN
```

Specifying `as_index=False` in `groupby` keeps the original index.

```python
>>> df.groupby('A', as_index=False).nth(1)
   A  B
1  1  2.0
4  2  5.0
```
pandas.core.groupby.GroupBy.ohlc

GroupBy.ohlc()
Compute open, high, low and close values of a group, excluding missing values.

For multiple groupings, the result index will be a MultiIndex

Returns

DataFrame Open, high, low and close values within each group.

See also:
Series.groupby
DataFrame.groupby

pandas.core.groupby.GroupBy.pad

GroupBy.pad(limit=None)
Forward fill the values.

Parameters

limit [int, optional] Limit of how many values to fill.

Returns

Series or DataFrame Object with missing values filled.

See also:
Series.pad
DataFrame.pad
Seriesfillna
DataFrame.fillna

pandas.core.groupby.GroupBy.prod

GroupBy.prod(numeric_only=True, min_count=0)
Compute prod of group values.

Parameters

numeric_only [bool, default True] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

min_count [int, default 0] The required number of valid values to perform the operation. If fewer than min_count non-NA values are present the result will be NA.

Returns

Series or DataFrame Computed prod of values within each group.
pandas.core.groupby.GroupBy.rank

GroupBy.rank (method='average', ascending=True, na_option='keep', pct=False, axis=0)
Provide the rank of values within each group.

Parameters

- **method** [(‘average’, ‘min’, ‘max’, ‘first’, ‘dense’), default ‘average’]
  - average: average rank of group.
  - min: lowest rank in group.
  - max: highest rank in group.
  - first: ranks assigned in order they appear in the array.
  - dense: like ‘min’, but rank always increases by 1 between groups.

- **ascending** [bool, default True] False for ranks by high (1) to low (N).

- **na_option** [{‘keep’, ‘top’, ‘bottom’}, default ‘keep’]
  - keep: leave NA values where they are.
  - top: smallest rank if ascending.
  - bottom: smallest rank if descending.

- **pct** [bool, default False] Compute percentage rank of data within each group.

- **axis** [int, default 0] The axis of the object over which to compute the rank.

Returns

- DataFrame with ranking of values within each group

See also:

- Series.groupby
- DataFrame.groupby

pandas.core.groupby.GroupBy.pct_change

GroupBy.pct_change (periods=1, fill_method='pad', limit=None, freq=None, axis=0)
Calculate pct_change of each value to previous entry in group.

Returns

- Series or DataFrame Percentage changes within each group.

See also:

- Series.groupby
- DataFrame.groupby
pandas.core.groupby.GroupBy.size

GroupBy.size()
Compute group sizes.
Returns
DataFrame or Series Number of rows in each group as a Series if as_index is True or a
DataFrame if as_index is False.
See also:
Series.groupby
DataFrame.groupby

pandas.core.groupby.GroupBy.sem

GroupBy.sem(ddof=1)
Compute standard error of the mean of groups, excluding missing values.
For multiple groupings, the result index will be a MultiIndex.
Parameters
ddf [int, default 1] Degrees of freedom.
Returns
Series or DataFrame Standard error of the mean of values within each group.
See also:
Series.groupby
DataFrame.groupby

pandas.core.groupby.GroupBy.std

GroupBy.std(ddof=1)
Compute standard deviation of groups, excluding missing values.
For multiple groupings, the result index will be a MultiIndex.
Parameters
ddf [int, default 1] Degrees of freedom.
Returns
Series or DataFrame Standard deviation of values within each group.
See also:
Series.groupby
DataFrame.groupby
pandas.core.groupby.GroupBy.sum

GroupBy.sum(numeric_only=True, min_count=0)
Compute sum of group values.

Parameters

numeric_only [bool, default True] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

min_count [int, default 0] The required number of valid values to perform the operation. If fewer than min_count non-NA values are present the result will be NA.

Returns

Series or DataFrame Computed sum of values within each group.

pandas.core.groupby.GroupBy.var

GroupBy.var(ddof=1)
Compute variance of groups, excluding missing values.
For multiple groupings, the result index will be a MultiIndex.

Parameters

ddof [int, default 1] Degrees of freedom.

Returns

Series or DataFrame Variance of values within each group.

See also:
Series.groupby
DataFrame.groupby

pandas.core.groupby.GroupBy.tail

GroupBy.tail(n=5)
Return last n rows of each group.
Similar to .apply(lambda x: x.tail(n)), but it returns a subset of rows from the original DataFrame with original index and order preserved (as_index flag is ignored).
Does not work for negative values of n.

Returns

Series or DataFrame

See also:
Series.groupby
DataFrame.groupby
Examples

```python
>>> df = pd.DataFrame([['a', 1], ['a', 2], ['b', 1], ['b', 2]], columns=['A', 'B'])
>>> df.groupby('A').tail(1)
   A  B
1 a  2
3 b  2
>>> df.groupby('A').tail(-1)
Empty DataFrame
Columns: [A, B]
Index: []
```

The following methods are available in both `SeriesGroupBy` and `DataFrameGroupBy` objects, but may differ slightly, usually in that the `DataFrameGroupBy` version usually permits the specification of an axis argument, and often an argument indicating whether to restrict application to columns of a specific data type.

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>DataFrameGroupBy.all([skipna])</code></td>
<td>Return True if all values in the group are truthful, else False.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.any([skipna])</code></td>
<td>Return True if any value in the group is truthful, else False.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.backfill([limit])</code></td>
<td>Backward fill the values.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.bfill([limit])</code></td>
<td>Backward fill the values.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.corr</code></td>
<td>Compute pairwise correlation of columns, excluding NA/null values.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.count()</code></td>
<td>Compute count of group, excluding missing values.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.cov</code></td>
<td>Compute pairwise covariance of columns, excluding NA/null values.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.cumcount([ascending])</code></td>
<td>Number each item in each group from 0 to the length of that group - 1.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.cummax([axis])</code></td>
<td>Cumulative max for each group.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.cummin([axis])</code></td>
<td>Cumulative min for each group.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.cumprod([axis])</code></td>
<td>Cumulative product for each group.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.cumsum([axis])</code></td>
<td>Cumulative sum for each group.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.describe(**kwargs)</code></td>
<td>Generate descriptive statistics.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.diff</code></td>
<td>First discrete difference of element.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.ffill([limit])</code></td>
<td>Forward fill the values.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.fillna(**kwargs)</code></td>
<td>Fill NA/NaN values using the specified method.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.filter(func[, dropna])</code></td>
<td>Return a copy of a DataFrame excluding filtered elements.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.hist</code></td>
<td>Make a histogram of the DataFrame’s.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.idxmax</code></td>
<td>Return index of first occurrence of maximum over requested axis.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.idxmin</code></td>
<td>Return index of first occurrence of minimum over requested axis.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.mad</code></td>
<td>Return the mean absolute deviation of the values for the requested axis.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.nunique([dropna])</code></td>
<td>Return DataFrame with counts of unique elements in each position.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.pad([limit])</code></td>
<td>Forward fill the values.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.pct_change([periods, . . . ])</code></td>
<td>Calculate pct_change of each value to previous entry in group.</td>
</tr>
</tbody>
</table>

continues on next page
Table 373 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>DataFrameGroupBy.plot</code></td>
<td>Class implementing the <code>.plot</code> attribute for groupby objects.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.quantile([q, interpolation])</code></td>
<td>Return group values at the given quantile, a la <code>numpy.percentile</code>.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.rank([method, ascending, ...])</code></td>
<td>Provide the rank of values within each group.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.resample(rule, *args, **kwargs)</code></td>
<td>Provide resampling when using a <code>TimeGrouper</code>.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.sample([n, frac, replace, ...])</code></td>
<td>Return a random sample of items from each group.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.shift([periods, freq, ...])</code></td>
<td>Shift each group by periods observations.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.size()</code></td>
<td>Compute group sizes.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.skew</code></td>
<td>Return unbiased skew over requested axis.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.take</code></td>
<td>Return the elements in the given positional indices along an axis.</td>
</tr>
<tr>
<td><code>DataFrameGroupBy.tshift</code></td>
<td>(DEPRECATED) Shift the time index, using the index’s frequency if available.</td>
</tr>
</tbody>
</table>

### `pandas.core.groupby.DataFrameGroupBy.all`

**DataFrameGroupBy.all** *(skipna=True)*

Return True if all values in the group are truthful, else False.

**Parameters**

- `skipna` [bool, default True] Flag to ignore nan values during truth testing.

**Returns**

- `bool` |

See also:

- `Series.groupby`
- `DataFrame.groupby`

### `pandas.core.groupby.DataFrameGroupBy.any`

**DataFrameGroupBy.any** *(skipna=True)*

Return True if any value in the group is truthful, else False.

**Parameters**

- `skipna` [bool, default True] Flag to ignore nan values during truth testing.

**Returns**

- `bool` |

See also:

- `Series.groupby`
- `DataFrame.groupby`
pandas.core.groupby.DataFrameGroupBy.backfill

DataFrameGroupBy.backfill(limit=None)
Backward fill the values.

Parameters

- limit [int, optional] Limit of how many values to fill.

Returns

Series or DataFrame Object with missing values filled.

See also:
Series.backfill
DataFrame.backfill
Series.fillna
DataFrame.fillna

pandas.core.groupby.DataFrameGroupBy.bfill

DataFrameGroupBy.bfill(limit=None)
Backward fill the values.

Parameters

- limit [int, optional] Limit of how many values to fill.

Returns

Series or DataFrame Object with missing values filled.

See also:
Series.backfill
DataFrame.backfill
Series.fillna
DataFrame.fillna

pandas.core.groupby.DataFrameGroupBy.corr

property DataFrameGroupBy.corr
Compute pairwise correlation of columns, excluding NA/null values.

Parameters

- method [{‘pearson’, ‘kendall’, ‘spearman’} or callable] Method of correlation:
  - pearson : standard correlation coefficient
  - kendall : Kendall Tau correlation coefficient
  - spearman : Spearman rank correlation
  - callable: callable with input two 1d ndarrays and returning a float. Note that the returned matrix from corr will have 1 along the diagonals and will be symmetric regardless of the callable’s behavior.

New in version 0.24.0.

- min_periods [int, optional] Minimum number of observations required per pair of columns to have a valid result. Currently only available for Pearson and Spearman correlation.

Returns
DataFrame  Correlation matrix.

See also:
DataFrame.corrwith  Compute pairwise correlation with another DataFrame or Series.
Series.corr  Compute the correlation between two Series.

Examples

```python
>>> def histogram_intersection(a, b):
...     v = np.minimum(a, b).sum().round(decimals=1)
...     return v
...>
>>> df = pd.DataFrame([(0.2, 0.3), (0.0, 0.6), (0.6, 0.0), (0.2, 0.1)],
...                     columns=['dogs', 'cats'])
...>
>>> df.corr(method=histogram_intersection)
     dogs   cats
dogs  1.0  0.3
cats  0.3  1.0
```

pandas.core.groupby.DataFrameGroupBy.count

DataFrameGroupBy.count()  
Compute count of group, excluding missing values.

Returns
DataFrame  Count of values within each group.

pandas.core.groupby.DataFrameGroupBy.cov

property DataFrameGroupBy.cov  
Compute pairwise covariance of columns, excluding NA/null values.

Compute the pairwise covariance among the series of a DataFrame. The returned data frame is the covariance matrix of the columns of the DataFrame.

Both NA and null values are automatically excluded from the calculation. (See the note below about bias from missing values.) A threshold can be set for the minimum number of observations for each value created. Comparisons with observations below this threshold will be returned as NaN.

This method is generally used for the analysis of time series data to understand the relationship between different measures across time.

Parameters

min_periods  [int, optional] Minimum number of observations required per pair of columns to have a valid result.

ddf  [int, default 1] Delta degrees of freedom. The divisor used in calculations is \( N - \) ddf, where \( N \) represents the number of elements.

New in version 1.1.0.

Returns
DataFrame  The covariance matrix of the series of the DataFrame.

See also:
Series.cov  Compute covariance with another Series.
core.window.ExponentialMovingWindow.cov  Exponential weighted sample covariance.
**Notes**

Returns the covariance matrix of the DataFrame’s time series. The covariance is normalized by N-ddof.

For DataFrames that have Series that are missing data (assuming that data is missing at random) the returned covariance matrix will be an unbiased estimate of the variance and covariance between the member Series.

However, for many applications this estimate may not be acceptable because the estimate covariance matrix is not guaranteed to be positive semi-definite. This could lead to estimate correlations having absolute values which are greater than one, and/or a non-invertible covariance matrix. See Estimation of covariance matrices for more details.

**Examples**

```python
>>> df = pd.DataFrame([(1, 2), (0, 3), (2, 0), (1, 1)],
                   columns=['dogs', 'cats'])
```

```output
dogs  cats
dogs 0.666667 -1.000000
cats -1.000000 1.666667
```

```python
>>> np.random.seed(42)
```

```python
>>> df = pd.DataFrame(np.random.randn(1000, 5),
                   columns=['a', 'b', 'c', 'd', 'e'])
```

```output
a b c d e
0.998438 -0.020161 0.059277 -0.008943 0.014144
-0.020161 1.059352 -0.008543 -0.024738 0.009826
0.059277 -0.008543 1.010670 -0.001486 -0.000271
-0.008943 -0.024738 -0.001486 0.921297 -0.013692
0.014144 0.009826 -0.000271 -0.013692 0.977795
```

**Minimum number of periods**

This method also supports an optional `min_periods` keyword that specifies the required minimum number of non-NA observations for each column pair in order to have a valid result:

```python
>>> np.random.seed(42)
```

```python
>>> df = pd.DataFrame(np.random.randn(20, 3),
                   columns=['a', 'b', 'c'])
```

```python
>>> df.loc[df.index[:5], 'a'] = np.nan
>>> df.loc[df.index[5:10], 'b'] = np.nan
```

```python
>>> df.cov(min_periods=12)
```

```output
a b c
a 0.316741 NaN -0.150812
b NaN 1.248003 0.191417
c -0.150812 0.191417 0.895202
```
### DataFrameGroupBy.cumcount

DataFrameGroupBy.cumcount(ascending=True)

Number each item in each group from 0 to the length of that group - 1.

Essentially this is equivalent to

```python
self.apply(lambda x: pd.Series(np.arange(len(x)), x.index))
```

**Parameters**

- **ascending** [bool, default True] If False, number in reverse, from length of group - 1 to 0.

**Returns**

- **Series** Sequence number of each element within each group.

**See also:**

- `ngroup` Number the groups themselves.

**Examples**

```python
>>> df = pd.DataFrame([[a], [a], [a], [b], [b], [a]],
                    columns=['A'])
>>> df
   A
0  a
1  a
2  a
3  b
4  b
5  a
>>> df.groupby('A').cumcount()
0  0
1  1
2  2
3  0
4  1
5  3
```

```python
>>> df.groupby('A').cumcount(ascending=False)
0  3
1  2
2  1
3  1
4  0
5  0
```

...
pandas.core.groupby.DataFrameGroupBy.cummax

DataFrameGroupBy.cummax(axis=0, **kwargs)
Cumulative max for each group.
Returns
Series or DataFrame
See also:
Series.groupby
DataFrame.groupby

pandas.core.groupby.DataFrameGroupBy.cummin

DataFrameGroupBy.cummin(axis=0, **kwargs)
Cumulative min for each group.
Returns
Series or DataFrame
See also:
Series.groupby
DataFrame.groupby

pandas.core.groupby.DataFrameGroupBy.cumprod

DataFrameGroupBy.cumprod(axis=0, *args, **kwargs)
Cumulative product for each group.
Returns
Series or DataFrame
See also:
Series.groupby
DataFrame.groupby

pandas.core.groupby.DataFrameGroupBy.cumsum

DataFrameGroupBy.cumsum(axis=0, *args, **kwargs)
Cumulative sum for each group.
Returns
Series or DataFrame
See also:
Series.groupby
DataFrame.groupby
pandas.core.groupby.DataFrameGroupBy.describe

`DataFrameGroupBy.describe(**kwargs)`

Generate descriptive statistics.

Descriptive statistics include those that summarize the central tendency, dispersion and shape of a dataset's distribution, excluding NaN values.

Analyzes both numeric and object series, as well as DataFrame column sets of mixed data types. The output will vary depending on what is provided. Refer to the notes below for more detail.

**Parameters**

- **percentiles** [list-like of numbers, optional] The percentiles to include in the output. All should fall between 0 and 1. The default is [.25, .5, .75], which returns the 25th, 50th, and 75th percentiles.

- **include** ['all', list-like of dtypes or None (default), optional] A white list of data types to include in the result. Ignored for Series. Here are the options:
  - 'all': All columns of the input will be included in the output.
  - A list-like of dtypes: Limits the results to the provided data types. To limit the result to numeric types submit `numpy.number`. To limit it instead to object columns submit the `numpy.object` data type. Strings can also be used in the style of `select_dtypes` (e.g. `df.describe(include=['O'])`). To select pandas categorical columns, use 'category'
  - None (default): The result will include all numeric columns.

- **exclude** [list-like of dtypes or None (default), optional] A black list of data types to omit from the result. Ignored for Series. Here are the options:
  - A list-like of dtypes: Excludes the provided data types from the result. To exclude numeric types submit `numpy.number`. To exclude object columns submit the data type `numpy.object`. Strings can also be used in the style of `select_dtypes` (e.g. `df.describe(include=['O'])`). To exclude pandas categorical columns, use 'category'
  - None (default): The result will exclude nothing.

- **datetime_is_numeric** [bool, default False] Whether to treat datetime dtypes as numeric. This affects statistics calculated for the column. For DataFrame input, this also controls whether datetime columns are included by default.

New in version 1.1.0.

**Returns**

Series or DataFrame Summary statistics of the Series or DataFrame provided.

**See also:**

- `DataFrame.count` Count number of non-NA/null observations.
- `DataFrame.max` Maximum of the values in the object.
- `DataFrame.min` Minimum of the values in the object.
- `DataFrame.mean` Mean of the values in the object.
- `DataFrame.std` Standard deviation of the observations.
- `DataFrame.select_dtypes` Subset of a DataFrame including/excluding columns based on their dtype.
Notes

For numeric data, the result’s index will include count, mean, std, min, max as well as lower, 50 and upper percentiles. By default the lower percentile is 25 and the upper percentile is 75. The 50 percentile is the same as the median.

For object data (e.g. strings or timestamps), the result’s index will include count, unique, top, and freq. The top is the most common value. The freq is the most common value’s frequency. Timestamps also include the first and last items.

If multiple object values have the highest count, then the count and top results will be arbitrarily chosen from among those with the highest count.

For mixed data types provided via a DataFrame, the default is to return only an analysis of numeric columns. If the dataframe consists only of object and categorical data without any numeric columns, the default is to return an analysis of both the object and categorical columns. If include='all' is provided as an option, the result will include a union of attributes of each type.

The include and exclude parameters can be used to limit which columns in a DataFrame are analyzed for the output. The parameters are ignored when analyzing a Series.

Examples

Describing a numeric Series.

```python
>>> s = pd.Series([1, 2, 3])
>>> s.describe()
count 3.0
mean 2.0
std 1.0
min 1.0
25% 1.5
50% 2.0
75% 2.5
max 3.0
dtype: float64
```

Describing a categorical Series.

```python
>>> s = pd.Series(['a', 'a', 'b', 'c'])
>>> s.describe()
count 4
unique 3
top a
freq 2
dtype: object
```

Describing a timestamp Series.

```python
>>> s = pd.Series([...
...   np.datetime64("2000-01-01"),
...   np.datetime64("2010-01-01"),
...   np.datetime64("2010-01-01")
... ])
>>> s.describe(datetime_is_numeric=True)
count 3
mean 2006-09-01 08:00:00
```

(continues on next page)
Describing a DataFrame. By default only numeric fields are returned.

```python
>>> df = pd.DataFrame({'categorical': pd.Categorical(['d','e','f']),
                      'numeric': [1, 2, 3],
                      'object': ['a', 'b', 'c']})
```

```python
>>> df.describe()
```

```
          numeric
count     3.0
mean      2.0
std       1.0
min       1.0
25%       1.5
50%       2.0
75%       2.5
max       3.0
```

Describing all columns of a DataFrame regardless of data type.

```python
>>> df.describe(include='all')
```

```
          categorical  numeric      object
count        3.0       3.0       3.0
unique       3.0       NaN       3.0
top           f         NaN       a
freq         1.0       NaN       1.0
mean        NaN       2.0       NaN
std        NaN       1.0       NaN
min        NaN       1.0       NaN
25%        NaN       1.5       NaN
50%        NaN       2.0       NaN
75%        NaN       2.5       NaN
max        NaN       3.0       NaN
```

Describing a column from a DataFrame by accessing it as an attribute.

```python
>>> df.numeric.describe()
```

```
          numeric
count     3.0
mean      2.0
std       1.0
min       1.0
25%       1.5
50%       2.0
75%       2.5
max       3.0
Name: numeric, dtype: float64
```

Including only numeric columns in a DataFrame description.

```python
>>> df.describe(include=[np.number])
```

(continues on next page)
Including only string columns in a DataFrame description.

```python
>>> df.describe(include=['object'])
  object
 count  3
 unique  3
  top a
  freq  1
```

Including only categorical columns from a DataFrame description.

```python
>>> df.describe(include=['category'])
  categorical
 count  3
 unique  3
  top f
  freq  1
```

Excluding numeric columns from a DataFrame description.

```python
>>> df.describe(exclude=[np.number])
  categorical  object
 count      3   3
 unique      3   3
  top       f   a
  freq      1   1
```

Excluding object columns from a DataFrame description.

```python
>>> df.describe(exclude=['object'])
  categorical   numeric
 count        3   3.0
 unique       3   NaN
  top         f   NaN
  freq        1   NaN
 mean         NaN  2.0
 std          NaN  1.0
 min          NaN  1.0
 25%          NaN  1.5
 50%          NaN  2.0
 75%          NaN  2.5
 max          NaN  3.0
```
pandas.core.groupby.DataFrameGroupBy.diff

**property DataFrameGroupBy.diff**

First discrete difference of element.

Calculates the difference of a Dataframe element compared with another element in the Dataframe (default is element in previous row).

**Parameters**

- **periods** [int, default 1] Periods to shift for calculating difference, accepts negative values.
- **axis** [[0 or ‘index’, 1 or ‘columns’], default 0] Take difference over rows (0) or columns (1).

**Returns**

- **DataFrame** First differences of the Series.

**See also:**
- `DataFrame.pct_change` Percent change over given number of periods.
- `DataFrame.shift` Shift index by desired number of periods with an optional time freq.
- `Series.diff` First discrete difference of object.

**Notes**

For boolean dtypes, this uses `operator.xor()` rather than `operator.sub()`. The result is calculated according to current dtype in Dataframe, however dtype of the result is always float64.

**Examples**

**Difference with previous row**

```python
>>> df = pd.DataFrame({'a': [1, 2, 3, 4, 5, 6],
... 'b': [1, 1, 2, 3, 5, 8],
... 'c': [1, 4, 9, 16, 25, 36]})

>>> df
   a  b  c
0  1  1  1
1  2  1  4
2  3  2  9
3  4  3 16
4  5  5 25
5  6  8 36

>>> df.diff()
   a  b  c
0  NaN NaN NaN
1  1.0  0.0  3.0
2  1.0  1.0  5.0
3  1.0  1.0  7.0
4  1.0  2.0  9.0
5  1.0  3.0 11.0
```

**Difference with previous column**

```python
>>> df.diff(axis=1)
   a  b  c
0  NaN NaN NaN
1  0.0  0.0  3.0
2  1.0  1.0  5.0
3  1.0  1.0  7.0
4  1.0  2.0  9.0
5  1.0  3.0 11.0
```

(continues on next page)
1 NaN -1.0 3.0
2 NaN -1.0 7.0
3 NaN -1.0 13.0
4 NaN 0.0 20.0
5 NaN 2.0 28.0

Difference with 3rd previous row

```python
>>> df.diff(periods=3)
a  b  c
0 NaN NaN NaN
1 NaN NaN NaN
2 NaN NaN NaN
3 3.0 2.0 15.0
4 3.0 4.0 21.0
5 3.0 6.0 27.0
```

Difference with following row

```python
>>> df.diff(periods=-1)
a  b  c
0 -1.0 0.0 -3.0
1 -1.0 -1.0 -5.0
2 -1.0 -1.0 -7.0
3 -1.0 -2.0 -9.0
4 -1.0 -3.0 -11.0
5 NaN NaN NaN
```

Overflow in input dtype

```python
>>> df = pd.DataFrame({'a': [1, 0]}, dtype=np.uint8)
```

```python
>>> df.diff()
a
0 NaN
1 255.0
```

**pandas.core.groupby.DataFrameGroupBy.ffill**

DataFrameGroupBy.ffill(*limit=None*)

Forward fill the values.

**Parameters**

- **limit** [int, optional] Limit of how many values to fill.

**Returns**

- **Series** or **DataFrame** Object with missing values filled.

**See also:**

- **Series.pad**
- **DataFrame.pad**
- **Series.fillna**
- **DataFrame.fillna**
pandas.core.groupby.DataFrameGroupBy.fillna

**property DataFrameGroupBy.fillna**
Fill NA/NaN values using the specified method.

**Parameters**

- **value** [scalar, dict, Series, or DataFrame] Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). Values not in the dict/Series/DataFrame will not be filled. This value cannot be a list.

- **method** [{'backfill', 'bfill', 'pad', 'ffill', None}, default None] Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use next valid observation to fill gap.

- **axis** [[0 or `index`, 1 or `columns`]] Axis along which to fill missing values.

- **inplace** [bool, default False] If True, fill in-place. Note: this will modify any other views on this object (e.g., a no-copy slice for a column in a DataFrame).

- **limit** [int, default None] If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled. Must be greater than 0 if not None.

- **downcast** [dict, default is None] A dict of item->dtype of what to downcast if possible, or the string ‘infer’ which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible).

**Returns**

DataFrame or None Object with missing values filled or None if inplace=True.

**See also:**

- **DataFrame** or None Object with missing values filled or None if inplace=True.

**Examples**

```python
>>> df = pd.DataFrame([[np.nan, 2, np.nan, 0],
...                     [3, 4, np.nan, 1],
...                     [np.nan, np.nan, np.nan, 5],
...                     [np.nan, 3, np.nan, 4]],
... columns=list('ABCD'))
>>> df
   A  B  C  D
0  NaN  2.0  NaN  0
1   3.0  4.0  NaN  1
2  NaN  NaN  NaN  5
3  NaN  3.0  NaN  4
>>> df.fillna(0)
   A  B  C  D
0  0.0  2.0  0.0  0
1  3.0  4.0  0.0  0
2  0.0  0.0  0.0  0
3  3.0  0.0  0.0  0
```

Replace all NaN elements with 0s.

```python
>>> df.fillna(0)
   A  B  C  D
0  0.0  2.0  0.0  0
1  3.0  4.0  0.0  0
2  0.0  0.0  0.0  0
3  3.0  0.0  0.0  0
```
We can also propagate non-null values forward or backward.

```python
>>> df.fillna(method='ffill')
  A   B   C   D
0  NaN  2.0  NaN  0
1  3.0  4.0  NaN  1
2  3.0  4.0  NaN  5
3  3.0  3.0  NaN  4
```

Replace all NaN elements in column ‘A’, ‘B’, ‘C’, and ‘D’, with 0, 1, 2, and 3 respectively.

```python
>>> values = {'A': 0, 'B': 1, 'C': 2, 'D': 3}
>>> df.fillna(value=values)
  A   B   C   D
0  0.0  2.0  2.0  0
1  3.0  4.0  2.0  1
2  0.0  1.0  2.0  5
3  0.0  3.0  2.0  4
```

Only replace the first NaN element.

```python
>>> df.fillna(value=values, limit=1)
  A   B   C   D
0  0.0  2.0  2.0  0
1  3.0  4.0  NaN  1
2  NaN  1.0  NaN  5
3  NaN  3.0  NaN  4
```

### pandas.core.groupby.DataFrameGroupBy.filter

DataFrameGroupBy.filter(func, dropna=True, *args, **kwargs)

Return a copy of a DataFrame excluding filtered elements.

Elements from groups are filtered if they do not satisfy the boolean criterion specified by func.

**Parameters**

- **func** [function] Function to apply to each subframe. Should return True or False.
- **dropna** [Drop groups that do not pass the filter. True by default;] If False, groups that evaluate False are filled with NaNs.

**Returns**

- **filtered** [DataFrame]
Notes

Each subframe is endowed the attribute `name` in case you need to know which group you are working on.

Examples

```python
>>> df = pd.DataFrame({'A' : ['foo', 'bar', 'foo', 'bar',
... 'foo', 'bar'],
...                      'B' : [1, 2, 3, 4, 5, 6],
...                      'C' : [2.0, 5., 8., 1., 2., 9.]})
>>> grouped = df.groupby('A')
>>> grouped.filter(lambda x: x['B'].mean() > 3.)
A   B   C
1   bar 2  5.0
3   bar 4  1.0
5   bar 6  9.0
```

**pandas.core.groupby.DataFrameGroupBy.hist**

**property DataFrameGroupBy.hist**

Make a histogram of the DataFrame's.

A histogram is a representation of the distribution of data. This function calls matplotlib.pyplot.hist(), on each series in the DataFrame, resulting in one histogram per column.

**Parameters**

- `data` [DataFrame] The pandas object holding the data.
- `column` [str or sequence] If passed, will be used to limit data to a subset of columns.
- `by` [object, optional] If passed, then used to form histograms for separate groups.
- `grid` [bool, default True] Whether to show axis grid lines.
- `xlabelsize` [int, default None] If specified changes the x-axis label size.
- `xrot` [float, default None] Rotation of x axis labels. For example, a value of 90 displays the x labels rotated 90 degrees clockwise.
- `ylabelsize` [int, default None] If specified changes the y-axis label size.
- `yrot` [float, default None] Rotation of y axis labels. For example, a value of 90 displays the y labels rotated 90 degrees clockwise.
- `ax` [Matplotlib axes object, default None] The axes to plot the histogram on.
- `sharex` [bool, default True if ax is None else False] In case subplots=True, share x axis and set some x axis labels to invisible; defaults to True if ax is None otherwise False if an ax is passed in. Note that passing in both an ax and sharex=True will alter all x axis labels for all subplots in a figure.
- `sharey` [bool, default False] In case subplots=True, share y axis and set some y axis labels to invisible.
- `figsize` [tuple] The size in inches of the figure to create. Uses the value in matplotlib.rcParams by default.
- `layout` [tuple, optional] Tuple of (rows, columns) for the layout of the histograms.
bins [int or sequence, default 10] Number of histogram bins to be used. If an integer is given, bins + 1 bin edges are calculated and returned. If bins is a sequence, gives bin edges, including left edge of first bin and right edge of last bin. In this case, bins is returned unmodified.

backend [str, default None] Backend to use instead of the backend specified in the option plotting.backend. For instance, ‘matplotlib’. Alternatively, to specify the plotting.backend for the whole session, set pd.options.plotting.backend.

New in version 1.0.0.

legend [bool, default False] Whether to show the legend.

New in version 1.1.0.

**kwargs All other plotting keyword arguments to be passed to matplotlib.pyplot.hist().

Returns

matplotlib.AxesSubplot or numpy.ndarray of them

See also:

matplotlib.pyplot.hist Plot a histogram using matplotlib.

Examples

This example draws a histogram based on the length and width of some animals, displayed in three bins

```python
>>> df = pd.DataFrame({
...         'length': [1.5, 0.5, 1.2, 0.9, 3],
...         'width': [0.7, 0.2, 0.15, 0.2, 1.1],
...     }, index=['pig', 'rabbit', 'duck', 'chicken', 'horse'])
>>> hist = df.hist(bins=3)
```

pandas.core.groupby.DataFrameGroupBy.idxmax

property DataFrameGroupBy.idxmax

Return index of first occurrence of maximum over requested axis. NA/null values are excluded.

Parameters

axis [{0 or 'index', 1 or 'columns'}, default 0] The axis to use. 0 or ‘index’ for row-wise, 1 or ‘columns’ for column-wise.

skipna [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

Returns

Series Indexes of maxima along the specified axis.

Raises

ValueError

• If the row/column is empty

See also:
3.11. GroupBy
**Series.idxmax** Return index of the maximum element.

**Notes**

This method is the DataFrame version of `ndarray.argmax`.

**Examples**

Consider a dataset containing food consumption in Argentina.

```python
>>> df = pd.DataFrame({'consumption': [10.51, 103.11, 55.48],
...                   'co2_emissions': [37.2, 19.66, 1712]},
...                   index=['Pork', 'Wheat Products', 'Beef'])
```

By default, it returns the index for the maximum value in each column.

```python
>>> df.idxmax()
consumption    Wheat Products
co2_emissions  Beef
```

To return the index for the maximum value in each row, use `axis="columns"`.

```python
>>> df.idxmax(axis="columns")
Pork       co2_emissions
Wheat Products consumption
Beef       co2_emissions
```

**pandas.core.groupby.DataFrameGroupBy.idxmin**

**property** DataFrameGroupBy.idxmin

Return index of first occurrence of minimum over requested axis.

NA/null values are excluded.

**Parameters**

- `axis` [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis to use. 0 or ‘index’ for row-wise, 1 or ‘columns’ for column-wise.

- `skipna` [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

**Returns**

- `Series` Indexes of minima along the specified axis.

**Raises**

- `ValueError`
• If the row/column is empty

See also:

Series.idxmin Return index of the minimum element.

Notes

This method is the DataFrame version of ndarray.argmin.

Examples

Consider a dataset containing food consumption in Argentina.

```python
>>> df = pd.DataFrame({'consumption': [10.51, 103.11, 55.48],
                     'co2_emissions': [37.2, 19.66, 1712]},
                    index=['Pork', 'Wheat Products', 'Beef'])

>>> df
     consumption  co2_emissions
Pork        10.51          37.2
Wheat Products  103.11       19.66
Beef          55.48        1712.0
```

By default, it returns the index for the minimum value in each column.

```python
>>> df.idxmin()
consumption    Pork
co2_emissions  Wheat Products
dtype: object
```

To return the index for the minimum value in each row, use `axis="columns"`.

```python
>>> df.idxmin(axis="columns")
Pork    consumption
Wheat Products  co2_emissions
Beef    consumption
dtype: object
```

pandas.core.groupby.DataFrameGroupBy.mad

**property** DataFrameGroupBy.mad

Return the mean absolute deviation of the values for the requested axis.

**Parameters**

- `axis` [[index (0), columns (1)]] Axis for the function to be applied on.
- `skipna` [bool, default None] Exclude NA/null values when computing the result.
- `level` [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

**Returns**

Series or DataFrame (if level specified)
DataFrameGroupBy.nunique (dropna=True)  
Return DataFrame with counts of unique elements in each position.

Parameters

- dropna [bool, default True] Don’t include NaN in the counts.

Returns

- nunique: DataFrame

Examples

```python
>>> df = pd.DataFrame(
    {'id': ['spam', 'egg', 'egg', 'spam', 'ham', 'ham'],
     'value1': [1, 5, 5, 2, 5, 5],
     'value2': list('abbaxy')})

>>> df
     id  value1 value2
0    spam     1     a
1     egg     5     b
2     egg     5     b
3    spam     2     a
4    ham     5     x
5    ham     5     y

>>> df.groupby('id').nunique()
     value1 value2
id
egg     1     1
ham     1     2
spam    2     1
```

Check for rows with the same id but conflicting values:

```python
>>> df.groupby('id').filter(lambda g: (g.nunique() > 1).any())
     id  value1 value2
0    spam     1     a
3    spam     2     a
4    ham     5     x
5    ham     5     y
```

DataFrameGroupBy.pad(limit=None)
Forward fill the values.

Parameters

- limit [int, optional] Limit of how many values to fill.

Returns

- Series or DataFrame Object with missing values filled.

See also:

- Series.pad
DataFrame.pad
Series.fillna
DataFrame.fillna

pandas.core.groupby.DataFrameGroupBy.pct_change

DataFrameGroupBy.pct_change(periods=1, fill_method='pad', limit=None, freq=None, axis=0)

Calculate pct_change of each value to previous entry in group.

Returns

Series or DataFrame Percentage changes within each group.

See also:

Series.groupby
DataFrame.groupby

pandas.core.groupby.DataFrameGroupBy.plot

property DataFrameGroupBy.plot
Class implementing the .plot attribute for groupby objects.

pandas.core.groupby.DataFrameGroupBy.quantile

DataFrameGroupBy.quantile(q=0.5, interpolation='linear')

Return group values at the given quantile, a la numpy.percentile.

Parameters

q [float or array-like, default 0.5 (50% quantile)] Value(s) between 0 and 1 providing the quantile(s) to compute.

interpolation [\{‘linear’, ‘lower’, ‘higher’, ‘midpoint’, ‘nearest’\}] Method to use when the desired quantile falls between two points.

Returns

Series or DataFrame Return type determined by caller of GroupBy object.

See also:

Series.quantile Similar method for Series.
DataFrame.quantile Similar method for DataFrame.
numpy.percentile NumPy method to compute qth percentile.

Examples

```python
>>> df = pd.DataFrame({
...         'a': [1, 2, 3, 4],
...         'b': [5, 6, 7, 8]
... }, columns=['key', 'val'])
>>> df.groupby('key').quantile()
   val
key
a  2.0
b  3.0
```
DataFrameGroupBy.rank

DataFrameGroupBy.rank (method='average', ascending=True, na_option='keep', pct=False, axis=0)

Provide the rank of values within each group.

Parameters

- **method**
  - ['average', 'min', 'max', 'first', 'dense'], default 'average'
  - average: average rank of group.
  - min: lowest rank in group.
  - max: highest rank in group.
  - first: ranks assigned in order they appear in the array.
  - dense: like 'min', but rank always increases by 1 between groups.

- **ascending** [bool, default True] False for ranks by high (1) to low (N).

- **na_option**
  - ['keep', 'top', 'bottom'], default 'keep'
  - keep: leave NA values where they are.
  - top: smallest rank if ascending.
  - bottom: smallest rank if descending.

- **pct** [bool, default False] Compute percentage rank of data within each group.

- **axis** [int, default 0] The axis of the object over which to compute the rank.

Returns

DataFrame with ranking of values within each group

See also:

- Series.groupby
- DataFrame.groupby

DataFrameGroupBy.resample

DataFrameGroupBy.resample (rule, *args, **kwargs)

Provide resampling when using a TimeGrouper.

Given a grouper, the function resamples it according to a string "string" -> "frequency".

See the frequency aliases documentation for more details.

Parameters

- **rule** [str or DateOffset] The offset string or object representing target grouper conversion.

- **args, **kwargs** Possible arguments are how, fill_method, limit, kind and on, and other arguments of TimeGrouper.

Returns

Grouper Return a new grouper with our resampler appended.

See also:

- Grouper Specify a frequency to resample with when grouping by a key.
- DatetimeIndex.resample Frequency conversion and resampling of time series.
### Examples

```python
>>> idx = pd.date_range('1/1/2000', periods=4, freq='T')
>>> df = pd.DataFrame(data=4 * [range(2)],
...                   index=idx,
...                   columns=['a', 'b'])
>>> df.iloc[2, 0] = 5
>>> df
   a    b
0  0    1
1  0    1
2  5    1
3  0    1

Downsample the DataFrame into 3 minute bins and sum the values of the timestamps falling into a bin.

```python
>>> df.groupby('a').resample('3T').sum()
   a  b
0  0  2
   5  1
```

Upsample the series into 30 second bins.

```python
>>> df.groupby('a').resample('30S').sum()
   a  b
0  0  1
   2
   1
   0
   0
   0
   0
   1
   0
   3
   0
   5
```

Resample by month. Values are assigned to the month of the period.

```python
>>> df.groupby('a').resample('M').sum()
   a  b
0  0  3
   5
```

Downsample the series into 3 minute bins as above, but close the right side of the bin interval.

```python
>>> df.groupby('a').resample('3T', closed='right').sum()
   a  b
0  1
   0
   2
   0
   0
   0
   0
   0
   5
   0
```

Downsample the series into 3 minute bins and close the right side of the bin interval, but label each bin using the right edge instead of the left.
pandas: powerful Python data analysis toolkit, Release 1.1.1

```python
>>> df.groupby('a').resample('3T', closed='right', label='right').sum()
a b
0 2000-01-01 00:00:00 0 1
2000-01-01 00:03:00 0 2
5 2000-01-01 00:03:00 5 1
```

pandas.core.groupby.DataFrameGroupBy.sample

DataFrameGroupBy.sample(n=None, frac=None, replace=False, weights=None, random_state=None)

Return a random sample of items from each group.

You can use random_state for reproducibility.

New in version 1.1.0.

Parameters

- **n** [int, optional] Number of items to return for each group. Cannot be used with frac and must be no larger than the smallest group unless replace is True. Default is one if frac is None.
- **frac** [float, optional] Fraction of items to return. Cannot be used with n.
- **replace** [bool, default False] Allow or disallow sampling of the same row more than once.
- **weights** [list-like, optional] Default None results in equal probability weighting. If passed a list-like then values must have the same length as the underlying DataFrame or Series object and will be used as sampling probabilities after normalization within each group. Values must be non-negative with at least one positive element within each group.
- **random_state** [int, array-like, BitGenerator, np.random.RandomState, optional] If int, array-like, or BitGenerator (NumPy>=1.17), seed for random number generator. If np.random.RandomState, use as numpy RandomState object.

Returns

Series or DataFrame A new object of same type as caller containing items randomly sampled within each group from the caller object.

See also:

- DataFrame.sample Generate random samples from a DataFrame object.
- numpy.random.choice Generate a random sample from a given 1-D numpy array.

Examples

```python
>>> df = pd.DataFrame(
...     {"a": ["red"] * 2 + ["blue"] * 2 + ["black"] * 2, "b": range(6)}
... )
>>> df
  a  b
0  red 0
1  red 1
2  blue 2
3  blue 3
4  black 4
5  black 5
```
Select one row at random for each distinct value in column a. The `random_state` argument can be used to guarantee reproducibility:

```python
df.groupby("a").sample(n=1, random_state=1)
```

<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>black</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
<td>blue</td>
<td>2</td>
</tr>
<tr>
<td>1</td>
<td>red</td>
<td>1</td>
</tr>
</tbody>
</table>

Set `frac` to sample fixed proportions rather than counts:

```python
df.groupby("a")["b"].sample(frac=0.5, random_state=2)
```

<table>
<thead>
<tr>
<th></th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Control sample probabilities within groups by setting weights:

```python
df.groupby("a").sample(
    n=1,
    weights=[1, 1, 1, 0, 0, 1],
    random_state=1,
)
```

<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>black</td>
<td>5</td>
</tr>
<tr>
<td>2</td>
<td>blue</td>
<td>2</td>
</tr>
<tr>
<td>0</td>
<td>red</td>
<td>0</td>
</tr>
</tbody>
</table>

---

**pandas.core.groupby.DataFrameGroupBy.shift**

`DataFrameGroupBy.shift(periods=1, freq=None, axis=0, fill_value=None)`

Shift each group by periods observations.

If `freq` is passed, the index will be increased using the periods and the `freq`.

**Parameters**

- `periods` [int, default 1] Number of periods to shift.
- `freq` [str, optional] Frequency string.
- `axis` [axis to shift, default 0] Shift direction.
- `fill_value` [optional] The scalar value to use for newly introduced missing values.

    New in version 0.24.0.

**Returns**

- **Series or DataFrame** Object shifted within each group.

**See also:**

- `Index.shift` Shift values of `Index`.
- `tshift` Shift the time index, using the index’s frequency if available.
pandas.core.groupby.DataFrameGroupBy.size

DataFrameGroupBy.size()
Compute group sizes.

Returns

DataFrame or Series Number of rows in each group as a Series if as_index is True or a
Dataframe if as_index is False.

See also:
Series.groupby
DataFrame.groupby

pandas.core.groupby.DataFrameGroupBy.skew

property DataFrameGroupBy.skew
Return unbiased skew over requested axis.
Normalized by N-1.

Parameters

axis [[index (0), columns (1)]] Axis for the function to be applied on.
skipna [bool, default True] Exclude NA/null values when computing the result.
level [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along
a particular level, collapsing into a Series.
numeric_only [bool, default None] Include only float, int, boolean columns. If None, will
attempt to use everything, then use only numeric data. Not implemented for Series.

**kwargs Additional keyword arguments to be passed to the function.

Returns

Series or DataFrame (if level specified)

pandas.core.groupby.DataFrameGroupBy.take

property DataFrameGroupBy.take
Return the elements in the given positional indices along an axis.
This means that we are not indexing according to actual values in the index attribute of the object. We are
indexing according to the actual position of the element in the object.

Parameters

indices [array-like] An array of ints indicating which positions to take.
axis [[0 or `index`, 1 or `columns`, None], default 0] The axis on which to select elements.
0 means that we are selecting rows, 1 means that we are selecting columns.
is_copy [bool] Before pandas 1.0, is_copy=False can be specified to ensure that the
return value is an actual copy. Starting with pandas 1.0, take always returns a copy,
and the keyword is therefore deprecated.
Deprecation since version 1.0.0.

**kwargs For compatibility with numpy.take(). Has no effect on the output.

Returns
taken [same type as caller] An array-like containing the elements taken from the object.

See also:

- DataFrame.loc: Select a subset of a DataFrame by labels.
- DataFrame.iloc: Select a subset of a DataFrame by positions.
- numpy.take: Take elements from an array along an axis.

Examples

```python
def = pd.DataFrame([('falcon', 'bird', 389.0),
                   ('parrot', 'bird', 24.0),
                   ('lion', 'mammal', 80.5),
                   ('monkey', 'mammal', np.nan)],
                   columns=['name', 'class', 'max_speed'],
                   index=[0, 2, 3, 1])
def

name  class     max_speed
0      falcon   bird       389.0
2      parrot   bird       24.0
3      lion     mammal     80.5
1      monkey   mammal     NaN

Take elements at positions 0 and 3 along the axis 0 (default).
Note how the actual indices selected (0 and 1) do not correspond to our selected indices 0 and 3. That's because we are selecting the 0th and 3rd rows, not rows whose indices equal 0 and 3.

```python
def.take([0, 3])
```

<table>
<thead>
<tr>
<th>name</th>
<th>class</th>
<th>max_speed</th>
</tr>
</thead>
<tbody>
<tr>
<td>falcon</td>
<td>bird</td>
<td>389.0</td>
</tr>
<tr>
<td>monkey</td>
<td>mammal</td>
<td>NaN</td>
</tr>
</tbody>
</table>

Take elements at indices 1 and 2 along the axis 1 (column selection).

```python
def.take([1, 2], axis=1)
```

<table>
<thead>
<tr>
<th>class</th>
<th>max_speed</th>
</tr>
</thead>
<tbody>
<tr>
<td>bird</td>
<td>389.0</td>
</tr>
<tr>
<td>bird</td>
<td>24.0</td>
</tr>
<tr>
<td>mammal</td>
<td>80.5</td>
</tr>
<tr>
<td>mammal</td>
<td>NaN</td>
</tr>
</tbody>
</table>

We may take elements using negative integers for positive indices, starting from the end of the object, just like with Python lists.

```python
def.take([-1, -2])
```

<table>
<thead>
<tr>
<th>name</th>
<th>class</th>
<th>max_speed</th>
</tr>
</thead>
<tbody>
<tr>
<td>monkey</td>
<td>mammal</td>
<td>NaN</td>
</tr>
<tr>
<td>lion</td>
<td>mammal</td>
<td>80.5</td>
</tr>
</tbody>
</table>
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.core.groupby.DataFrameGroupBy.tshift

**property DataFrameGroupBy.tshift**
Shift the time index, using the index’s frequency if available.

Deprecated since version 1.1.0: Use `shift` instead.

**Parameters**

- **periods** [int] Number of periods to move, can be positive or negative.
- **freq** [DateOffset, timedelta, or str, default None] Increment to use from the tseries module or time rule expressed as a string (e.g. ‘EOM’).
- **axis** [{0 or ‘index’, 1 or ‘columns’, None}, default 0] Corresponds to the axis that contains the Index.

**Returns**

- **shifted** [Series/DataFrame]

**Notes**

If freq is not specified then tries to use the freq or inferred_freq attributes of the index. If neither of those attributes exist, a ValueError is thrown.

The following methods are available only for `SeriesGroupBy` objects.

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>SeriesGroupBy.hist</code></td>
<td>Draw histogram of the input series using matplotlib.</td>
</tr>
<tr>
<td><code>SeriesGroupBy.nlargest</code></td>
<td>Return the largest $n$ elements.</td>
</tr>
<tr>
<td><code>SeriesGroupBy.nsmallest</code></td>
<td>Return the smallest $n$ elements.</td>
</tr>
<tr>
<td><code>SeriesGroupBy.nunique([dropna])</code></td>
<td>Return number of unique elements in the group.</td>
</tr>
<tr>
<td><code>SeriesGroupBy.unique</code></td>
<td>Return unique values of Series object.</td>
</tr>
<tr>
<td><code>SeriesGroupBy.value_counts([normalize, ...])</code></td>
<td></td>
</tr>
<tr>
<td><code>SeriesGroupBy.is_monotonic_increasing</code></td>
<td>Alias for <code>is_monotonic</code>.</td>
</tr>
<tr>
<td><code>SeriesGroupBy.is_monotonic_decreasing</code></td>
<td>Return boolean if values in the object are monotonic_decreasing.</td>
</tr>
</tbody>
</table>

pandas.core.groupby.SeriesGroupBy.hist

**property SeriesGroupBy.hist**
Draw histogram of the input series using matplotlib.

**Parameters**

- **by** [object, optional] If passed, then used to form histograms for separate groups.
- **ax** [matplotlib axis object] If not passed, uses `gca()`.
- **grid** [bool, default True] Whether to show axis grid lines.
- **xlabelsize** [int, default None] If specified changes the x-axis label size.
- **xrot** [float, default None] Rotation of x axis labels.
- **ylabelsize** [int, default None] If specified changes the y-axis label size.
- **yrot** [float, default None] Rotation of y axis labels.
- **figsize** [tuple, default None] Figure size in inches by default.
**bins** [int or sequence, default 10] Number of histogram bins to be used. If an integer is given, bins + 1 bin edges are calculated and returned. If bins is a sequence, gives bin edges, including left edge of first bin and right edge of last bin. In this case, bins is returned unmodified.

**backend** [str, default None] Backend to use instead of the backend specified in the option `plotting.backend`. For instance, `matplotlib`. Alternatively, to specify the `plotting.backend` for the whole session, set `pd.options.plotting.backend`.

New in version 1.0.0.

**legend** [bool, default False] Whether to show the legend.

New in version 1.1.0.

**kwargs** To be passed to the actual plotting function.

Returns

`matplotlib.AxesSubplot` A histogram plot.

See also:

`matplotlib.axes.Axes.hist` Plot a histogram using matplotlib.

---

**pandas.core.groupby.SeriesGroupBy.nlargest**

**property** `SeriesGroupBy.nlargest`

Return the largest \( n \) elements.

**Parameters**

- **n** [int, default 5] Return this many descending sorted values.
- **keep** [{‘first’, ‘last’, ‘all’}, default ‘first’] When there are duplicate values that cannot all fit in a Series of \( n \) elements:
  - **first** [return the first \( n \) occurrences in order] of appearance.
  - **last** [return the last \( n \) occurrences in reverse] order of appearance.
  - **all** [keep all occurrences. This can result in a Series of] size larger than \( n \).

**Returns**

`Series` The \( n \) largest values in the Series, sorted in decreasing order.

See also:

`Series.nsmallest` Get the \( n \) smallest elements.

`Series.sort_values` Sort Series by values.

`Series.head` Return the first \( n \) rows.
Notes

Faster than .sort_values(ascending=False).head(n) for small n relative to the size of the Series object.

Examples

```python
>>> countries_population = {"Italy": 59000000, "France": 65000000,
... "Malta": 434000, "Maldives": 434000,
... "Brunei": 434000, "Iceland": 337000,
... "Nauru": 11300, "Tuvalu": 11300,
... "Anguilla": 11300, "Montserrat": 5200}

>>> s = pd.Series(countries_population)

>>> s
Italy 59000000
France 65000000
Malta 434000
Maldives 434000
Brunei 434000
Iceland 337000
Nauru 11300
Tuvalu 11300
Anguilla 11300
Montserrat 5200
dtype: int64

The n largest elements where n=5 by default.

```python
>>> s.nlargest()
France 65000000
Italy 59000000
Malta 434000
Maldives 434000
Brunei 434000
dtype: int64
```

The n largest elements where n=3. Default keep value is ‘first’ so Malta will be kept.

```python
>>> s.nlargest(3)
France 65000000
Italy 59000000
Malta 434000
Maldives 434000
Brunei 434000
dtype: int64
```

The n largest elements where n=3 and keeping the last duplicates. Brunei will be kept since it is the last with value 434000 based on the index order.

```python
>>> s.nlargest(3, keep='last')
France 65000000
Italy 59000000
Brunei 434000
```

The n largest elements where n=3 with all duplicates kept. Note that the returned Series has five elements due to the three duplicates.
pandas: powerful Python data analysis toolkit, Release 1.1.1

```python
>>> s.nlargest(3, keep='all')
France   65000000
Italy    59000000
Malta    434000
Maldives 434000
Brunei   434000
dtype: int64
```

```python
pandas.core.groupby.SeriesGroupBy.nsmallest

**property** SeriesGroupBy.nsmallest
Return the smallest n elements.

**Parameters**

- **n** [int, default 5] Return this many ascending sorted values.
- **keep** [{'first', 'last', 'all'}, default 'first'] When there are duplicate values that cannot all fit in a Series of n elements:
  - **first** [return the first n occurrences in order] of appearance.
  - **last** [return the last n occurrences in reverse] order of appearance.
  - **all** [keep all occurrences. This can result in a Series of] size larger than n.

**Returns**

Series The n smallest values in the Series, sorted in increasing order.

**See also:**

- **Series.nlargest** Get the n largest elements.
- **Series.sort_values** Sort Series by values.
- **Series.head** Return the first n rows.

**Notes**

Faster than .sort_values().head(n) for small n relative to the size of the Series object.

**Examples**

```python
>>> countries_population = {'Italy': 59000000, 'France': 65000000,
...                        'Brunei': 434000, 'Malta': 434000,
...                        'Maldives': 434000, 'Iceland': 337000,
...                        'Nauru': 11300, 'Tuvalu': 11300,
...                        'Anguilla': 11300, 'Montserrat': 5200}
```

```python
>>> s = pd.Series(countries_population)
```
Montserrat 5200
dtype: int64

The $n$ smallest elements where $n=5$ by default.

```python
>>> s.nsmallest()
Montserrat    5200
     Nauru    11300
    Tuvalu     11300
   Anguilla    11300
   Iceland    337000
dtype: int64
```

The $n$ smallest elements where $n=3$. Default `keep` value is ‘first’ so Nauru and Tuvalu will be kept.

```python
>>> s.nsmallest(3)
Montserrat    5200
     Nauru    11300
    Tuvalu     11300
dtype: int64
```

The $n$ smallest elements where $n=3$ and keeping the last duplicates. Anguilla and Tuvalu will be kept since they are the last with value 11300 based on the index order.

```python
>>> s.nsmallest(3, keep='last')
Montserrat    5200
   Anguilla    11300
    Tuvalu     11300
dtype: int64
```

The $n$ smallest elements where $n=3$ with all duplicates kept. Note that the returned Series has four elements due to the three duplicates.

```python
>>> s.nsmallest(3, keep='all')
Montserrat    5200
     Nauru    11300
    Tuvalu     11300
  Anguilla     11300
dtype: int64
```

---

### pandas.core.groupby.SeriesGroupBy.nunique

SeriesGroupBy.nunique(dropna=True)

Return number of unique elements in the group.

**Returns**

- **Series**  Number of unique values within each group.
pandas.core.groupby.SeriesGroupBy.unique

property SeriesGroupBy.unique
Return unique values of Series object.

Uniques are returned in order of appearance. Hash table-based unique, therefore does NOT sort.

Returns

ndarray or ExtensionArray The unique values returned as a NumPy array. See Notes.

See also:
unique Top-level unique method for any 1-d array-like object.
Index.unique Return Index with unique values from an Index object.

Notes

Returns the unique values as a NumPy array. In case of an extension-array backed Series, a new ExtensionArray of that type with just the unique values is returned. This includes

- Categorical
- Period
- Datetime with Timezone
- Interval
- Sparse
- IntegerNA

See Examples section.

Examples

```python
>>> pd.Series([2, 1, 3, 3], name='A').unique()
array([2, 1, 3])
```

```python
>>> pd.Series([pd.Timestamp('2016-01-01') for _ in range(3)]).unique()
array(['2016-01-01T00:00:00.000000000'], dtype='datetime64[ns]')
```

```python
>>> pd.Series([pd.Timestamp('2016-01-01', tz='US/Eastern') for _ in range(3)]).unique()
<DatetimeArray>
['2016-01-01 00:00:00-05:00']
Length: 1, dtype: datetime64[ns, US/Eastern]
```

An unordered Categorical will return categories in the order of appearance.

```python
>>> pd.Series(pd.Categorical(list('baabc'))).unique()
['b', 'a', 'c']
Categories (3, object): ['b', 'a', 'c']
```

An ordered Categorical preserves the category ordering.

```python
>>> pd.Series(pd.Categorical(list('baabc'), categories=list('abc'), ordered=True)).unique()
['b', 'a', 'c']
Categories (3, object): ['a' < 'b' < 'c']
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

`pandas.core.groupby.SeriesGroupBy.value_counts`

```
SeriesGroupBy.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)
```

`pandas.core.groupby.SeriesGroupBy.is_monotonic_increasing`

```
property SeriesGroupBy.is_monotonic_increasing

Alias for is_monotonic.
```

`pandas.core.groupby.SeriesGroupBy.is_monotonic_decreasing`

```
property SeriesGroupBy.is_monotonic_decreasing

Return boolean if values in the object are monotonic_decreasing.

Returns

bool
```

The following methods are available only for DataFrameGroupBy objects.

```
DataFrameGroupBy.corrwith

Compute pairwise correlation.

DataFrameGroupBy.boxplot([subplots, column,...])

Make box plots from DataFrameGroupBy data.
```

`pandas.core.groupby.DataFrameGroupBy.corrwith`

```
property DataFrameGroupBy.corrwith

Compute pairwise correlation.

Pairwise correlation is computed between rows or columns of DataFrame with rows or columns of Series or DataFrame. DataFrames are first aligned along both axes before computing the correlations.

Parameters

other [DataFrame, Series] Object with which to compute correlations.

axis [{0 or 'index', 1 or 'columns'}, default 0] The axis to use. 0 or 'index' to compute column-wise, 1 or 'columns' for row-wise.

drop [bool, default False] Drop missing indices from result.

method [{'pearson', 'kendall', 'spearman'} or callable] Method of correlation:

- pearson : standard correlation coefficient
- kendall : Kendall Tau correlation coefficient
- spearman : Spearman rank correlation
- callable: callable with input two 1d ndarrays and returning a float.

New in version 0.24.0.

Returns

Series Pairwise correlations.

See also:

DataFrame.corr Compute pairwise correlation of columns.
pandas.core.groupby.DataFrameGroupBy.boxplot

DataFrameGroupBy.boxplot(subplots=True, column=None, fontsize=None, rot=0, grid=True, ax=None, figsize=None, layout=None, sharex=False, sharey=True, backend=None, **kwargs)

Make box plots from DataFrameGroupBy data.

Parameters

- **grouped** [Grouped DataFrame]
- **subplots** [bool]
  - False - no subplots will be used
  - True - create a subplot for each group.
- **column** [column name or list of names, or vector] Can be any valid input to groupby.
- **fontsize** [int or str]
- **rot** [label rotation angle]
- **grid** [Setting this to True will show the grid]
- **ax** [Matplotlib axis object, default None]
- **figsize** [A tuple (width, height) in inches]
- **layout** [tuple (optional)] The layout of the plot: (rows, columns).
- **sharex** [bool, default False] Whether x-axes will be shared among subplots.
  
  New in version 0.23.1.
- **sharey** [bool, default True] Whether y-axes will be shared among subplots.
  
  New in version 0.23.1.
- **backend** [str, default None] Backend to use instead of the backend specified in the option plotting.backend. For instance, `matplotlib`. Alternatively, to specify the plotting.backend for the whole session, set pd.options.plotting.backend.
  
  New in version 1.0.0.
- **kwargs** All other plotting keyword arguments to be passed to matplotlib's boxplot function.

Returns

- dict of key/value = group key/DataFrame.boxplot return value
- or DataFrame.boxplot return value in case subplots=figures=False
Examples

You can create boxplots for grouped data and show them as separate subplots:

```python
>>> import itertools

>>> tuples = [t for t in itertools.product(range(1000), range(4))]

>>> index = pd.MultiIndex.from_tuples(tuples, names=['lvl0', 'lvl1'])

>>> data = np.random.randn(len(index), 4)

>>> df = pd.DataFrame(data, columns=list('ABCD'), index=index)

>>> grouped = df.groupby(level='lvl1')

>>> grouped.boxplot(rot=45, fontsize=12, figsize=(8,10))
```

The `subplots=False` option shows the boxplots in a single figure.

```python
>>> grouped.boxplot(subplots=False, rot=45, fontsize=12)
```

3.12 Resampling

Resampler objects are returned by resample calls: `pandas.DataFrame.resample()`, `pandas.Series.resample()`.

3.12.1 Indexing, iteration

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Resampler.__iter__()</code></td>
<td>Resampler iterator.</td>
</tr>
<tr>
<td><code>Resampler.groups</code></td>
<td>Dict {group name -&gt; group labels}.</td>
</tr>
<tr>
<td><code>Resampler.indices</code></td>
<td>Dict {group name -&gt; group indices}.</td>
</tr>
<tr>
<td><code>Resampler.get_group(name[, obj])</code></td>
<td>Construct DataFrame from group with provided name.</td>
</tr>
</tbody>
</table>

**pandas.core.resample.Resampler.__iter__**

Resampler iterator.

```python
def __iter__(self):
    Resampler iterator.
    
    Returns
    -------
    Generator yielding sequence of (name, subsetted object)
    for each group.
```

See also:

`GroupBy.__iter__`
3.12. Resampling
pandas.core.resample.Resampler.groups

**property** `Resampler.groups`

Dict {group name -> group labels}.

pandas.core.resample.Resampler.indices

**property** `Resampler.indices`

Dict {group name -> group indices}.

pandas.core.resample.Resampler.get_group

`Resampler.get_group(name, obj=None)`

Construct DataFrame from group with provided name.  

**Parameters**

- `name` [object] The name of the group to get as a DataFrame.  
- `obj` [DataFrame, default None] The DataFrame to take the DataFrame out of. If it is None, the object groupby was called on will be used.  

**Returns**

- `group` [same type as obj]

3.12.2 Function application

| `Resampler.apply(func, *args, **kwargs)` | Aggregate using one or more operations over the specified axis. |
| `Resampler.aggregate(func, *args, **kwargs)` | Aggregate using one or more operations over the specified axis. |
| `Resampler.transform(arg, *args, **kwargs)` | Call function producing a like-indexed Series on each group and return a Series with the transformed values. |
| `Resampler.pipe(func, *args, **kwargs)` | Apply a function `func` with arguments to this Resampler object and return the function’s result. |

pandas.core.resample.Resampler.apply

`Resampler.apply(func, *args, **kwargs)`  
Aggregate using one or more operations over the specified axis.  

**Parameters**

- `func` [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a DataFrame or when passed to DataFrame.apply.  

Accepted combinations are:

- function
- string function name
- list of functions and/or function names, e.g. [np.sum, 'mean']
- dict of axis labels -> functions, function names or list of such.

3.12. Resampling
*args  Positional arguments to pass to `func`.

**kwargs  Keyword arguments to pass to `func`.

Returns

**scalar, Series or DataFrame**  The return can be:

- scalar : when Series.agg is called with single function
- Series : when DataFrame.agg is called with a single function
- DataFrame : when DataFrame.agg is called with several functions

Return scalar, Series or DataFrame.

See also:

- `DataFrame.groupby.aggregate`
- `DataFrame.resample.transform`
- `DataFrame.aggregate`

Notes

agg is an alias for aggregate. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

Examples

```python
>>> s = pd.Series([1,2,3,4,5],
                 index=pd.date_range('20130101', periods=5,freq='s'))
          2013-01-01 00:00:00   1
          2013-01-01 00:00:01   2
          2013-01-01 00:00:02   3
          2013-01-01 00:00:03   4
          2013-01-01 00:00:04   5
Freq: S, dtype: int64
```

```python
>>> r = s.resample('2s')
```

```python
>>> r.agg(np.sum)
          2013-01-01 00:00:00   3
          2013-01-01 00:00:02   7
          2013-01-01 00:00:04   5
Freq: 2S, dtype: int64
```

```python
>>> r.agg(['sum','mean','max'])

<table>
<thead>
<tr>
<th></th>
<th>sum</th>
<th>mean</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013-01-01 00:00:00</td>
<td>3</td>
<td>1.5</td>
<td>2</td>
</tr>
<tr>
<td>2013-01-01 00:00:02</td>
<td>7</td>
<td>3.5</td>
<td>4</td>
</tr>
<tr>
<td>2013-01-01 00:00:04</td>
<td>5</td>
<td>5.0</td>
<td>5</td>
</tr>
</tbody>
</table>
```

```python
>>> r.agg({'result' : lambda x: x.mean() / x.std(),
         'total' : np.sum})

<table>
<thead>
<tr>
<th></th>
<th>total</th>
<th>result</th>
</tr>
</thead>
</table>
```

(continues on next page)
Resampler. **aggregate** *(func, *args, **kwargs)*

Aggregate using one or more operations over the specified axis.

**Parameters**

- **func**  [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a DataFrame or when passed to DataFrame.apply.

  Accepted combinations are:
  - function
  - string function name
  - list of functions and/or function names, e.g. `[np.sum, 'mean']`
  - dict of axis labels -> functions, function names or list of such.

- **args** Positional arguments to pass to `func`.

- **kwargs** Keyword arguments to pass to `func`.

**Returns**

- **scalar, Series or DataFrame**  The return can be:
  - scalar : when Series.agg is called with single function
  - Series : when DataFrame.agg is called with a single function
  - DataFrame : when DataFrame.agg is called with several functions

  Return scalar, Series or DataFrame.

**See also:**

- `DataFrame.groupby.aggregate`
- `DataFrame.resample.transform`
- `DataFrame.aggregate`

**Notes**

`agg` is an alias for `aggregate`. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.
Examples

```python
>>> s = pd.Series([1,2,3,4,5],
                index=pd.date_range('20130101', periods=5,freq='s'))
2013-01-01 00:00:00    1
2013-01-01 00:00:01    2
2013-01-01 00:00:02    3
2013-01-01 00:00:03    4
2013-01-01 00:00:04    5
Freq: S, dtype: int64
```

```python
>>> r = s.resample('2s')
```

```python
>>> r.agg(np.sum)
2013-01-01 00:00:00  3
2013-01-01 00:00:02  7
2013-01-01 00:00:04  5
Freq: 2S, dtype: int64
```

```python
>>> r.agg(['sum','mean','max'])
       sum  mean  max
2013-01-01 00:00:00  3  1.5  2
2013-01-01 00:00:02  7  3.5  4
2013-01-01 00:00:04  5  5.0  5
```

```python
>>> r.agg({'result' : lambda x: x.mean() / x.std(),
         'total' : np.sum})
       total  result
2013-01-01 00:00:00  3  2.121320
2013-01-01 00:00:02  7  4.949747
2013-01-01 00:00:04  5  NaN
```

**pandas.core.resample.Resampler.transform**

Resampler.transform(arg, *args, **kwargs)

Call function producing a like-indexed Series on each group and return a Series with the transformed values.

Parameters

- **arg** [function] To apply to each group. Should return a Series with the same index.

Returns

- **transformed** [Series]
Examples

```python
>>> resampled.transform(lambda x: (x - x.mean()) / x.std())
```

**pandas.core.resample.Resampler.pipe**

Resampler.pipe(func, *args, **kwargs)

Apply a function `func` with arguments to this Resampler object and return the function’s result.

New in version 0.23.0.

Use `.pipe` when you want to improve readability by chaining together functions that expect Series, DataFrames, GroupBy or Resampler objects. Instead of writing

```python
>>> h(g(f(df.groupby('group')), arg1=a), arg2=b, arg3=c)
```

You can write

```python
>>> (df.groupby('group')
... .pipe(f)
... .pipe(g, arg1=a)
... .pipe(h, arg2=b, arg3=c))
```

which is much more readable.

**Parameters**

- **func** [callable or tuple of (callable, str)] Function to apply to this Resampler object or, alternatively, a (callable, data_keyword) tuple where data_keyword is a string indicating the keyword of callable that expects the Resampler object.

- **args** [iterable, optional] Positional arguments passed into func.

- **kwargs** [dict, optional] A dictionary of keyword arguments passed into func.

**Returns**

- **object** [the return type of func.]

See also:

pandas.Series.pipe Apply a function with arguments to a series.

pandas.DataFrame.pipe Apply a function with arguments to a dataframe.

**apply** Apply function to each group instead of to the full Resampler object.

**Notes**

See more [here](#).
Examples

```python
>>> df = pd.DataFrame({'A': [1, 2, 3, 4]},
                   index=pd.date_range('2012-08-02', periods=4))
>>> df
   A
2012-08-02    1
2012-08-03    2
2012-08-04    3
2012-08-05    4
```

To get the difference between each 2-day period’s maximum and minimum value in one pass, you can do

```python
>>> df.resample('2D').pipe(lambda x: x.max() - x.min())
   A
2012-08-02    1
2012-08-04    1
```

### 3.12.3 Upsampling

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>ffill</code></td>
<td>Forward fill the values.</td>
</tr>
<tr>
<td><code>backfill</code></td>
<td>Backward fill the new missing values in the resampled data.</td>
</tr>
<tr>
<td><code>bfill</code></td>
<td>Backward fill the new missing values in the resampled data.</td>
</tr>
<tr>
<td><code>pad</code></td>
<td>Forward fill the values.</td>
</tr>
<tr>
<td><code>nearest</code></td>
<td>Resample by using the nearest value.</td>
</tr>
<tr>
<td><code>fillna</code></td>
<td>Fill missing values introduced by upsampling.</td>
</tr>
<tr>
<td><code>asfreq</code></td>
<td>Return the values at the new freq, essentially a reindex.</td>
</tr>
<tr>
<td><code>interpolate</code></td>
<td>Interpolate values according to different methods.</td>
</tr>
</tbody>
</table>

**pandas.core.resample.Resampler.ffill**

Resampler(ffill)(limit)

Forward fill the values.

**Parameters**

- `limit` [int, optional] Limit of how many values to fill.

**Returns**

An upsampled Series.

**See also:**

- `Series.fillna`
- `DataFrame.fillna`
pandas.core.resample.Resampler.backfill

Resampler.backfill(limit=None)
Backward fill the new missing values in the resampled data.

In statistics, imputation is the process of replacing missing data with substituted values [1]. When resampling data, missing values may appear (e.g., when the resampling frequency is higher than the original frequency). The backward fill will replace NaN values that appeared in the resampled data with the next value in the original sequence. Missing values that existed in the original data will not be modified.

Parameters

- limit [int, optional] Limit of how many values to fill.

Returns

Series, DataFrame An upsampled Series or DataFrame with backward filled NaN values.

See also:

- bfill Alias of backfill.
- fillna Fill NaN values using the specified method, which can be ‘backfill’.
- nearest Fill NaN values with nearest neighbor starting from center.
- pad Forward fill NaN values.
- Series.fillna Fill NaN values in the Series using the specified method, which can be ‘backfill’.
- DataFrame.fillna Fill NaN values in the DataFrame using the specified method, which can be ‘backfill’.

References

[1]

Examples

Resampling a Series:

```python
>>> s = pd.Series([1, 2, 3],
                 index=pd.date_range('20180101', periods=3, freq='h'))
>>> s
2018-01-01 00:00:00    1
2018-01-01 01:00:00    2
2018-01-01 02:00:00    3
Freq: H, dtype: int64

>>> s.resample('30min').backfill()
2018-01-01 00:00:00    1
2018-01-01 00:30:00    2
2018-01-01 01:00:00    2
2018-01-01 01:30:00    3
2018-01-01 02:00:00    3
Freq: 30T, dtype: int64

>>> s.resample('15min').backfill(limit=2)
2018-01-01 00:00:00    1.0
2018-01-01 00:15:00    NaN
2018-01-01 00:30:00    2.0
2018-01-01 00:45:00    2.0
2018-01-01 01:00:00    2.0
Freq: 15T, dtype: float64
```

(continues on next page)
Resampling a DataFrame that has missing values:

```python
>>> df = pd.DataFrame({'a': [2, np.nan, 6], 'b': [1, 3, 5]},
                    index=pd.date_range('20180101', periods=3,
                    freq='h'))
>>> df
   a  b
2018-01-01 00:00:00  2.0  1
2018-01-01 01:00:00  NaN  3
2018-01-01 02:00:00  6.0  5

>>> df.resample('30min').backfill()
   a  b
2018-01-01 00:00:00  2.0  1
2018-01-01 00:30:00  NaN  3
2018-01-01 01:00:00  NaN  3
2018-01-01 01:30:00  6.0  5
2018-01-01 02:00:00  6.0  5

>>> df.resample('15min').backfill(limit=2)
   a   b
2018-01-01 00:00:00  2.0  1.0
2018-01-01 00:15:00  NaN  NaN
2018-01-01 00:30:00  NaN  3.0
2018-01-01 00:45:00  NaN  3.0
2018-01-01 01:00:00  NaN  3.0
2018-01-01 01:15:00  NaN  NaN
2018-01-01 01:30:00  6.0  5.0
2018-01-01 01:45:00  6.0  5.0
2018-01-01 02:00:00  6.0  5.0
```

`pandas.core.resample.Resampler.bfill`

Resampler.bfill (limit=None)

Backward fill the new missing values in the resampled data.

In statistics, imputation is the process of replacing missing data with substituted values [1]. When resampling data, missing values may appear (e.g., when the resampling frequency is higher than the original frequency). The backward fill will replace NaN values that appeared in the resampled data with the next value in the original sequence. Missing values that existed in the original data will not be modified.

Parameters

- **limit** [int, optional]: Limit of how many values to fill.

Returns

- **Series, DataFrame**: An upsampled Series or DataFrame with backward filled NaN values.

See also:

- `bfill`: Alias of backfill.
**fillna** Fill NaN values using the specified method, which can be ‘backfill’.

**nearest** Fill NaN values with nearest neighbor starting from center.

**pad** Forward fill NaN values.

**Series.fillna** Fill NaN values in the Series using the specified method, which can be ‘backfill’.

**DataFrame.fillna** Fill NaN values in the DataFrame using the specified method, which can be ‘backfill’.

### References

[1]

### Examples

**Resampling a Series:**

```python
>>> s = pd.Series([1, 2, 3],
                 index=pd.date_range('20180101', periods=3, freq='h'))
>>> s
2018-01-01 00:00:00    1
2018-01-01 01:00:00    2
2018-01-01 02:00:00    3
Freq: H, dtype: int64

>>> s.resample('30min').backfill()
2018-01-01 00:00:00    1
2018-01-01 00:30:00    2
2018-01-01 01:00:00    2
2018-01-01 01:30:00    3
2018-01-01 02:00:00    3
Freq: 30T, dtype: int64

>>> s.resample('15min').backfill(limit=2)
2018-01-01 00:00:00    1.0
2018-01-01 00:15:00   NaN
2018-01-01 00:30:00    2.0
2018-01-01 00:45:00    2.0
2018-01-01 01:00:00    2.0
2018-01-01 01:15:00   NaN
2018-01-01 01:30:00    3.0
2018-01-01 01:45:00    3.0
2018-01-01 02:00:00    3.0
Freq: 15T, dtype: float64
```

**Resampling a DataFrame that has missing values:**

```python
>>> df = pd.DataFrame({'a': [2, np.nan, 6], 'b': [1, 3, 5]},
                    index=pd.date_range('20180101', periods=3, freq='h'))
>>> df
     a   b
2018-01-01 2.0 1
2018-01-01 NaN 3
2018-01-01 6.0 5
```
>>> df.resample('30min').backfill()
    a    b
2018-01-01 00:00:00  2.0 1.0
2018-01-01 00:30:00  NaN 3.0
2018-01-01 01:00:00  NaN 3.0
2018-01-01 01:30:00  6.0 5.0
2018-01-01 02:00:00  6.0 5.0

>>> df.resample('15min').backfill(limit=2)
    a    b
2018-01-01 00:00:00  2.0 1.0
2018-01-01 00:15:00  NaN NaN
2018-01-01 00:30:00  NaN 3.0
2018-01-01 00:45:00  NaN 3.0
2018-01-01 01:00:00  NaN 3.0
2018-01-01 01:15:00  NaN NaN
2018-01-01 01:30:00  6.0 5.0
2018-01-01 01:45:00  6.0 5.0
2018-01-01 02:00:00  6.0 5.0

pandas.core.resample.Resampler.pad

Resampler.pad(limit=None)
Forward fill the values.

Parameters

    limit [int, optional] Limit of how many values to fill.

Returns

    An upsampled Series.

See also:

    Series.fillna
    DataFrame.fillna

pandas.core.resample.Resampler.nearest

Resampler.nearest(limit=None)
Resample by using the nearest value.

When resampling data, missing values may appear (e.g., when the resampling frequency is higher than the original frequency). The nearest method will replace NaN values that appeared in the resampled data with the value from the nearest member of the sequence, based on the index value. Missing values that existed in the original data will not be modified. If limit is given, fill only this many values in each direction for each of the original values.

Parameters

    limit [int, optional] Limit of how many values to fill.

Returns

    Series or DataFrame An upsampled Series or DataFrame with NaN values filled with their nearest value.

See also:

    backfill Backward fill the new missing values in the resampled data.
pad Forward fill NaN values.

Examples

```python
>>> s = pd.Series([1, 2],
...                 index=pd.date_range('20180101',
...                 periods=2,
...                 freq='1h'))
>>> s
2018-01-01 00:00:00  1
2018-01-01 01:00:00  2
Freq: H, dtype: int64

>>> s.resample('15min').nearest()
2018-01-01 00:00:00  1
2018-01-01 00:15:00  NaN
2018-01-01 00:30:00  2
2018-01-01 00:45:00  2
2018-01-01 01:00:00  2
Freq: 15T, dtype: int64
```

Limit the number of upsampled values imputed by the nearest:

```python
>>> s.resample('15min').nearest(limit=1)
2018-01-01 00:00:00  1.0
2018-01-01 00:15:00  1.0
2018-01-01 00:30:00  NaN
2018-01-01 00:45:00  2.0
2018-01-01 01:00:00  2.0
Freq: 15T, dtype: float64
```

pandas.core.resample.Resampler.fillna

Resampler.fillna(method, limit=None)
Fill missing values introduced by upsampling.

In statistics, imputation is the process of replacing missing data with substituted values [1]. When resampling data, missing values may appear (e.g., when the resampling frequency is higher than the original frequency).

Missing values that existed in the original data will not be modified.

Parameters

- **method** [{‘pad’, ‘backfill’, ‘ffill’, ‘bfill’, ‘nearest’}] Method to use for filling holes in resampled data
  - ‘pad’ or ‘ffill’: use previous valid observation to fill gap (forward fill).
  - ‘backfill’ or ‘bfill’: use next valid observation to fill gap.
  - ‘nearest’: use nearest valid observation to fill gap.

- **limit** [int, optional] Limit of how many consecutive missing values to fill.

Returns

Series or DataFrame An upsampled Series or DataFrame with missing values filled.

See also:

- backfill Backward fill NaN values in the resampled data.
**pad**  Forward fill NaN values in the resampled data.

**nearest**  Fill NaN values in the resampled data with nearest neighbor starting from center.

**interpolate**  Fill NaN values using interpolation.

**Series.fillna**  Fill NaN values in the Series using the specified method, which can be ‘bfill’ and ‘ffill’.

**DataFrame.fillna**  Fill NaN values in the DataFrame using the specified method, which can be ‘bfill’ and ‘ffill’.

**References**

[1]

**Examples**

Resampling a Series:

```python
>>> s = pd.Series([1, 2, 3],
...                 index=pd.date_range('20180101', periods=3, freq='h'))
>>> s
2018-01-01 00:00:00    1
2018-01-01 01:00:00    2
2018-01-01 02:00:00    3
Freq: H, dtype: int64
```

Without filling the missing values you get:

```python
>>> s.resample("30min").asfreq()
2018-01-01 00:00:00    1.0
2018-01-01 00:30:00    NaN
2018-01-01 01:00:00    2.0
2018-01-01 01:30:00    NaN
2018-01-01 02:00:00    3.0
Freq: 30T, dtype: float64
```

```python
>>> s.resample('30min').fillna("backfill")
2018-01-01 00:00:00    1
2018-01-01 00:30:00    2
2018-01-01 01:00:00    2
2018-01-01 01:30:00    3
2018-01-01 02:00:00    3
Freq: 30T, dtype: int64
```

```python
>>> s.resample('15min').fillna("backfill", limit=2)
2018-01-01 00:00:00    1.0
2018-01-01 00:15:00    NaN
2018-01-01 00:30:00    2.0
2018-01-01 00:45:00    2.0
2018-01-01 01:00:00    2.0
2018-01-01 01:15:00    NaN
2018-01-01 01:30:00    3.0
2018-01-01 01:45:00    3.0
2018-01-01 02:00:00    3.0
Freq: 15T, dtype: float64
```
```python
>>> s.resample('30min').fillna("pad")
2018-01-01 00:00:00 1
2018-01-01 00:30:00 1
2018-01-01 01:00:00 2
2018-01-01 01:30:00 2
2018-01-01 02:00:00 3
Freq: 30T, dtype: int64
```

```python
>>> s.resample('30min').fillna("nearest")
2018-01-01 00:00:00 1
2018-01-01 00:30:00 2
2018-01-01 01:00:00 2
2018-01-01 01:30:00 3
2018-01-01 02:00:00 3
Freq: 30T, dtype: int64
```

Missing values present before the upsampling are not affected.

```python
>>> sm = pd.Series([1, None, 3],
...                 index=pd.date_range('20180101', periods=3, freq='h'))
>>> sm
2018-01-01 00:00:00 1.0
2018-01-01 01:00:00 NaN
2018-01-01 02:00:00 3.0
Freq: H, dtype: float64
```

```python
>>> sm.resample('30min').fillna('backfill')
2018-01-01 00:00:00 1.0
2018-01-01 00:30:00 NaN
2018-01-01 01:00:00 NaN
2018-01-01 01:30:00 3.0
2018-01-01 02:00:00 3.0
Freq: 30T, dtype: float64
```

```python
>>> sm.resample('30min').fillna('pad')
2018-01-01 00:00:00 1.0
2018-01-01 00:30:00 1.0
2018-01-01 01:00:00 NaN
2018-01-01 01:30:00 NaN
2018-01-01 02:00:00 3.0
Freq: 30T, dtype: float64
```

```python
>>> sm.resample('30min').fillna('nearest')
2018-01-01 00:00:00 1.0
2018-01-01 00:30:00 NaN
2018-01-01 01:00:00 NaN
2018-01-01 01:30:00 3.0
2018-01-01 02:00:00 3.0
Freq: 30T, dtype: float64
```

Dataframe resampling is done column-wise. All the same options are available.

```python
>>> df = pd.DataFrame({'a': [2, np.nan, 6], 'b': [1, 3, 5]},
...                    index=pd.date_range('20180101', periods=3, freq='h'))
>>> df
3.12. Resampling 2307
```

(continues on next page)
pandas.core.resample.Resampler.asfreq

Resampler.asfreq(fill_value=None)

Return the values at the new freq, essentially a reindex.

Parameters

fill_value [scalar, optional] Value to use for missing values, applied during upsampling (note this does not fill NaNs that already were present).

Returns

DataFrame or Series Values at the specified freq.

See also:

Series.asfreq
DataFrame.asfreq

pandas.core.resample.Resampler.interpolate

Resampler.interpolate(method='linear', axis=0, limit=None, inplace=False, limit_direction='forward', limit_area=None, downcast=None, **kwargs)

Interpolate values according to different methods.

Please note that only method='linear' is supported for DataFrame/Series with a MultiIndex.

Parameters

method [str, default ‘linear’] Interpolation technique to use. One of:

- ‘linear’: Ignore the index and treat the values as equally spaced. This is the only method supported on MultiIndexes.
- ‘time’: Works on daily and higher resolution data to interpolate given length of interval.
- ‘index’, ‘values’: use the actual numerical values of the index.
- ‘pad’: Fill in NaNs using existing values.
- ‘nearest’, ‘zero’, ‘slinear’, ‘quadratic’, ‘cubic’, ‘spline’, ‘barycentric’, ‘polynomial’: Passed to scipy.interpolate.interp1d. These methods use the numerical values of the index. Both ‘polynomial’ and ‘spline’ require that you also specify an order (int), e.g. df.interpolate(method='polynomial', order=5).
from_derivatives': Refers to `scipy.interpolate.BPoly.from_derivatives` which replaces 'piecewise_polynomial' interpolation method in scipy 0.18.

• 'axis': [[0 or 'index', 1 or 'columns', None], default None] Axis to interpolate along.

• 'limit': [int, optional] Maximum number of consecutive NaNs to fill. Must be greater than 0.

• 'inplace': [bool, default False] Update the data in place if possible.

• 'limit_direction': [{'forward', 'backward', 'both'}], Optional] Consecutive NaNs will be filled in this direction.

  If limit is specified:
  • If 'method' is 'pad' or 'ffill', 'limit_direction' must be 'forward'.
  • If 'method' is 'backfill' or 'bfill', 'limit_direction' must be 'backwards'.

  If 'limit' is not specified:
  • If 'method' is 'backfill' or 'bfill', the default is 'backward'
  • else the default is 'forward'

Changed in version 1.1.0: raises ValueError if limit_direction is 'forward' or 'both' and method is 'backfill' or 'bfill'. raises ValueError if limit_direction is 'backward' or 'both' and method is 'pad' or 'ffill'.

• 'limit_area': [{None, 'inside', 'outside'}], default None] If limit is specified, consecutive NaNs will be filled with this restriction.

  • None: No fill restriction.
  • 'inside': Only fill NaNs surrounded by valid values (interpolate).
  • 'outside': Only fill NaNs outside valid values (extrapolate).

  New in version 0.23.0.

• 'downcast': [optional, 'infer' or None, defaults to None] Downcast dtypes if possible.

• '**kwargs': Keyword arguments to pass on to the interpolating function.

Returns

Series or DataFrame Returns the same object type as the caller, interpolated at some or all NaN values.

See also:

fillna Fill missing values using different methods.
scipy.interpolate.Akima1DInterpolator Piecewise cubic polynomials (Akima interpolator).
scipy.interpolate.BPoly.from_derivatives Piecewise polynomial in the Bernstein basis.
scipy.interpolate.interpl1d Interpolate a 1-D function.
scipy.interpolate.KroghInterpolator Interpolate polynomial (Krogh interpolator).
scipy.interpolate.PchipInterpolator PCHIP 1-d monotonic cubic interpolation.
scipy.interpolate.CubicSpline Cubic spline data interpolator.
Notes

The ‘krogh’, ‘piecewise_polynomial’, ‘spline’, ‘pchip’ and ‘akima’ methods are wrappers around the respective SciPy implementations of similar names. These use the actual numerical values of the index. For more information on their behavior, see the SciPy documentation and SciPy tutorial.

Examples

Filling in NaN in a Series via linear interpolation.

```python
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s
0 0.0
1 1.0
2 NaN
3 3.0
dtype: float64
>>> s.interpolate()
0 0.0
1 1.0
2 2.0
3 3.0
dtype: float64
```

Filling in NaN in a Series by padding, but filling at most two consecutive NaN at a time.

```python
>>> s = pd.Series([np.nan, "single_one", np.nan, ... "fill_two_more", np.nan, np.nan, np.nan, ... 4.71, np.nan])
>>> s
0 NaN
1 single_one
2 NaN
3 fill_two_more
4 NaN
5 NaN
6 NaN
7 4.71
8 NaN
dtype: object
>>> s.interpolate(method='pad', limit=2)
0 NaN
1 single_one
2 single_one
3 fill_two_more
4 fill_two_more
5 fill_two_more
6 NaN
7 4.71
8 4.71
dtype: object
```

Filling in NaN in a Series via polynomial interpolation or splines: Both ‘polynomial’ and ‘spline’ methods require that you also specify an order (int).
Fill the DataFrame forward (that is, going down) along each column using linear interpolation.

Note how the last entry in column ‘a’ is interpolated differently, because there is no entry after it to use for interpolation. Note how the first entry in column ‘b’ remains NaN, because there is no entry before it to use for interpolation.

Using polynomial interpolation.

<table>
<thead>
<tr>
<th>3.12.4 Computations / descriptive stats</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Resampler.count()</strong></td>
</tr>
<tr>
<td><strong>Resampler.nunique([_method])</strong></td>
</tr>
<tr>
<td><strong>Resampler.first([_method])</strong></td>
</tr>
<tr>
<td><strong>Resampler.last([_method])</strong></td>
</tr>
<tr>
<td><strong>Resampler.max([_method])</strong></td>
</tr>
<tr>
<td><strong>Resampler.mean([_method])</strong></td>
</tr>
<tr>
<td><strong>Resampler.median([_method])</strong></td>
</tr>
<tr>
<td><strong>Resampler.min([_method])</strong></td>
</tr>
<tr>
<td><strong>Resampler.ohlc([_method])</strong></td>
</tr>
</tbody>
</table>

continues on next page
Table 379 – continued from previous page

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Resampler.prod([_method, min_count])</code></td>
<td>Compute prod of group values.</td>
</tr>
<tr>
<td><code>Resampler.size()</code></td>
<td>Compute group sizes.</td>
</tr>
<tr>
<td><code>Resampler.sem([_method])</code></td>
<td>Compute standard error of the mean of groups, excluding missing values.</td>
</tr>
<tr>
<td><code>Resampler.std([ddof])</code></td>
<td>Compute standard deviation of groups, excluding missing values.</td>
</tr>
<tr>
<td><code>Resampler.sum([_method, min_count])</code></td>
<td>Compute sum of group values.</td>
</tr>
<tr>
<td><code>Resampler.var([ddof])</code></td>
<td>Compute variance of groups, excluding missing values.</td>
</tr>
<tr>
<td><code>Resampler.quantile([q])</code></td>
<td>Return value at the given quantile.</td>
</tr>
</tbody>
</table>

**pandas.core.resample.Resampler.count**

`Resampler.count()`
Compute count of group, excluding missing values.

**Returns**
- Series or DataFrame  Count of values within each group.

**See also:**
- Series.groupby
- DataFrame.groupby

**pandas.core.resample.Resampler.nunique**

`Resampler.nunique(_method='nunique')`
Return number of unique elements in the group.

**Returns**
- Series  Number of unique values within each group.

**pandas.core.resample.Resampler.first**

`Resampler.first(_method='first', *args, **kwargs)`
Compute first of group values.

**Parameters**
- **numeric_only** [bool, default False] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.
- **min_count** [int, default -1] The required number of valid values to perform the operation. If fewer than min_count non-NA values are present the result will be NA.

**Returns**
- Series or DataFrame  Computed first of values within each group.
pandas.core.resample.Resampler.last

\texttt{Resampler.last(_method='last', *args, **kwargs)}

Compute last of group values.

**Parameters**

- \texttt{numeric_only} [bool, default False] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

- \texttt{min_count} [int, default -1] The required number of valid values to perform the operation. If fewer than \texttt{min_count} non-NA values are present the result will be NA.

**Returns**

- **Series or DataFrame** Computed last of values within each group.

pandas.core.resample.Resampler.max

\texttt{Resampler.max(_method='max', *args, **kwargs)}

Compute max of group values.

**Parameters**

- \texttt{numeric_only} [bool, default False] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

- \texttt{min_count} [int, default -1] The required number of valid values to perform the operation. If fewer than \texttt{min_count} non-NA values are present the result will be NA.

**Returns**

- **Series or DataFrame** Computed max of values within each group.

pandas.core.resample.Resampler.mean

\texttt{Resampler.mean(_method='mean', *args, **kwargs)}

Compute mean of groups, excluding missing values.

**Parameters**

- \texttt{numeric_only} [bool, default True] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

**Returns**

- **pandas.Series or pandas.DataFrame**

See also:

- \texttt{Series.groupby}
- \texttt{DataFrame.groupby}
Examples

```python
>>> df = pd.DataFrame({'A': [1, 1, 2, 1, 2],
... 'B': [np.nan, 2, 3, 4, 5],
... 'C': [1, 2, 1, 1, 2], columns=['A', 'B', 'C'])

Groupby one column and return the mean of the remaining columns in each group.

```python
>>> df.groupby('A').mean()
B   C
A  
1  3.0  1.333333
2  4.0  1.500000
```

Groupby two columns and return the mean of the remaining column.

```python
>>> df.groupby(['A', 'B']).mean()
C
A   B
1  2.0  2
   4.0  1
2  3.0  1
   5.0  2
```

Groupby one column and return the mean of only particular column in the group.

```python
>>> df.groupby('A')['B'].mean()
A
1  3.0
2  4.0
Name: B, dtype: float64
```

pandas.core.resample.Resampler.median

Resampler.median(_method='median', *args, **kwargs)
Compute median of groups, excluding missing values.
For multiple groupings, the result index will be a MultiIndex

Parameters

- numeric_only [bool, default True] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

Returns

- Series or DataFrame Median of values within each group.

See also:

- Series.groupby
- DataFrame.groupby
pandas.core.resample.Resampler.min

Resampler.min(_method='min', *args, **kwargs)
Compute min of group values.

Parameters

   numeric_only [bool, default False] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

   min_count [int, default -1] The required number of valid values to perform the operation. If fewer than min_count non-NA values are present the result will be NA.

Returns

Series or DataFrame  Computed min of values within each group.

pandas.core.resample.Resampler.ohlc

Resampler.ohlc(_method='ohlc', *args, **kwargs)
Compute open, high, low and close values of a group, excluding missing values.

For multiple groupings, the result index will be a MultiIndex

Returns

DataFrame  Open, high, low and close values within each group.

See also:

Series.groupby
DataFrame.groupby

pandas.core.resample.Resampler.prod

Resampler.prod(_method='prod', min_count=0, *args, **kwargs)
Compute prod of group values.

Parameters

   numeric_only [bool, default True] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

   min_count [int, default 0] The required number of valid values to perform the operation. If fewer than min_count non-NA values are present the result will be NA.

Returns

Series or DataFrame  Computed prod of values within each group.

pandas.core.resample.Resampler.size

Resampler.size()
Compute group sizes.

Returns

DataFrame or Series  Number of rows in each group as a Series if as_index is True or a DataFrame if as_index is False.

See also:

Series.groupby
DataFrame.groupby
pandas.core.resample.Resampler.sem

`Resampler.sem(_method='sem', *args, **kwargs)`

Compute standard error of the mean of groups, excluding missing values.

For multiple groupings, the result index will be a MultiIndex.

**Parameters**

- `ddof [int, default 1]` Degrees of freedom.

**Returns**

- `Series or DataFrame` Standard error of the mean of values within each group.

See also:
- `Series.groupby`
- `DataFrame.groupby`

pandas.core.resample.Resampler.std

`Resampler.std(ddof=1, *args, **kwargs)`

Compute standard deviation of groups, excluding missing values.

**Parameters**

- `ddof [int, default 1]` Degrees of freedom.

**Returns**

- `DataFrame or Series` Standard deviation of values within each group.

pandas.core.resample.Resampler.sum

`Resampler.sum(_method='sum', min_count=0, *args, **kwargs)`

Compute sum of group values.

**Parameters**

- `numeric_only [bool, default True]` Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data.

- `min_count [int, default 0]` The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

**Returns**

- `Series or DataFrame` Computed sum of values within each group.

pandas.core.resample.Resampler.var

`Resampler.var(ddof=1, *args, **kwargs)`

Compute variance of groups, excluding missing values.

**Parameters**

- `ddof [int, default 1]` Degrees of freedom.

**Returns**

- `DataFrame or Series` Variance of values within each group.
**pandas.core.resample.Resampler.quantile**

Resampler.quantile(q=0.5, **kwargs)

Return value at the given quantile.

New in version 0.24.0.

**Parameters**

- `q` [float or array-like, default 0.5 (50% quantile)]

**Returns**

DataFrame or Series Quantile of values within each group.

See also:

Series.quantile
DataFrame.quantile
DataFrameGroupBy.quantile

### 3.13 Style

Styler objects are returned by pandas.DataFrame.style.

#### 3.13.1 Styler constructor

| **Styler**(data[, precision, table_styles, ...]) | Helps style a DataFrame or Series according to the data with HTML and CSS. |
| **Styler.from_custom_template**(searchpath, name) | Factory function for creating a subclass of Styler. |

**pandas.io.formats.style.Styler**

class pandas.io.formats.style.Styler(data, precision=None, table_styles=None, uuid=None, caption=None, table_attributes=None, cell_ids=True, na_rep=None)

Helps style a DataFrame or Series according to the data with HTML and CSS.

**Parameters**

- `data` [Series or DataFrame] Data to be styled - either a Series or DataFrame.
- `precision` [int] Precision to round floats to, defaults to pd.options.display.precision.
- `table_styles` [list-like, default None] List of [selector: (attr, value)] dicts; see Notes.
- `uuid` [str, default None] A unique identifier to avoid CSS collisions; generated automatically.
- `caption` [str, default None] Caption to attach to the table.
- `table_attributes` [str, default None] Items that show up in the opening <table> tag in addition to automatic (by default) id.
- `cell_ids` [bool, default True] If True, each cell will have an id attribute in their HTML tag. The id takes the form T_<uuid>_row<num_row>_col<num_col> where <uuid> is the unique identifier, <num_row> is the row number and <num_col> is the column number.
**na_rep** [str, optional] Representation for missing values. If `na_rep` is None, no special formatting is applied.

    New in version 1.0.0.

**See also:**

**DataFrame.style** Return a Styler object containing methods for building a styled HTML representation for the DataFrame.

**Notes**

Most styling will be done by passing style functions into `Styler.apply` or `Styler.applymap`. Style functions should return values with strings containing CSS `'attr: value'` that will be applied to the indicated cells.

If using in the Jupyter notebook, Styler has defined a `_repr_html_` to automatically render itself. Otherwise call Styler.render to get the generated HTML.

CSS classes are attached to the generated HTML

- Index and Column names include `index_name` and `level<k>` where `k` is its level in a MultiIndex
- Index label cells include
  - `row_heading`
  - `row<n>` where `n` is the numeric position of the row
  - `level<k>` where `k` is the level in a MultiIndex
- Column label cells include `* col_heading` `* col<n>` where `n` is the numeric position of the column
  `* level<k>` where `k` is the level in a MultiIndex
- Blank cells include `blank`
- Data cells include `data`

**Attributes**

<table>
<thead>
<tr>
<th>env</th>
<th>(Jinja2 jinja2.Environment)</th>
</tr>
</thead>
<tbody>
<tr>
<td>template</td>
<td>(Jinja2 Template)</td>
</tr>
<tr>
<td>loader</td>
<td>(Jinja2 Loader)</td>
</tr>
</tbody>
</table>

**Methods**

**apply**(func[, axis, subset]) Apply a function column-wise, row-wise, or table-wise.

**applymap**(func[, subset]) Apply a function elementwise.

**background_gradient**(cmap, low, high, axis, ...) Color the background in a gradient style.

**bar**(subset, axis, color, width, align, ...) Draw bar chart in the cell backgrounds.

**clear**() Reset the styler, removing any previously applied styles.

**export**() Export the styles to applied to the current Styler.

**format**(formatter[, subset, na_rep]) Format the text display value of cells.

**from_custom_template**(searchpath, name) Factory function for creating a subclass of Styler.

**hide_columns**(subset) Hide columns from rendering.

continues on next page
Table 381 – continued from previous page

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>hide_index()</td>
<td>Hide any indices from rendering.</td>
</tr>
<tr>
<td>highlight_max([subset, color, axis])</td>
<td>Highlight the maximum by shading the background.</td>
</tr>
<tr>
<td>highlight_min([subset, color, axis])</td>
<td>Highlight the minimum by shading the background.</td>
</tr>
<tr>
<td>highlight_null([null_color, subset])</td>
<td>Shade the background null_color for missing values.</td>
</tr>
<tr>
<td>pipe(func, *args, **kwargs)</td>
<td>Apply func(self, *args, **kwargs), and return the result.</td>
</tr>
<tr>
<td>render(**kwargs)</td>
<td>Render the built up styles to HTML.</td>
</tr>
<tr>
<td>set_caption(caption)</td>
<td>Set the caption on a Styler.</td>
</tr>
<tr>
<td>set_na_rep(na_rep)</td>
<td>Set the missing data representation on a Styler.</td>
</tr>
<tr>
<td>set_precision(precision)</td>
<td>Set the precision used to render.</td>
</tr>
<tr>
<td>set_properties([subset])</td>
<td>Method to set one or more non-data dependent properties or each cell.</td>
</tr>
<tr>
<td>set_table_attributes(attributes)</td>
<td>Set the table attributes.</td>
</tr>
<tr>
<td>set_table_styles(table_styles)</td>
<td>Set the table styles on a Styler.</td>
</tr>
<tr>
<td>set_uuid(uuid)</td>
<td>Set the uuid for a Styler.</td>
</tr>
<tr>
<td>to_excel(excel_writer[, sheet_name, na_rep, ...])</td>
<td>Write Styler to an Excel sheet.</td>
</tr>
<tr>
<td>use(styles)</td>
<td>Set the styles on the current Styler.</td>
</tr>
<tr>
<td>where(cond, value[, other, subset])</td>
<td>Apply a function elementwise.</td>
</tr>
</tbody>
</table>

**pandas.io.formats.style.Styler.apply**

Styler.apply(func, axis=0, subset=None, **kwargs)

Apply a function column-wise, row-wise, or table-wise.

Updates the HTML representation with the result.

**Parameters**

- **func** [function] func should take a Series or DataFrame (depending on axis), and return an object with the same shape. Must return a DataFrame with identical index and column labels when axis=None.

- **axis** [[0 or 'index', 1 or 'columns', None], default 0] Apply to each column (axis=0 or 'index'), to each row (axis=1 or 'columns'), or to the entire DataFrame at once with axis=None.

- **subset** [IndexSlice] A valid indexer to limit data to before applying the function. Consider using a pandas.IndexSlice.

- ****kwargs [dict] Pass along to func.

**Returns**

- **self** [Styler]
Notes

The output shape of func should match the input, i.e. if x is the input row, column, or table (depending on axis), then func(x).shape == x.shape should be true.

This is similar to DataFrame.apply, except that axis=None applies the function to the entire DataFrame at once, rather than column-wise or row-wise.

Examples

```python
>>> def highlight_max(x):
...   return ['background-color: yellow' if v == x.max() else ''
...           for v in x]
... >>> df = pd.DataFrame(np.random.randn(5, 2))
>>> df.style.apply(highlight_max)
```

pandas.io.formats.style.Styler.applymap

Styler.applymap(func, subset=None, **kwargs)

Apply a function elementwise.

Parameters

- **func** [function] func should take a scalar and return a scalar.
- **subset** [IndexSlice] A valid indexer to limit data to before applying the function. Consider using a pandas.IndexSlice.
- **kwargs** [dict] Pass along to func.

Returns

self [Styler]

See also:

Styler.where

pandas.io.formats.style.Styler.background_gradient

Styler.background_gradient(cmap='PuBu', low=0, high=0, axis=0, subset=None, text_color_threshold=0.408, vmin=None, vmax=None)

Color the background in a gradient style.

The background color is determined according to the data in each column (optionally row). Requires matplotlib.

Parameters

- **cmap** [str or colormap] Matplotlib colormap.
- **low** [float] Compress the range by the low.
- **high** [float] Compress the range by the high.
axis  [{0 or 'index', 1 or 'columns', None}, default 0] Apply to each column (axis=0 or 'index'), to each row (axis=1 or 'columns'), or to the entire DataFrame at once with axis=None.

subset  [IndexSlice] A valid slice for data to limit the style application to.

text_color_threshold  [float or int] Luminance threshold for determining text color. Facilitates text visibility across varying background colors. From 0 to 1. 0 = all text is dark colored, 1 = all text is light colored.

New in version 0.24.0.

vmin  [float, optional] Minimum data value that corresponds to colormap minimum value. When None (default): the minimum value of the data will be used.

New in version 1.0.0.

vmax  [float, optional] Maximum data value that corresponds to colormap maximum value. When None (default): the maximum value of the data will be used.

New in version 1.0.0.

Returns

self  [Styler]

Raises

ValueError  If text_color_threshold is not a value from 0 to 1.

Notes

Set text_color_threshold or tune low and high to keep the text legible by not using the entire range of the color map. The range of the data is extended by low * (x.max() - x.min()) and high * (x.max() - x.min()) before normalizing.

pandas.io.formats.style.Styler.bar

Styler.bar  (subset=None, axis=0, color='#d65f5f', width=100, align='left', vmin=None, vmax=None)

Draw bar chart in the cell backgrounds.

Parameters

subset  [IndexSlice, optional] A valid slice for data to limit the style application to.

axis  [{0 or 'index', 1 or 'columns', None}, default 0] Apply to each column (axis=0 or 'index'), to each row (axis=1 or 'columns'), or to the entire DataFrame at once with axis=None.

color  [str or 2-tuple/list] If a str is passed, the color is the same for both negative and positive numbers. If 2-tuple/list is used, the first element is the color_negative and the second is the color_positive (eg: ['#d65f5f', '#5fba7d']).

width  [float, default 100] A number between 0 or 100. The largest value will cover width percent of the cell’s width.

align  [{‘left’, ‘zero’, ‘mid’}, default ‘left’] How to align the bars with the cells.

• ‘left’ : the min value starts at the left of the cell.
• ‘zero’ : a value of zero is located at the center of the cell.
• ‘mid’ : the center of the cell is at (max-min)/2, or if values are all negative (positive) the zero is aligned at the right (left) of the cell.

**vmin** [float, optional] Minimum bar value, defining the left hand limit of the bar drawing range, lower values are clipped to vmin. When None (default): the minimum value of the data will be used.

New in version 0.24.0.

**vmax** [float, optional] Maximum bar value, defining the right hand limit of the bar drawing range, higher values are clipped to vmax. When None (default): the maximum value of the data will be used.

New in version 0.24.0.

Returns
self [Styler]

`pandas.io.formats.style.Styler.clear`

Styler.clear()

Reset the styler, removing any previously applied styles.

Returns None.

`pandas.io.formats.style.Styler.export`

Styler.export()

Export the styles to applied to the current Styler.

Can be applied to a second style with Styler.use.

Returns
styles [list]

See also:

Styler.use

`pandas.io.formats.style.Styler.format`

Styler.format(formatter, subset=None, na_rep=None)

Format the text display value of cells.

Parameters

*formatter* [str, callable, dict or None] If formatter is None, the default formatter is used.

*subset* [IndexSlice] An argument to DataFrame.loc that restricts which elements formatter is applied to.

*na_rep* [str, optional] Representation for missing values. If na_rep is None, no special formatting is applied.

New in version 1.0.0.
Returns

self [Styler]

Notes

formatter is either a or a dict {column name: a} where a is one of

- str: this will be wrapped in: a.format(x)
- callable: called with the value of an individual cell

The default display value for numeric values is the “general” (g) format with pd.options.display.precision.precision.

Examples

```python
df = pd.DataFrame(np.random.randn(4, 2), columns=['a', 'b'])
df.style.format("{:.2%}")
df['c'] = ['a', 'b', 'c', 'd']
df.style.format({'c': str.upper})
```

pandas.io.formats.style.Styler.from_custom_template

classmethod Styler.from_custom_template(searchpath, name)

Factory function for creating a subclass of Styler.

Uses a custom template and Jinja environment.

Parameters

- searchpath [str or list] Path or paths of directories containing the templates.
- name [str] Name of your custom template to use for rendering.

Returns

MyStyler [subclass of Styler] Has the correct env and template class attributes set.

pandas.io.formats.style.Styler.hide_columns

Styler.hide_columns(subset)

Hide columns from rendering.

New in version 0.23.0.

Parameters

- subset [IndexSlice] An argument to DataFrame.loc that identifies which columns are hidden.

Returns

self [Styler]
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.io.formats.style.Styler.hide_index

Styler.hide_index()
Hide any indices from rendering.
New in version 0.23.0.

Returns

self [Styler]

pandas.io.formats.style.Styler.highlight_max

Styler.highlight_max(subset=None, color='yellow', axis=0)
Highlight the maximum by shading the background.

Parameters

subset [IndexSlice, default None] A valid slice for data to limit the style application to.
color [str, default ‘yellow’]
axis [[0 or ‘index’, 1 or ‘columns’, None], default 0] Apply to each column (axis=0 or ‘index’), to each row (axis=1 or ‘columns’), or to the entire DataFrame at once with axis=None.

Returns

self [Styler]

pandas.io.formats.style.Styler.highlight_min

Styler.highlight_min(subset=None, color='yellow', axis=0)
Highlight the minimum by shading the background.

Parameters

subset [IndexSlice, default None] A valid slice for data to limit the style application to.
color [str, default ‘yellow’]
axis [[0 or ‘index’, 1 or ‘columns’, None], default 0] Apply to each column (axis=0 or ‘index’), to each row (axis=1 or ‘columns’), or to the entire DataFrame at once with axis=None.

Returns

self [Styler]
pandas.io.formats.style.Styler.highlight_null

Styler.highlight_null(null_color='red', subset=None)
Shade the background null_color for missing values.

Parameters

null_color [str, default 'red']
subset [label or list of labels, default None] A valid slice for data to limit the style
application to.

Returns

self [Styler]

pandas.io.formats.style.Styler.pipe

Styler.pipe(func, *args, **kwargs)
Apply func(self, *args, **kwargs), and return the result.

New in version 0.24.0.

Parameters

func [function] Function to apply to the Styler. Alternatively, a (callable,
keyword) tuple where keyword is a string indicating the keyword of
callable that expects the Styler.

*args [optional] Arguments passed to func.

**kwargs [optional] A dictionary of keyword arguments passed into func.

Returns

object [] The value returned by func.

See also:

DataFrame.pipe Analogous method for DataFrame.

Styler.apply Apply a function row-wise, column-wise, or table-wise to modify the dataframe’s
styling.

Notes

Like DataFrame.pipe(), this method can simplify the application of several user-defined functions
to a styler. Instead of writing:

```
f(g(df.style.set_precision(3), arg1=a), arg2=b, arg3=c)
```

users can write:

```
(df.style.set_precision(3)
 .pipe(g, arg1=a)
 .pipe(f, arg2=b, arg3=c))
```
In particular, this allows users to define functions that take a styler object, along with other parameters, and return the styler after making styling changes (such as calling `Styler.apply()` or `Styler.set_properties()`). Using `.pipe`, these user-defined style “transformations” can be interleaved with calls to the built-in Styler interface.

### Examples

```python
>>> def format_conversion(styler):
...     return (styler.set_properties(**{'text-align': 'right'}))
...         .format({'conversion': '{:.1%}'}))
```

The user-defined `format_conversion` function above can be called within a sequence of other style modifications:

```python
>>> df = pd.DataFrame({'trial': list(range(5)),
...                   'conversion': [0.75, 0.85, np.nan, 0.7, 0.72]})
>>> (df.style
...     .highlight_min(subset=['conversion'], color='yellow')
...     .pipe(format_conversion)
...     .set_caption("Results with minimum conversion highlighted."))
```

### pandas.io.formats.style.Styler.render

`Styler.render(**kwargs)`

Render the built up styles to HTML.

**Parameters**

**kwargs Any additional keyword arguments are passed through to self. template.render. This is useful when you need to provide additional variables for a custom template.**

**Returns**

rendered [str] The rendered HTML.

### Notes

`Styler` objects have defined the `_repr_html_` method which automatically calls `self.render()` when it’s the last item in a Notebook cell. When calling `Styler.render()` directly, wrap the result in `IPython.display.HTML` to view the rendered HTML in the notebook.

Pandas uses the following keys in `render`. Arguments passed in `**kwargs` take precedence, so think carefully if you want to override them:

- head
- cellstyle
- body
- uuid
- precision
- table_styles
- caption
• table_attributes

**pandas.io.formats.style.Styler.set_caption**

Styler.set_caption(caption)
Set the caption on a Styler.

Parameters

- caption [str]

Returns

self [Styler]

**pandas.io.formats.style.Styler.set_na_rep**

Styler.set_na_rep(na_rep)
Set the missing data representation on a Styler.

New in version 1.0.0.

Parameters

- na_rep [str]

Returns

self [Styler]

**pandas.io.formats.style.Styler.set_precision**

Styler.set_precision(precision)
Set the precision used to render.

Parameters

- precision [int]

Returns

self [Styler]

**pandas.io.formats.style.Styler.set_properties**

Styler.set_properties(subset=None, **kwargs)
Method to set one or more non-data dependent properties or each cell.

Parameters

- subset [IndexSlice] A valid slice for data to limit the style application to.
- **kwargs [dict] A dictionary of property, value pairs to be set for each cell.

Returns

self [Styler]
Examples

```python
>>> df = pd.DataFrame(np.random.randn(10, 4))
>>> df.style.set_properties(color="white", align="right")
>>> df.style.set_properties(**{"background-color": "yellow"})
```

pandas.io.formats.style.Styler.set_table_attributes

Styler.set_table_attributes(attributes)

Set the table attributes.

These are the items that show up in the opening `<table>` tag in addition to to automatic (by default) id.

Parameters

- attributes [str]

Returns

- self [Styler]

Examples

```python
>>> df = pd.DataFrame(np.random.randn(10, 4))
>>> df.style.set_table_attributes('class="pure-table"')
# ... <table class="pure-table"> ...
```

pandas.io.formats.style.Styler.set_table_styles

Styler.set_table_styles(table_styles)

Set the table styles on a Styler.

These are placed in a `<style>` tag before the generated HTML table.

Parameters

- table_styles [list] Each individual table_style should be a dictionary with selector and props keys. selector should be a CSS selector that the style will be applied to (automatically prefixed by the table’s UUID) and props should be a list of tuples with (attribute, value).

Returns

- self [Styler]
Examples

```python
>>> df = pd.DataFrame(np.random.randn(10, 4))
>>> df.style.set_table_styles(
...    [{'selector': 'tr:hover',
...      'props': [('background-color', 'yellow')]}]
...)
```

**pandas.io.formats.style.Styler.set_uuid**

Set the uuid for a Styler.

**Parameters**

- **uuid** [str]

**Returns**

- **self** [Styler]

**pandas.io.formats.style.Styler.to_excel**

Write Styler to an Excel sheet.

To write a single Styler to an Excel .xlsx file it is only necessary to specify a target file name. To write to multiple sheets it is necessary to create an ExcelWriter object with a target file name, and specify a sheet in the file to write to.

Multiple sheets may be written to by specifying unique `sheet_name`. With all data written to the file it is necessary to save the changes. Note that creating an ExcelWriter object with a file name that already exists will result in the contents of the existing file being erased.

**Parameters**

- **excel_writer** [str or ExcelWriter object] File path or existing ExcelWriter.
- **sheet_name** [str, default 'Sheet1'] Name of sheet which will contain DataFrame.
- **na_rep** [str, default ''] Missing data representation.
- **float_format** [str, optional] Format string for floating point numbers. For example `float_format="%.2f"` will format 0.1234 to 0.12.
- **columns** [sequence or list of str, optional] Columns to write.
- **header** [bool or list of str, default True] Write out the column names. If a list of string is given it is assumed to be aliases for the column names.
- **index** [bool, default True] Write row names (index).
- **index_label** [str or sequence, optional] Column label for index column(s) if desired. If not specified, and `header` and `index` are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.
- **startrow** [int, default 0] Upper left cell row to dump data frame.
**startcol** [int, default 0] Upper left cell column to dump data frame.

**engine** [str, optional] Write engine to use, ‘openpyxl’ or ‘xlsxwriter’. You can also set this via the options `io.excel.xlsx.writer`, `io.excel.xls.writer`, and `io.excel.xlsm.writer`.

**merge_cells** [bool, default True] Write MultiIndex and Hierarchical Rows as merged cells.

**encoding** [str, optional] Encoding of the resulting excel file. Only necessary for xlwt, other writers support unicode natively.

**inf_rep** [str, default ‘inf’] Representation for infinity (there is no native representation for infinity in Excel).

**verbose** [bool, default True] Display more information in the error logs.

**freeze_panes** [tuple of int (length 2), optional] Specifies the one-based bottommost row and rightmost column that is to be frozen.

---

**See also:**

- **to_csv** Write DataFrame to a comma-separated values (csv) file.
- **ExcelWriter** Class for writing DataFrame objects into excel sheets.
- **read_excel** Read an Excel file into a pandas DataFrame.
- **read_csv** Read a comma-separated values (csv) file into DataFrame.

---

**Notes**

For compatibility with `to_csv()`, `to_excel` serializes lists and dicts to strings before writing.

Once a workbook has been saved it is not possible write further data without rewriting the whole workbook.

---

**Examples**

Create, write to and save a workbook:

```python
>>> df1 = pd.DataFrame([[['a', 'b'], ['c', 'd']],
        ...     index=['row 1', 'row 2'],
        ...     columns=['col 1', 'col 2'])
>>> df1.to_excel("output.xlsx")
```

To specify the sheet name:

```python
>>> df1.to_excel("output.xlsx",
        ...     sheet_name='Sheet_name_1')
```

If you wish to write to more than one sheet in the workbook, it is necessary to specify an ExcelWriter object:

```python
>>> df2 = df1.copy()
>>> with pd.ExcelWriter('output.xlsx') as writer:
...     df1.to_excel(writer, sheet_name='Sheet_name_1')
...     df2.to_excel(writer, sheet_name='Sheet_name_2')
```
ExcelWriter can also be used to append to an existing Excel file:

```python
>>> with pd.ExcelWriter('output.xlsx', mode='a') as writer:
    df.to_excel(writer, sheet_name='Sheet_name_3')
```

To set the library that is used to write the Excel file, you can pass the `engine` keyword (the default engine is automatically chosen depending on the file extension):

```python
>>> df1.to_excel('output1.xlsx', engine='xlsxwriter')
```

### pandas.io.formats.style.Styler.use

**Styler.use**(styles)

Set the styles on the current Styler. Possibly uses uses styles from `Styler.export`.

**Parameters**

- **styles** [list] List of style functions.

**Returns**

- **self** [Styler]

**See also:**

- `Styler.export`

### pandas.io.formats.style.Styler.where

**Styler.where**(cond, value=None, other=None, subset=None, **kwargs)

Apply a function elementwise. Updates the HTML representation with a style which is selected in accordance with the return value of a function.

**Parameters**

- **cond** [callable] `cond` should take a scalar and return a boolean.
- **value** [str] Applied when `cond` returns true.
- **other** [str] Applied when `cond` returns false.
- **subset** [IndexSlice] A valid indexer to limit data to before applying the function. Consider using a pandas.IndexSlice.
- **kwargs** [dict] Pass along to `cond`.

**Returns**

- **self** [Styler]

**See also:**

- `Styler.applymap`
### 3.13.2 Styler properties

- `Styler.env`  
- `Styler.template`  
- `Styler.loader`

```python
pandas.io.formats.style.Styler.env
Styler.env = <jinja2.environment.Environment object>
```

```python
pandas.io.formats.style.Styler.template
Styler.template = <Template 'html.tpl'>
```

```python
pandas.io.formats.style.Styler.loader
Styler.loader = <jinja2.loaders.PackageLoader object>
```

### 3.13.3 Style application

- `Styler.apply(func[, axis, subset])`  
  - Apply a function column-wise, row-wise, or table-wise.
- `Styler.applymap(func[, subset])`  
  - Apply a function elementwise.
- `Styler.where(cond, value[, other, subset])`  
  - Apply a function elementwise.
- `Styler.format(formatter[, subset, na_rep])`  
  - Format the text display value of cells.
- `Styler.set_precision(precision)`  
  - Set the precision used to render.
- `Styler.set_table_styles(table_styles)`  
  - Set the table styles on a Styler.
- `Styler.set_table_attributes(attributes)`  
  - Set the table attributes.
- `Styler.set_caption(caption)`  
  - Set the caption on a Styler.
- `Styler.set_properties([subset])`  
  - Method to set one or more non-data dependent properties or each cell.
- `Styler.set_uuid(uuid)`  
  - Set the uuid for a Styler.
- `Styler.set_na_rep(na_rep)`  
  - Set the missing data representation on a Styler.
- `Styler.clear()`  
  - Reset the styler, removing any previously applied styles.
- `Styler.pipe(func, *args, **kwargs)`  
  - Apply `func(self, *args, **kwargs)`, and return the result.

### 3.13.4 Built-in styles

- `Styler.highlight_max([subset, color, axis])`  
  - Highlight the maximum by shading the background.
- `Styler.highlight_min([subset, color, axis])`  
  - Highlight the minimum by shading the background.
- `Styler.highlight_null([null_color, subset])`  
  - Shade the background `null_color` for missing values.
- `Styler.background_gradient([cmap, low, ...])`  
  - Color the background in a gradient style.
- `Styler.bar([subset, axis, color, width, ...])`  
  - Draw bar chart in the cell backgrounds.
3.13.5 Style export and import

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Styler.render(**kwargs)</code></td>
<td>Render the built up styles to HTML.</td>
</tr>
<tr>
<td><code>Styler.export()</code></td>
<td>Export the styles to applied to the current Styler.</td>
</tr>
<tr>
<td><code>Styler.use(styles)</code></td>
<td>Set the styles on the current Styler.</td>
</tr>
<tr>
<td><code>Styler.to_excel(excel_writer[, sheet_name, ...])</code></td>
<td>Write Styler to an Excel sheet.</td>
</tr>
</tbody>
</table>

3.14 Plotting

The following functions are contained in the `pandas.plotting` module.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>andrews_curves(frame, class_column[, ax, ...])</code></td>
<td>Generate a matplotlib plot of Andrews curves, for visualising clusters of multivariate data.</td>
</tr>
<tr>
<td><code>autocorrelation_plot(series[, ax])</code></td>
<td>Autocorrelation plot for time series.</td>
</tr>
<tr>
<td><code>bootstrap_plot(series[, fig, size, samples])</code></td>
<td>Bootstrap plot on mean, median and mid-range statistics.</td>
</tr>
<tr>
<td><code>boxplot(data[, column, by, ax, fontsize, ...])</code></td>
<td>Make a box plot from DataFrame columns.</td>
</tr>
<tr>
<td><code>deregister_matplotlib_converters()</code></td>
<td>Remove pandas formatters and converters.</td>
</tr>
<tr>
<td><code>lag_plot(series[, lag, ax])</code></td>
<td>Lag plot for time series.</td>
</tr>
<tr>
<td><code>parallel_coordinates(frame, class_column[, ...])</code></td>
<td>Parallel coordinates plotting.</td>
</tr>
<tr>
<td><code>plot_params</code></td>
<td>Stores pandas plotting options.</td>
</tr>
<tr>
<td><code>radviz(frame, class_column[, ax, color, ...])</code></td>
<td>Plot a multidimensional dataset in 2D.</td>
</tr>
<tr>
<td><code>register_matplotlib_converters()</code></td>
<td>Register pandas formatters and converters with matplotlib.</td>
</tr>
<tr>
<td><code>scatter_matrix(frame[, alpha, figsize, ax, ...])</code></td>
<td>Draw a matrix of scatter plots.</td>
</tr>
<tr>
<td><code>table(ax, data[, rowLabels, colLabels])</code></td>
<td>Helper function to convert DataFrame and Series to matplotlib.table.</td>
</tr>
</tbody>
</table>

3.14.1 pandas.plotting.andrews_curves

`pandas.plotting.andrews_curves(frame, class_column, ax=None, samples=200, color=None, colormap=None, **kwargs)`

Generate a matplotlib plot of Andrews curves, for visualising clusters of multivariate data.

Andrews curves have the functional form:

\[ f(t) = \frac{x_1}{\sqrt{2}} + x_2 \sin(t) + x_3 \cos(t) + x_4 \sin(2t) + x_5 \cos(2t) + \ldots \]

Where \( x \) coefficients correspond to the values of each dimension and \( t \) is linearly spaced between -\( \pi \) and +\( \pi \).

Each row of \( \text{frame} \) then corresponds to a single curve.

**Parameters**

- **frame** [DataFrame] Data to be plotted, preferably normalized to \((0.0, 1.0)\).
- **class_column** [Name of the column containing class names]
- **ax** [matplotlib axes object, default None]
- **samples** [Number of points to plot in each curve]
- **color** [list or tuple, optional] Colors to use for the different classes.
- **colormap** [str or matplotlib colormap object, default None] Colormap to select colors from.
  - If string, load colormap with that name from matplotlib.
**kwargs Options to pass to matplotlib plotting method.

**Returns**

class: `matplotlib.axis.Axes`

**Examples**

```python
>>> df = pd.read_csv(
...     'https://raw.github.com/pandas-dev/
...     'pandas/master/pandas/tests/io/data/csv/iris.csv'
... )
>>> pd.plotting.andrews_curves(df, 'Name')
```
3.14.2 pandas.plotting.autocorrelation_plot

pandas.plotting.autocorrelation_plot(series, ax=None, **kwargs)

Autocorrelation plot for time series.

Parameters

- **series**: [Time series]
- **ax**: [Matplotlib axis object, optional]
- **kwargs**: Options to pass to matplotlib plotting method.

Returns

- class: matplotlib.axis.Axes

Examples

The horizontal lines in the plot correspond to 95% and 99% confidence bands.

The dashed line is 99% confidence band.

```python
>>> spacing = np.linspace(-9 * np.pi, 9 * np.pi, num=1000)
>>> s = pd.Series(0.7 * np.random.rand(1000) + 0.3 * np.sin(spacing))
>>> pd.plotting.autocorrelation_plot(s)
```
3.14.3 pandas.plotting.bootstrap_plot

**pandas.plotting.bootstrap_plot** (series, fig=None, size=50, samples=500, **kwds)

Bootstrap plot on mean, median and mid-range statistics.

The bootstrap plot is used to estimate the uncertainty of a statistic by relying on random sampling with replacement [1]. This function will generate bootstrapping plots for mean, median and mid-range statistics for the given number of samples of the given size.

**Parameters**

- **series** [pandas.Series] Series from where to get the samplings for the bootstrapping.
- **fig** [matplotlib.figure.Figure, default None] If given, it will use the fig reference for plotting instead of creating a new one with default parameters.
- **size** [int, default 50] Number of data points to consider during each sampling. It must be less than or equal to the length of the series.
- **samples** [int, default 500] Number of times the bootstrap procedure is performed.
- **kwds** Options to pass to matplotlib plotting method.

**Returns**

- **matplotlib.figure.Figure** Matplotlib figure.

**See also:**

- DataFrame.plot Basic plotting for DataFrame objects.
- Series.plot Basic plotting for Series objects.

**Examples**

This example draws a basic bootstap plot for a Series.

```python
>>> s = pd.Series(np.random.uniform(size=100))
>>> pd.plotting.bootstrap_plot(s)
```

3.14.4 pandas.plotting.boxplot

**pandas.plotting.boxplot** (data, column=None, by=None, ax=None, fontsize=None, rot=0, grid=True, figsize=None, layout=None, return_type=None, **kwargs)

Make a box plot from DataFrame columns.

Make a box-and-whisker plot from DataFrame columns, optionally grouped by some other columns. A box plot is a method for graphically depicting groups of numerical data through their quartiles. The box extends from the Q1 to Q3 quartile values of the data, with a line at the median (Q2). The whiskers extend from the edges of the box to show the range of the data. By default, they extend no more than $1.5 \times IQR (IQR = Q3 - Q1)$ from the edges of the box, ending at the farthest data point within that interval. Outliers are plotted as separate dots.

For further details see Wikipedia’s entry for boxplot.

**Parameters**

- **column** [str or list of str, optional] Column name or list of names, or vector. Can be any valid input to pandas.DataFrame.groupby().
- **by** [str or array-like, optional] Column in the DataFrame to pandas.DataFrame.groupby(). One box-plot will be done per value of columns in by.
- **ax** [object of class matplotlib.axes.Axes, optional] The matplotlib axes to be used by boxplot.
Boxplot parameters:

- **fontsize** [float or str] Tick label font size in points or as a string (e.g., `large`).
- **rot** [int or float, default 0] The rotation angle of labels (in degrees) with respect to the screen coordinate system.
- **grid** [bool, default True] Setting this to True will show the grid.
- **figsize** [A tuple (width, height) in inches] The size of the figure to create in matplotlib.
- **layout** [tuple (rows, columns), optional] For example, (3, 5) will display the subplots using 3 columns and 5 rows, starting from the top-left.
- **return_type** [[‘axes’, ‘dict’, ‘both’] or None, default ‘axes’] The kind of object to return. The default is **axes**.
  - ‘axes’ returns the matplotlib axes the boxplot is drawn on.
  - ‘dict’ returns a dictionary whose values are the matplotlib Lines of the boxplot.
  - ‘both’ returns a namedtuple with the axes and dict.
  - when grouping with by, a Series mapping columns to **return_type** is returned.
    - If **return_type** is None, a NumPy array of axes with the same shape as **layout** is returned.

**kwargs** All other plotting keyword arguments to be passed to **matplotlib.pyplot.boxplot**.

Returns

result See Notes.

See also:

- **Series.plot.hist** Make a histogram.
- **matplotlib.pyplot.boxplot** Matplotlib equivalent plot.

Notes

The return type depends on the **return_type** parameter:

- ‘axes’ : object of class matplotlib.axes.Axes
- ‘dict’ : dict of matplotlib.lines.Line2D objects
- ‘both’ : a namedtuple with structure (ax, lines)

For data grouped with by, return a Series of the above or a numpy array:

- **Series**
- **array** (for **return_type** = None)

Use **return_type=’dict’** when you want to tweak the appearance of the lines after plotting. In this case a dict containing the Lines making up the boxes, caps, fliers, medians, and whiskers is returned.

Examples

Boxplots can be created for every column in the dataframe by **df.boxplot()** or indicating the columns to be used:

```python
>>> np.random.seed(1234)
>>> df = pd.DataFrame(np.random.randn(10, 4),
...                   columns=['Col1', 'Col2', 'Col3', 'Col4'])
>>> boxplot = df.boxplot(column=['Col1', 'Col2', 'Col3'])
```
3.14. Plotting
Boxplots of variables distributions grouped by the values of a third variable can be created using the option `by`. For instance:

```python
>>> df = pd.DataFrame(np.random.randn(10, 2),
                   columns=['Col1', 'Col2'])
>>> boxplot = df.boxplot(by='X')
```

A list of strings (i.e. `['X', 'Y']`) can be passed to `boxplot` in order to group the data by combination of the variables in the x-axis:

```python
>>> df = pd.DataFrame(np.random.randn(10, 3),
                   columns=['Col1', 'Col2', 'Col3'])
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by=['X', 'Y'])
```

The layout of boxplot can be adjusted giving a tuple to `layout`:

```python
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by='X',
                        layout=(2, 1))
```

Additional formatting can be done to the boxplot, like suppressing the grid (`grid=False`), rotating the labels...
Boxplot grouped by ['X', 'Y']

Col1

Col2
in the x-axis (i.e. rot=45) or changing the fontsize (i.e. fontsize=15):

```python
>>> boxplot = df.boxplot(grid=False, rot=45, fontsize=15)
```

The parameter `return_type` can be used to select the type of element returned by `boxplot`. When `return_type='axes'` is selected, the matplotlib axes on which the boxplot is drawn are returned:

```python
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], return_type='axes')
>>> type(boxplot)
<class 'matplotlib.axes._subplots.AxesSubplot'>
```

When grouping with `by`, a Series mapping columns to `return_type` is returned:

```python
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by='X',
                       return_type='axes')
>>> type(boxplot)
<class 'pandas.core.series.Series'>
```

If `return_type` is `None`, a NumPy array of axes with the same shape as `layout` is returned:

```python
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by='X',
                       return_type=None)
>>> type(boxplot)
<class 'numpy.ndarray'>
```
3.14.5 pandas.plotting.deregister_matplotlib_converters

```python
pandas.plotting.deregister_matplotlib_converters()

Remove pandas formatters and converters.
```

Removes the custom converters added by `register()`. This attempts to set the state of the registry back to the state before pandas registered its own units. Converters for pandas’ own types like Timestamp and Period are removed completely. Converters for types pandas overwrites, like `datetime.datetime`, are restored to their original value.

See also:

- `register_matplotlib_converters` Register pandas formatters and converters with matplotlib.

3.14.6 pandas.plotting.lag_plot

```python
pandas.plotting.lag_plot(series, lag=1, ax=None, **kwds)

Lag plot for time series.
```

Parameters

- `series` [Time series]
- `lag` [lag of the scatter plot, default 1]
- `ax` [Matplotlib axis object, optional]
- `**kwds` Matplotlib scatter method keyword arguments.

Returns

- `Axes` Matplotlib axes.

Examples

Lag plots are most commonly used to look for patterns in time series data.

Given the following time series

```python
>>> np.random.seed(5)
>>> x = np.cumsum(np.random.normal(loc=1, scale=5, size=50))
>>> s = pd.Series(x)
>>> s.plot()
```

A lag plot with `lag=1` returns

```python
>>> pd.plotting.lag_plot(s, lag=1)
```

3.14.7 pandas.plotting.parallel_coordinates

```python
pandas.plotting.parallel_coordinates(frame, class_column, cols=None, ax=None, color=None, use_columns=False, xticks=None, colormap=None, axvlines=True, axvlines_kwds=None, sort_labels=False, **kwargs)

Parallel coordinates plotting.
```

Parameters

- `frame` [DataFrame]
class_column [str] Column name containing class names.
cols [list, optional] A list of column names to use.
color [list or tuple, optional] Colors to use for the different classes.
use_columns [bool, optional] If true, columns will be used as xticks.
xticks [list or tuple, optional] A list of values to use for xticks.
colormap [str or matplotlib colormap, default None] Colormap to use for line colors.
axvlines [bool, optional] If true, vertical lines will be added at each xtick.
axvlines_kwds [keywords, optional] Options to be passed to axvline method for vertical lines.
sort_labels [bool, default False] Sort class_column labels, useful when assigning colors.
**kwds Options to pass to matplotlib plotting method.

Returns
class:matplotlib.axis.Axes

Examples

```python
>>> df = pd.read_csv(
...   'https://raw.github.com/pandas-dev/
...   'pandas/master/pandas/tests/io/data/csv/iris.csv'
... )
>>> pd.plotting.parallel_coordinates(
...   df, 'Name', color=('#556270', '#4ECDC4', '#C7F464')
... )
```

3.14.8 pandas.plotting.plot_params

pandas.plotting.plot_params = {'xaxis.compat': False}
Stores pandas plotting options.
Allows for parameter aliasing so you can just use parameter names that are the same as the plot function parameters, but is stored in a canonical format that makes it easy to breakdown into groups later.

3.14.9 pandas.plotting.radviz

pandas.plotting.radviz (frame, class_column, ax=None, color=None, colormap=None, **kwds)
Plot a multidimensional dataset in 2D.

Each Series in the DataFrame is represented as a evenly distributed slice on a circle. Each data point is rendered in the circle according to the value on each Series. Highly correlated Series in the DataFrame are placed closer on the unit circle.

RadViz allow to project a N-dimensional data set into a 2D space where the influence of each dimension can be interpreted as a balance between the influence of all dimensions.

More info available at the original article describing RadViz.

Parameters
frame [DataFrame] Object holding the data.
class_column [str] Column name containing the name of the data point category.
ax [matplotlib.axes.Axes, optional] A plot instance to which to add the information.
color [list[str] or tuple[str], optional] Assign a color to each category. Example: ['blue', 'green'].
colormap [str or matplotlib.colors.Colormap, default None] Colormap to select colors from. If string, load colormap with that name from matplotlib.
**kwds Options to pass to matplotlib scatter plotting method.

Returns
class:matplotlib.axes.Axes

See also:
plotting.andrews_curves Plot clustering visualization.

Examples

```python
>>> df = pd.DataFrame(
...     {
...         'SepalLength': [6.5, 7.7, 5.1, 5.8, 7.6, 5.0, 5.4, 4.6, 6.7, 4.6],
...         'SepalWidth': [3.0, 3.8, 3.8, 2.7, 3.0, 2.3, 3.0, 3.2, 3.3, 3.6],
...         'PetalLength': [5.5, 6.7, 1.9, 5.1, 6.6, 3.3, 4.5, 1.4, 5.7, 1.0],
...         'PetalWidth': [1.8, 2.2, 0.4, 1.9, 2.1, 1.0, 1.5, 0.2, 2.1, 0.2],
...         'Category': ['virginica', 'virginica', 'setosa', 'virginica', 'virginica', 'versicolor', 'versicolor', 'setosa', 'virginica', 'setosa']
...     }
... )
>>> pd.plotting.radviz(df, 'Category')
```

3.14.10 pandas.plotting.register_matplotlib_converters

pandas.plotting.register_matplotlib_converters()
Register pandas formatters and converters with matplotlib.

This function modifies the global matplotlib.units.registry dictionary. pandas adds custom converters for
- pd.Timestamp
- pd.Period
- np.datetime64
- datetime.datetime
- datetime.date
- datetime.time
See also: 

`deregister_matplotlib_converters` Remove pandas formatters and converters.

### 3.14.11 pandas.plotting.scatter_matrix

**pandas.plotting.scatter_matrix** *(frame, alpha=0.5, figsize=None, ax=None, grid=False, diagonal='hist', marker='.', density_kwds=None, hist_kwds=None, range_padding=0.05, **kwargs)*

Draw a matrix of scatter plots.

**Parameters**

- **frame** *DataFrame*
- **alpha** *[float, optional]* Amount of transparency applied.
- **figsize** *[((float, float), optional)]* A tuple (width, height) in inches.
- **ax** *[Matplotlib axis object, optional]*
- **grid** *[bool, optional]* Setting this to True will show the grid.
- **diagonal** *[{'hist', 'kde'}]* Pick between ‘kde’ and ‘hist’ for either Kernel Density Estimation or Histogram plot in the diagonal.
- **marker** *[str, optional]* Matplotlib marker type, default ‘.’.
- **density_kwds** *[keywords]* Keyword arguments to be passed to kernel density estimate plot.
- **hist_kwds** *[keywords]* Keyword arguments to be passed to hist function.
- **range_padding** *[float, default 0.05]* Relative extension of axis range in x and y with respect to (x_max - x_min) or (y_max - y_min).

**Returns**

*numpy.ndarray* A matrix of scatter plots.

**Examples**

```python
>>> df = pd.DataFrame(np.random.randn(1000, 4), columns=['A', 'B', 'C', 'D'])
>>> pd.plotting.scatter_matrix(df, alpha=0.2)
```

### 3.14.12 pandas.plotting.table

**pandas.plotting.table** *(ax, data, rowLabels=None, colLabels=None, **kwargs)*

Helper function to convert DataFrame and Series to matplotlib.table.

**Parameters**

- **ax** *[Matplotlib axes object]*
- **data** *[DataFrame or Series]* Data for table contents.

**Returns**

*matplotlib table object*
3.15 General utility functions

3.15.1 Working with options

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>describe_option(pat[, _print_desc])</code></td>
<td>Prints the description for one or more registered options.</td>
</tr>
<tr>
<td><code>reset_option(pat)</code></td>
<td>Reset one or more options to their default value.</td>
</tr>
<tr>
<td><code>get_option(pat)</code></td>
<td>Retrieves the value of the specified option.</td>
</tr>
<tr>
<td><code>set_option(pat, value)</code></td>
<td>Sets the value of the specified option.</td>
</tr>
<tr>
<td><code>option_context(*args)</code></td>
<td>Context manager to temporarily set options in the <code>with</code> statement context.</td>
</tr>
</tbody>
</table>

**pandas.describe_option**

```python
def pandas.describe_option(pat, _print_desc=False) = <pandas._config.config.CallableDynamicDoc object>
```

Prints the description for one or more registered options.

Call with not arguments to get a listing for all registered options.

Available options:

- compute.[use_bottleneck, use_numba, use_numexpr]
- display.[chop_threshold, colheader_justify, column_space, date_dayfirst, date_yearfirst, encoding, expand_frame_repr, float_format]
- display.html.[border, table_schema, use_mathjax]
- display.[large_repr]
- display.latex.[escape, longtable, multicolumn, multicolumn_format, multirow, repr]
- display.[max_categories, max_columns, max_colwidth, max_info_columns, max_info_rows, max_rows, max_seq_items, memory_usage, min_rows, multi_sparse, notebook_repr_html, pprint_nest_depth, precision, show_dimensions]
- display.unicode.[ambiguous_as_wide, east_asian_width]
- display.[width]
- io.excel.ods.[reader, writer]
- io.excel.xls.[reader, writer]
- io.excel.xlsb.[reader]
- io.excel.xlsxm.[reader, writer]
- io.excel.xlsx.[reader, writer]
- io.hdf.[default_format, dropna_table]
- io.parquet.[engine]
- mode.[chained_assignment, sim_interactive, use_inf_as_na, use_inf_as_null]
- plotting.[backend]
- plotting.matplotlib.[register_converters]

**Parameters**

- `pat` [str] Regexp pattern. All matching keys will have their description displayed.
- `_print_desc` [bool, default True] If True (default) the description(s) will be printed to stdout. Otherwise, the description(s) will be returned as a unicode string (for testing).

**Returns**

None by default, the description(s) as a unicode string if `_print_desc` is False
Notes

The available options with its descriptions:

- **compute.use_bottleneck** [bool] Use the bottleneck library to accelerate if it is installed, the default is True. Valid values: False, True [default: True] [currently: True]
- **compute.use_numba** [bool] Use the numba engine option for select operations if it is installed, the default is False. Valid values: False, True [default: False] [currently: False]
- **compute.use_numexpr** [bool] Use the numexpr library to accelerate computation if it is installed, the default is True. Valid values: False, True [default: True] [currently: True]
- **display.chop_threshold** [float or None] if set to a float value, all float values smaller then the given threshold will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]
- **display.colheader_justify** ['left'/'right'] Controls the justification of column headers. used by DataFrameFormatter. [default: right] [currently: right]
- **display.column_space** No description available. [default: 12] [currently: 12]
- **display.date_dayfirst** [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default: False] [currently: False]
- **display.date_yearfirst** [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default: False] [currently: False]
- **display.encoding** [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by to_string, these are generally strings meant to be displayed on the console. [default: utf-8] [currently: utf-8]
- **display.expand_frame_repr** [boolean] Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, max_columns is still respected, but the output will wrap-around across multiple “pages” if its width exceeds display.width. [default: True] [currently: True]
- **display.float_format** [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See formats.format.EngFormatter for an example. [default: None] [currently: None]
- **display.html.border** [int] A border=value attribute is inserted in the <table> tag for the DataFrame HTML repr. [default: 1] [currently: 1]
- **display.html.table_schema** [boolean] Whether to publish a Table Schema representation for frontends that support it. (default: False) [default: False] [currently: False]
- **display.html.use_mathjax** [boolean] When True, Jupyter notebook will process table contents using MathJax, rendering mathematical expressions enclosed by the dollar symbol. (default: True) [default: True] [currently: True]
- **display.large_repr** ['truncate'/'info'] For DataFrames exceeding max_rows/max_cols, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from df.info() (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]
- **display.latex.escape** [bool] This specifies if the to_latex method of a Dataframe uses escapes special characters. Valid values: False,True [default: True] [currently: True]
- **display.latex.longtable** :bool This specifies if the to_latex method of a Dataframe uses the longtable format. Valid values: False,True [default: False] [currently: False]
- **display.latex.multicolumn** [bool] This specifies if the to_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: True] [currently: True]
- **display.latex.multicolumn_format** [bool] This specifies if the to_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: 1] [currently: 1]
- **display.latex.multirow** [bool] This specifies if the to_latex method of a Dataframe uses multirows to pretty-print MultiIndex rows. Valid values: False,True [default: False] [currently: False]
- **display.latex.repr** [boolean] Whether to produce a latex DataFrame representation for jupyter environments that support it. (default: False) [default: False] [currently: False]
- **display.max_categories** [int] This sets the maximum number of categories pandas should output when printing out a Categorical or a Series of dtype “category”. [default: 8] [currently: 8]
- **display.max_columns** [int] If max_cols is exceeded, switch to truncate view. Depending on large_repr, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.
In case python/IPython is running in a terminal and large_repr equals ‘truncate’ this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 0] [currently: 0]

display.max_colwidth [int or None] The maximum width in characters of a column in the repr of a pandas data structure. When the column overflows, a “…” placeholder is embedded in the output. A ‘None’ value means unlimited. [default: 50] [currently: 50]

display.max_info_columns [int] max_info_columns is used in DataFrame.info method to decide if per column information will be printed. [default: 100] [currently: 100]

display.max_info_rows [int or None] df.info() will usually show null-counts for each column. For large frames this can be quite slow. max_info_rows and max_info_cols limit this null check only to frames with smaller dimensions than specified. [default: 1690785] [currently: 1690785]

display.max_rows [int] If max_rows is exceeded, switch to truncate view. Depending on large_repr, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and large_repr equals ‘truncate’ this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 60] [currently: 15]

display.max_seq_items [int or None] when pretty-printing a long sequence, no more then max_seq_items will be printed. If items are omitted, they will be denoted by the addition of “…” to the resulting string.

If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]

display.memory_usage [bool, string or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. Valid values True,False,’deep’ [default: True] [currently: True]

display.min_rows [int] The numbers of rows to show in a truncated view (when max_rows is exceeded). Ignored when max_rows is set to None or 0. When set to None, follows the value of max_rows. [default: 10] [currently: 10]

display.multi_sparse [boolean] “sparsify” MultiIndex display (don’t display repeated elements in outer levels within groups) [default: True] [currently: True]

display.notebook_repr_html [boolean] When True, IPython notebook will use html representation for pandas objects (if it is available). [default: True] [currently: True]

display.pprint_nest_depth [int] Controls the number of nested levels to process when pretty-printing [default: 3] [currently: 3]

display.precision [int] Floating point output precision (number of significant digits). This is only a suggestion [default: 6] [currently: 6]

display.show_dimensions [boolean or ‘truncate’) Whether to print out dimensions at the end of DataFrame repr. If ‘truncate’ is specified, only print out the dimensions if the frame is truncated (e.g. not display all rows and/or columns) [default: truncate] [currently: truncate]

display.unicode.ambiguous_as_wide [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance (default: False) [default: False] [currently: False]

display.unicode.east_asian_width [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance (default: False) [default: False] [currently: False]

display.width [int] Width of the display in characters. In case python/IPython is running in a terminal this can be set to None and pandas will correctly auto-detect the width. Note that the IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to correctly detect the width. [default: 80] [currently: 80]


pandas: powerful Python data analysis toolkit, Release 1.1.1


io.hdf.default_format [format] default format writing format, if None, then put will default to ‘fixed’ and append will default to ‘table’ [default: None] [currently: None]

io.hdf.dropna_table [boolean] drop ALL nan rows when appending to a table [default: False] [currently: False]


mode.chained_assignment  [string] Raise an exception, warn, or no action if trying to use chained assignment, The default is warn [default: warn] [currently: warn]

mode.sim_interactive  [boolean] Whether to simulate interactive mode for purposes of testing [default: False] [currently: False]

mode.use_inf_as_na  [boolean] True means treat None, NaN, INF, -INF as NA (old way), False means None and NaN are null, but INF, -INF are not NA (new way). [default: False] [currently: False]

mode.use_inf_as_null  [boolean] use_inf_as_null had been deprecated and will be removed in a future version. Use use_inf_as_na instead. [default: False] [currently: False] (Deprecated, use mode.use_inf_as_na instead.)

plotting.backend  [str] The plotting backend to use. The default value is “matplotlib”, the backend provided with pandas. Other backends can be specified by providing the name of the module that implements the backend. [default: matplotlib] [currently: matplotlib]

plotting.matplotlib.register_converters  [bool or ‘auto’] Whether to register converters with matplotlib’s units registry for dates, times, datetimes, and Periods. Toggling to False will remove the converters, restoring any converters that pandas overwrote. [default: auto] [currently: auto]

pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.reset_option  = <pandas._config.config.CallableDynamicDoc object>

Reset one or more options to their default value.

Pass “all” as argument to reset all options.

Available options:
- compute.[use_bottleneck, use_numba, use_numexpr]
- display.[chop_threshold, colheader_justify, column_space, date_dayfirst, date_yearfirst, encoding, expand_frame_repr, float_format]
- display.html.[border, table_schema, use_mathjax]
- display.[large_repr]
- display.latex.[escape, longtable, multicolumn, multicolumn_format, multirow, repr]
- display.[max_categories, max_columns, max_colwidth, max_info_columns, max_info_rows, max_rows, max_seq_items, memory_usage, min_rows, multi_sparse, notebook_repr_html, pprint_nest_depth, precision, show_dimensions]
- display.unicode.[ambiguous_as_wide, east_asian_width]
- display.[width]
• io.excel.ods.[reader, writer]
• io.excel.xls.[reader, writer]
• io.excel.xlsb.[reader]
• io.excel.xlsm.[reader, writer]
• io.excel.xlsx.[reader, writer]
• io.hdf.[default_format, dropna_table]
• io.parquet.[engine]
• mode.[chained_assignment, sim_interactive, use_inf_as_na, use_inf_as_null]
• plotting.[backend]
• plotting.matplotlib.[register_converters]

Parameters

**pat** [str/regex] If specified only options matching *prefix* will be reset. Note: partial matches are supported for convenience, but unless you use the full option name (e.g. `x.y.z.option_name`), your code may break in future versions if new options with similar names are introduced.

Returns

None

Notes

The available options with its descriptions:

- **compute.use_bottleneck** [bool] Use the bottleneck library to accelerate if it is installed, the default is True
  
  Valid values: False, True [default: True] [currently: True]

- **compute.use_numba** [bool] Use the numba engine option for select operations if it is installed, the default is False
  
  Valid values: False, True [default: False] [currently: False]

- **compute.use_numexpr** [bool] Use the numexpr library to accelerate computation if it is installed, the default is True
  
  Valid values: False, True [default: True] [currently: True]

- **display.chop_threshold** [float or None] if set to a float value, all float values smaller than the given threshold will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]

- **display.colheader_justify** ['left'/'right'] Controls the justification of column headers. used by DataFrameFormatter. [default: right] [currently: right]

- **display.column_space** No description available. [default: 12] [currently: 12]

- **display.date_dayfirst** [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default: False] [currently: False]

- **display.date_yearfirst** [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default: False] [currently: False]

- **display.encoding** [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by to_string, these are generally strings meant to be displayed on the console. [default: utf-8] [currently: utf-8]

- **display.expand_frame_repr** [boolean] Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, **max_columns** is still respected, but the output will wrap-around across multiple “pages” if its width exceeds **display.width**. [default: True] [currently: True]

- **display.float_format** [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See formats.format.EngFormatter for an example. [default: None] [currently: None]

- **display.html.border** [int] A border=value attribute is inserted in the **<table>** tag for the DataFrame HTML repr. [default: 1] [currently: 1]

- **display.html.table_schema** [boolean] Whether to publish a Table Schema representation for frontends that support it. [default: False] [currently: False]

- **display.html.use_mathjax** [boolean] When True, Jupyter notebook will process table contents using MathJax, rendering mathematical expressions enclosed by the dollar symbol. [default: True] [currently: True]
display.large_repr ['truncate'/info'] For DataFrames exceeding max_rows/max_cols, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from df.info() (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]
display.latex.escape [bool] This specifies if the to_latex method of a DataFrame uses escapes special characters. Valid values: False,True [default: True] [currently: True]
display.latex.longtable [bool] This specifies if the to_latex method of a DataFrame uses the longtable format. Valid values: False,True [default: False] [currently: False]
display.latex.multicolumn [bool] This specifies if the to_latex method of a DataFrame uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: True] [currently: True]
display.latex.multicolumn_format [bool] This specifies if the to_latex method of a DataFrame uses multi-columns to pretty-print MultiIndex columns. Valid values: False,True [default: l] [currently: l]
display.latex.multirow [bool] This specifies if the to_latex method of a DataFrame uses multirows to pretty-print MultiIndex rows. Valid values: False,True [default: False] [currently: False]
display.latex.repr [boolean] Whether to produce a latex DataFrame representation for jupyter environments that support it. (default: False) [default: False] [currently: False]
display.max_categories [int] This sets the maximum number of categories pandas should output when printing out a Categorical or a Series of dtype “category”. [default: 8] [currently: 8]
display.max_columns [int] If max_cols is exceeded, switch to truncate view. Depending on large_repr, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and large_repr equals ‘truncate’ this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 0] [currently: 0]
display.max_colwidth [int or None] The maximum width in characters of a column in the repr of a pandas data structure. When the column overflows, a “…” placeholder is embedded in the output. A ‘None’ value means unlimited. [default: 50] [currently: 50]
display.max_info_columns [int] max_info_columns is used in DataFrame.info method to decide if per column information will be printed. [default: 100] [currently: 100]
display.max_info_rows [int or None] df.info() will usually show null-counts for each column. For large frames this can be quite slow. max_info_rows and max_info_cols limit this null check only to frames with smaller dimensions than specified. [default: 1690785] [currently: 1690785]
display.max_rows [int] If max_rows is exceeded, switch to truncate view. Depending on large_repr, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and large_repr equals ‘truncate’ this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 0] [currently: 15]
display.max_seq_items [int or None] when pretty-printing a long sequence, no more then max_seq_items will be printed. If items are omitted, they will be denoted by the addition of “…” to the resulting string.

If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]
display.memory_usage [bool, string or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. Valid values True,False,‘deep’ [default: True] [currently: True]
display.min_rows [int] The numbers of rows to show in a truncated view (when max_rows is exceeded). Ignored when max_rows is set to None or 0. When set to None, follows the value of max_rows. [default: 10] [currently: 10]
display.multi_sparse [boolean] “sparsify” MultiIndex display (don’t display repeated elements in outer levels within groups) [default: True] [currently: True]
display.notebook_repr_html [boolean] When True, IPython notebook will use html representation for pandas objects (if it is available). [default: True] [currently: True]
display.pprint_nest_depth [int] Controls the number of nested levels to process when pretty-printing [default: 3] [currently: 3]
**display.precision** [int] Floating point output precision (number of significant digits). This is only a suggestion [default: 6] [currently: 6]

**display.show_dimensions** [boolean or ‘truncate’) Whether to print out dimensions at the end of DataFrame repr. If ‘truncate’ is specified, only print out the dimensions if the frame is truncated (e.g. not display all rows and/or columns) [default: truncate] [currently: truncate]

**display.unicode.ambiguous_as_wide** [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance (default: False) [currently: False]

**display.unicode.east_asian_width** [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance (default: False) [currently: False]

**display.width** [int] Width of the display in characters. In case python/IPython is running in a terminal this can be set to None and pandas will correctly auto-detect the width. Note that the IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to correctly detect the width. [default: 80] [currently: 80]


**io.hdf.default_format** [format] default format writing format, if None, then put will default to ‘fixed’ and append will default to ‘table’ [default: None] [currently: None]

**io.hdf.dropna_table** [boolean] drop ALL nan rows when appending to a table [default: False] [currently: False]


**mode.chained_assignment** [string] Raise an exception, warn, or no action if trying to use chained assignment, The default is warn [default: warn] [currently: warn]

**mode.sim_interactive** [boolean] Whether to simulate interactive mode for purposes of testing [default: False] [currently: False]

**mode.use_inf_as_na** [boolean] True means treat None, NaN, INF, -INF as NA (old way), False means None and NaN are null, but INF, -INF are not NA (new way). [default: False] [currently: False]

**mode.use_inf_as_null** [boolean] use_inf_as_null had been deprecated and will be removed in a future version. Use `use_inf_as_na` instead. [default: False] [currently: False] (Deprecated, use `mode.use_inf_as_na` instead.)

**plotting.backend** [str] The plotting backend to use. The default value is “matplotlib”, the backend provided with pandas. Other backends can be specified by providing the name of the module that implements the backend. [default: matplotlib] [currently: matplotlib]

**plotting.matplotlib.register_converters** [bool or ‘auto’.] Whether to register converters with matplotlib’s units registry for dates, times, datetimes, and Periods. Toggling to False will remove the converters, restoring any converters that pandas overwrote. [default: auto] [currently: auto]
pandas.get_option

**pandas.get_option(pat)**  
Retrieves the value of the specified option.

**Available options:**

- **compute.**
  - use_bottleneck, use_numba, use_numexpr
- **display.**
  - chop_threshold, colheader_justify, column_space, date_dayfirst, date_yearfirst, encoding, expand_frame_repr, float_format
  - html.border, table_schema, use_mathjax
  - display.large
  - display.latex.escape, longtable, multicolumn, multicolumn_format, multirow, repr
  - display.max_categories, max_columns, max_colwidth, max_info_columns, max_info_rows, max_rows, max_seq_items, memory_usage, min_rows, multi_sparse, notebook_repr_html, pprint_nest_depth, precision, show_dimensions
- **display.unicode.**
  - ambiguous_as_wide, east_asian_width
- **display.**
  - width
- **io.excel.**
  - ods.reader, writer
  - xls.reader, writer
  - xlsx.reader, writer
  - xlsb.reader
  - xlsm.reader, writer
  - xlsx.reader, writer
  - hdf.default_format, dropna_table
  - parquet.engine
- **mode.**
  - chained_assignment, sim_interactive, use_inf_as_na, use_inf_as_null
- **plotting.**
  - backend
  - matplotlib.register_converters

**Parameters**

- **pat** [str] Regexp which should match a single option. Note: partial matches are supported for convenience, but unless you use the full option name (e.g. x.y.z.option_name), your code may break in future versions if new options with similar names are introduced.

**Returns**

- **result** [the value of the option]

**Raises**

- **OptionError** [if no such option exists]

**Notes**

The available options with its descriptions:

- **compute.use_bottleneck** [bool] Use the bottleneck library to accelerate if it is installed, the default is True  
  Valid values: False, True [default: True] [currently: True]

- **compute.use_numba** [bool] Use the numba engine option for select operations if it is installed, the default is False  
  Valid values: False, True [default: False] [currently: False]

- **compute.use_numexpr** [bool] Use the numexpr library to accelerate computation if it is installed, the default is True  
  Valid values: False, True [default: True] [currently: True]

- **display.chop_threshold** [float or None] if set to a float value, all float values smaller then the given threshold will be displayed as exactly 0 by repr and friends.  
  [default: None] [currently: None]

- **display.colheader_justify** ['left'/'right'] Controls the justification of column headers. used by DataFrameFormatter.  
  [default: right] [currently: right]

- **display.column_space** No description available.  
  [default: 12] [currently: 12]
**display.date_dayfirst** [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default: False] [currently: False]

**display.date_yearfirst** [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default: False] [currently: False]

**display.encoding** [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by to_string, these are generally strings meant to be displayed on the console. [default: utf-8] [currently: utf-8]

**display.expand_frame_repr** [boolean] Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, max_columns is still respected, but the output will wrap-around across multiple “pages” if its width exceeds display.width. [default: True] [currently: True]

**display.float_format** [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See formats.format.EngFormatter for an example. [default: None] [currently: None]

**display.html.border** [int] A border=value attribute is inserted in the <table> tag for the DataFrame HTML repr. [default: 1] [currently: 1]

**display.html.table_schema** [boolean] Whether to publish a Table Schema representation for frontends that support it. (default: False) [default: False] [currently: False]

**display.html.use_mathjax** [boolean] When True, Jupyter notebook will process table contents using MathJax, rendering mathematical expressions enclosed by the dollar symbol. (default: True) [default: True] [currently: True]

**display.large_repr** ['truncate'/'info'] For DataFrames exceeding max_rows/max_cols, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from df.info() (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]

**display.latex.escape** [bool] This specifies if the to_latex method of a Dataframe uses escapes special characters. Valid values: False,True [default: False] [currently: True]

**display.latex.longtable** [bool] This specifies if the to_latex method of a Dataframe uses the longtable format. Valid values: False,True [default: False] [currently: False]

**display.latex.multicolumn** [bool] This specifies if the to_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: False] [currently: False]

**display.latex.multicolumn_format** [bool] This specifies if the to_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: True] [currently: True]

**display.latex.repr** [boolean] Whether to produce a latex DataFrame representation for jupyter environments that support it. (default: False) [default: False] [currently: False]

**display.max_categories** [int] This sets the maximum number of categories pandas should output when printing out a Categorical or a Series of dtype “category”. [default: 8] [currently: 8]

**display.max_columns** [int] If max_cols is exceeded, switch to truncate view. Depending on large_repr, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and large_repr equals ‘truncate’ this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 0] [currently: 0]

**display.max_colwidth** [int or None] The maximum width in characters of a column in the repr of a pandas data structure. When the column overflows, a “…” placeholder is embedded in the output. A ‘None’ value means unlimited. [default: 50] [currently: 50]

**display.max_info_columns** [int] max_info_columns is used in DataFrame.info method to decide if per column information will be printed. [default: 100] [currently: 100]

**display.max_info_rows** [int or None] df.info() will usually show null-counts for each column. For large frames this can be quite slow. max_info_rows and max_info_cols limit this null check only to frames with smaller dimensions than specified. [default: 1690785] [currently: 1690785]

**display.max_rows** [int] If max_rows is exceeded, switch to truncate view. Depending on large_repr, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

3.15. General utility functions 2361
In case python/IPython is running in a terminal and `large_repr` equals ‘truncate’ this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 60] [currently: 15]

**display.max_seq_items** [int or None] when pretty-printing a long sequence, no more then `max_seq_items` will be printed. If items are omitted, they will be denoted by the addition of “…” to the resulting string.

If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]

**display.memory_usage** [bool, string or None] This specifies if the memory usage of a DataFrame should be displayed when `df.info()` is called. Valid values True,False,’deep’ [default: True] [currently: True]

**display.min_rows** [int] The numbers of rows to show in a truncated view (when `max_rows` is exceeded). Ignored when `max_rows` is set to None or 0. When set to None, follows the value of `max_rows`. [default: 10] [currently: 10]

**display.multi_sparse** [boolean] “sparsify” MultiIndex display (don’t display repeated elements in outer levels within groups) [default: True] [currently: True]

**display.notebook_repr_html** [boolean] When True, IPython notebook will use html representation for pandas objects (if it is available). [default: True] [currently: True]

**display.pprint_nest_depth** [int] Controls the number of nested levels to process when pretty-printing [default: 3] [currently: 3]

**display.precision** [int] Floating point output precision (number of significant digits). This is only a suggestion [default: 6] [currently: 6]

**display.show_dimensions** [boolean or ‘truncate’] Whether to print out dimensions at the end of DataFrame repr. If ‘truncate’ is specified, only print out the dimensions if the frame is truncated (e.g. not display all rows and/or columns) [default: truncate] [currently: truncate]

**display.unicode.ambiguous_as_wide** [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance (default: False) [default: False] [currently: False]

**display.unicode.east_asian_width** [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance (default: False) [default: False] [currently: False]

**display.width** [int] Width of the display in characters. In case python/IPython is running in a terminal this can be set to None and pandas will correctly auto-detect the width. Note that the IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to correctly detect the width. [default: 80] [currently: 80]


**io.hdf.default_format** [format] default format writing format, if None, then put will default to ‘fixed’ and append will default to ‘table’ [default: None] [currently: None]
io.hdf.dropna_table [boolean] drop ALL nan rows when appending to a table [default: False] [currently: False]
mode.chained_assignment [string] Raise an exception, warn, or no action if trying to use chained assignment, The default is warn [default: warn] [currently: warn]
mode.sim_interactive [boolean] Whether to simulate interactive mode for purposes of testing [default: False] [currently: False]
mode.use_inf_as_na [boolean] True means treat None, NaN, INF, -INF as NA (old way), False means None and NaN are null, but INF, -INF are not NA (new way). [default: False] [currently: False]
mode.use_inf_as_null [boolean] use_inf_as_null had been deprecated and will be removed in a future version. Use use_inf_as_na instead. [default: False] [currently: False] (Deprecated, use mode.use_inf_as_na instead.)
plotting.backend [str] The plotting backend to use. The default value is “matplotlib”, the backend provided with pandas. Other backends can be specified by providing the name of the module that implements the backend. [default: matplotlib] [currently: matplotlib]
plotting.matplotlib.register_converters [bool or ‘auto’] Whether to register converters with matplotlib’s units registry for dates, times, datetimes, and Periods. Toggling to False will remove the converters, restoring any converters that pandas overwrote. [default: auto] [currently: auto]

pandas.set_option

pandas.set_option(pat, value) = <pandas._config.config.CallableDynamicDoc object>
Sets the value of the specified option.

Available options:
- compute.[use_bottleneck, use_numba, use_numexpr]
- display.[chop_threshold, colheader_justify, column_space, date_dayfirst, date_yearfirst, encoding, expand_frame_repr, float_format]
- display.html.[border, table_schema, use_mathjax]
- display.[large_repr]
- display.latex.[escape, longtable, multicolumn, multicolumn_format, multirow, repr]
- display.[max_categories, max_columns, max_colwidth, max_info_columns, max_info_rows, max_rows, max_seq_items, memory_usage, min_rows, multi_sparse, notebook_repr_html, pprint_nest_depth, precision, show_dimensions]
- display.unicode.[ambiguous_as_wide, east_asian_width]
- display.[width]
- io.excel.[ods.[reader, writer]
- io.excel.xlsb.[reader]
- io.excel.xle.[reader, writer]
- io.excel.xls.[reader, writer]
- io.excel.xlsm.[reader, writer]
- io.excel.xlw.[reader, writer]
- io.hdf.[default_format, dropna_table]
- io.parquet.[engine]
- mode.[chained_assignment, sim_interactive, use_inf_as_na, use_inf_as_null]
- plotting.[backend]
- plotting.matplotlib.[register_converters]

Parameters
- pat [str] Regexp which should match a single option. Note: partial matches are supported for convenience, but unless you use the full option name (e.g. x.y.z.option_name), your code may break in future versions if new options with similar names are introduced.
value  [object] New value of option.

Returns

None

Raises

OptionError if no such option exists

Notes

The available options with its descriptions:

- **compute.use_bottleneck** [bool] Use the bottleneck library to accelerate if it is installed, the default is True
  Valid values: False,True [default: True] [currently: True]

- **compute.use_numba** [bool] Use the numba engine option for select operations if it is installed, the default is False
  Valid values: False,True [default: False] [currently: False]

- **compute.use_numexpr** [bool] Use the numexpr library to accelerate computation if it is installed, the default is True
  Valid values: False,True [default: True] [currently: True]

- **display.chop_threshold** [float or None] if set to a float value, all float values smaller then the given threshold will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]

- **display.colheader_justify** ['left'/'right'] Controls the justification of column headers. used by DataFrameFormatter. [default: right] [currently: right]

- **display.column_space** No description available. [default: 12] [currently: 12]

- **display.date_dayfirst** [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default: False] [currently: False]

- **display.date_yearfirst** [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default: False] [currently: False]

- **display.encoding** [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by to_string, these are generally strings meant to be displayed on the console. [default: utf-8] [currently: utf-8]

- **display.expand_frame_repr** [boolean] Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, max_columns is still respected, but the output will wrap-around across multiple “pages” if its width exceeds display.width. [default: True] [currently: True]

- **display.float_format** [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See formats.format.EngFormatter for an example. [default: None] [currently: None]

- **display.html.border** [int] A border=value attribute is inserted in the <table> tag for the DataFrame HTML repr. [default: 1] [currently: 1]

- **display.html.table_schema** [boolean] Whether to publish a Table Schema representation for frontends that support it. (default: False) [default: False] [currently: False]

- **display.html.use_mathjax** [boolean] When True, Jupyter notebook will process table contents using MathJax, rendering mathematical expressions enclosed by the dollar symbol. (default: True) [default: True] [currently: True]

- **display.large_repr** ['truncate’/’info’] For DataFrames exceeding max_rows/max_cols, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from df.info() (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]

- **display.latex.escape** [bool] This specifies if the to_latex method of a Dataframe uses escapes special characters. Valid values: False,True [default: True] [currently: True]

- **display.latex.longtable** [bool] This specifies if the to_latex method of a Dataframe uses the longtable format. Valid values: False,True [default: False] [currently: False]

- **display.latex.multicolumn** [bool] This specifies if the to_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: True] [currently: True]

- **display.latex.multicolumn_format** [bool] This specifies if the to_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: l] [currently: l]
display.latex.multirow [bool] This specifies if the to_latex method of a Dataframe uses multirows to pretty-print MultiIndex rows. Valid values: False,True [default: False] [currently: False]
display.latex.repr [boolean] Whether to produce a latex DataFrame representation for jupyter environments that support it. (default: False) [default: False] [currently: False]
display.max_categories [int] This sets the maximum number of categories pandas should output when printing out a Categorical or a Series of dtype “category”. [default: 8] [currently: 8]
display.max_columns [int] If max_cols is exceeded, switch to truncate view. Depending on large_repr, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.
In case python/IPython is running in a terminal and large_repr equals ‘truncate’ this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 0] [currently: 0]
display.max_colwidth [int or None] The maximum width in characters of a column in the repr of a pandas data structure. When the column overflows, a “…” placeholder is embedded in the output. A ‘None’ value means unlimited. [default: 50] [currently: 50]
display.max_info_columns [int] max_info_columns is used in DataFrame.info method to decide if per column information will be printed. [default: 100] [currently: 100]
display.max_info_rows [int or None] df.info() will usually show null-counts for each column. For large frames this can be quite slow. max_info_rows and max_info_cols limit this null check only to frames with smaller dimensions than specified. [default: 1690785] [currently: 1690785]
display.max_rows [int] If max_rows is exceeded, switch to truncate view. Depending on large_repr, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.
In case python/IPython is running in a terminal and large_repr equals ‘truncate’ this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 60] [currently: 15]
display.max_seq_items [int or None] When pretty-printing a long sequence, no more then max_seq_items will be printed. If items are omitted, they will be denoted by the addition of “…” to the resulting string.
If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]
display.memory_usage [bool, string or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. Valid values True,False,’deep’ [default: True] [currently: True]
display.min_rows [int] The numbers of rows to show in a truncated view (when max_rows is exceeded). Ignored when max_rows is set to None or 0. When set to None, follows the value of max_rows. [default: 10] [currently: 10]
display.multi_sparse [boolean] “sparsify” MultiIndex display (don’t display repeated elements in outer levels within groups) [default: True] [currently: True]
display.notebook_repr_html [boolean] When True, IPython notebook will use html representation for pandas objects (if it is available). [default: True] [currently: True]
display.pprint_nest_depth [int] Controls the number of nested levels to process when pretty-printing [default: 3] [currently: 3]
display.precision [int] Floating point output precision (number of significant digits). This is only a suggestion [default: 6] [currently: 6]
display.show_dimensions [boolean or ‘truncate’] Whether to print out dimensions at the end of DataFrame repr. If ‘truncate’ is specified, only print out the dimensions if the frame is truncated (e.g. not display all rows and/or columns) [default: truncate] [currently: truncate]
display.unicode.ambiguous_as_wide [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance [default: False] [currently: False]
display.unicode.east_asian_width [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance [default: False] [currently: False]
display.width [int] Width of the display in characters. In case python/IPython is running in a terminal this can
be set to None and pandas will correctly auto-detect the width. Note that the IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to correctly detect the width.

[default: 80] [currently: 80]


io.hdf.default_format [format] default format writing format, if None, then put will default to ‘fixed’ and append will default to ‘table’ [default: None] [currently: None]

io.hdf.dropna_table [boolean] drop ALL nan rows when appending to a table [default: False] [currently: False]


mode.chained_assignment [string] Raise an exception, warn, or no action if trying to use chained assignment, The default is warn [default: warn] [currently: warn]

mode.sim_interactive [boolean] Whether to simulate interactive mode for purposes of testing [default: False] [currently: False]

mode.use_inf_as_na [boolean] True means treat None, NaN, INF, -INF as NA (old way), False means None and NaN are null, but INF, -INF are not NA (new way). [default: False] [currently: False]

mode.use_inf_as_null [boolean] use_inf_as_null had been deprecated and will be removed in a future version. Use use_inf_as_na instead. [default: False] [currently: False] (Deprecated, use mode.use_inf_as_na instead.)

plotting.backend [str] The plotting backend to use. The default value is “matplotlib”, the backend provided with pandas. Other backends can be specified by providing the name of the module that implements the backend. [default: matplotlib] [currently: matplotlib]

plotting.matplotlib.register_converters [bool or ‘auto’.] Whether to register converters with matplotlib’s units registry for dates, times, datetimes, and Periods. Toggling to False will remove the converters, restoring any converters that pandas overwrote. [default: auto] [currently: auto]
pandas: powerful Python data analysis toolkit, Release 1.1.1

pandas.option_context

class pandas.option_context(*args)

Context manager to temporarily set options in the with statement context.

You need to invoke as `option_context(pat, val, [(pat, val), ...]).`

Examples

```python
>>> with option_context('display.max_rows', 10, 'display.max_columns', 5):
...     ...
```

Methods

`__call__(func)`

Call self as a function.

pandas.option_context.__call__

option_context.__call__(func)

Call self as a function.

3.15.2 Testing functions

```
testing.assert_frame_equal(left, right[, ...,]

testing.assert_series_equal(left, right[, ...])

testing.assert_index_equal(left, right[, ...])

testing.assert_extension_array_equal(left, right)
```

pandas.testing.assert_frame_equal

```
pandas.testing.assert_frame_equal(left, right, check_dtypes=True, check_index_type='equiv',
check_column_type='equiv', check_frame_type=True,
check_less_precise=<object object>,
check_names=True, by_blocks=False,
check_exact=False, check_datetimelike_compat=False,
check_categorical=True, check_like=False,
check_freq=True, rtol=1e-05, atol=1e-08,
obj='DataFrame')
```

Check that left and right DataFrame are equal.

This function is intended to compare two DataFrames and output any differences. It is mostly intended for use in unit tests. Additional parameters allow varying the strictness of the equality checks performed.

Parameters

- `left` [DataFrame] First DataFrame to compare.
right [DataFrame] Second DataFrame to compare.

check_dtype [bool, default True] Whether to check the DataFrame dtype is identical.

check_index_type [bool or {'equiv'}, default 'equiv'] Whether to check the Index class, dtype and inferred_type are identical.

check_column_type [bool or {'equiv'}, default 'equiv'] Whether to check the columns class, dtype and inferred_type are identical. Is passed as the exact argument of assert_index_equal().

check_frame_type [bool, default True] Whether to check the DataFrame class is identical.

check_less_precise [bool or int, default False] Specify comparison precision. Only used when check_exact is False. 5 digits (False) or 3 digits (True) after decimal points are compared. If int, then specify the digits to compare.

When comparing two numbers, if the first number has magnitude less than 1e-5, we compare the two numbers directly and check whether they are equivalent within the specified precision. Otherwise, we compare the ratio of the second number to the first number and check whether it is equivalent to 1 within the specified precision.

Deprecated since version 1.1.0: Use rtol and atol instead to define relative/absolute tolerance, respectively. Similar to math.isclose().

check_names [bool, default True] Whether to check that the names attribute for both the index and column attributes of the DataFrame is identical.

by_blocks [bool, default False] Specify how to compare internal data. If False, compare by columns. If True, compare by blocks.

check_exact [bool, default False] Whether to compare number exactly.

check_datetimelike_compat [bool, default False] Compare datetime-like which is comparable ignoring dtype.

check_categorical [bool, default True] Whether to compare internal Categorical exactly.

check_like [bool, default False] If True, ignore the order of index & columns. Note: index labels must match their respective rows (same as in columns) - same labels must be with the same data.

check_freq [bool, default True] Whether to check the freq attribute on a DatetimeIndex or TimedeltaIndex.

rtol [float, default 1e-5] Relative tolerance. Only used when check_exact is False.

New in version 1.1.0.

atol [float, default 1e-8] Absolute tolerance. Only used when check_exact is False.

New in version 1.1.0.

obj [str, default 'DataFrame'] Specify object name being compared, internally used to show appropriate assertion message.

See also:

assert_series_equal Equivalent method for asserting Series equality.

DataFrame.equals Check DataFrame equality.
Examples

This example shows comparing two DataFrames that are equal but with columns of differing dtypes.

```python
>>> from pandas._testing import assert_frame_equal
>>> df1 = pd.DataFrame({'a': [1, 2], 'b': [3, 4]})
>>> df2 = pd.DataFrame({'a': [1, 2], 'b': [3.0, 4.0]})
```

df1 equals itself.

```python
>>> assert_frame_equal(df1, df1)
```

df1 differs from df2 as column ‘b’ is of a different type.

```python
>>> assert_frame_equal(df1, df2)
Traceback (most recent call last):
...  
AssertionError: Attributes of DataFrame.iloc[:, 1] (column name="b") are different
```

Attribute “dtype” are different [left]: int64 [right]: float64

Ignore differing dtypes in columns with check_dtype.

```python
>>> assert_frame_equal(df1, df2, check_dtype=False)
```

pandas.testing.assert_series_equal

```python
pandas.testing.assert_series_equal (left, right, check_dtype=True, check_index_type='equiv', check_series_type=True, check_less_precise=<object object>, check_names=True, check_exact=False, check_datetimelike_compat=False, check_categorical=True, check_category_order=True, check_freq=True, rtol=1e-05, atol=1e-08, obj='Series')
```

Check that left and right Series are equal.

**Parameters**

- `left` [Series]
- `right` [Series]
- `check_dtype` [bool, default True] Whether to check the Series dtype is identical.
- `check_index_type` [bool or {'equiv'}, default 'equiv'] Whether to check the Index class, dtype and inferred_type are identical.
- `check_series_type` [bool, default True] Whether to check the Series class is identical.
- `check_less_precise` [bool or int, default False] Specify comparison precision. Only used when check_exact is False. 5 digits (False) or 3 digits (True) after decimal points are compared. If int, then specify the digits to compare.

When comparing two numbers, if the first number has magnitude less than 1e-5, we compare the two numbers directly and check whether they are equivalent within the specified precision. Otherwise, we compare the ratio of the second number to the first number and check whether it is equivalent to 1 within the specified precision.

Deprecated since version 1.1.0: Use rtol and atol instead to define relative/absolute tolerance, respectively. Similar to `math.isclose()`.
check_names [bool, default True] Whether to check the Series and Index names attribute.

check_exact [bool, default False] Whether to compare number exactly.

check_datetimelike_compat [bool, default False] Compare datetime-like which is comparable ignoring dtype.

check_categorical [bool, default True] Whether to compare internal Categorical exactly.

check_category_order [bool, default True] Whether to compare category order of internal Categoricals.

New in version 1.0.2.

check_freq [bool, default True] Whether to check the freq attribute on a DatetimeIndex or TimedeltaIndex.

rtol [float, default 1e-5] Relative tolerance. Only used when check_exact is False.

New in version 1.1.0.

atol [float, default 1e-8] Absolute tolerance. Only used when check_exact is False.

New in version 1.1.0.

obj [str, default ‘Series’] Specify object name being compared, internally used to show appropriate assertion message.

pandas.testing.assert_index_equal

pandas.testing.assert_index_equal(left, right, exact='equiv', check_names=True, check_less_precise=<object object>, check_exact=True, check_categorical=True, rtol=1e-05, atol=1e-08, obj='Index')

Check that left and right Index are equal.

Parameters

left [Index]

right [Index]

exact [bool or {'equiv'}, default ‘equiv’] Whether to check the Index class, dtype and inferred_type are identical. If ‘equiv’, then RangeIndex can be substituted for Int64Index as well.

check_names [bool, default True] Whether to check the names attribute.

check_less_precise [bool or int, default False] Specify comparison precision. Only used when check_exact is False. 5 digits (False) or 3 digits (True) after decimal points are compared. If int, then specify the digits to compare.

Deprecated since version 1.1.0: Use rtol and atol instead to define relative/absolute tolerance, respectively. Similar to math.isclose().

check_exact [bool, default True] Whether to compare number exactly.

check_categorical [bool, default True] Whether to compare internal Categorical exactly.

rtol [float, default 1e-5] Relative tolerance. Only used when check_exact is False.

New in version 1.1.0.

atol [float, default 1e-8] Absolute tolerance. Only used when check_exact is False.

New in version 1.1.0.
obj [str, default ‘Index’] Specify object name being compared, internally used to show appropriate assertion message.

**pandas.testing.assert_extension_array_equal**

pandas.testing.assert_extension_array_equal(left, right, check_dtype=True, index_values=None, check_less_precise=<object object>, check_exact=False, rtol=1e-05, atol=1e-08)

Check that left and right ExtensionArrays are equal.

**Parameters**

- **left, right** [ExtensionArray] The two arrays to compare.
- **check_dtype** [bool, default True] Whether to check if the ExtensionArray dtypes are identical.
- **index_values** [numpy.ndarray, default None] Optional index (shared by both left and right), used in output.
- **check_less_precise** [bool or int, default False] Specify comparison precision. Only used when check_exact is False. 5 digits (False) or 3 digits (True) after decimal points are compared. If int, then specify the digits to compare.
  
  Deprecated since version 1.1.0: Use `rtol` and `atol` instead to define relative/absolute tolerance, respectively. Similar to `math.isclose()`.
- **check_exact** [bool, default False] Whether to compare number exactly.
- **rtol** [float, default 1e-5] Relative tolerance. Only used when check_exact is False.
  
  New in version 1.1.0.
- **atol** [float, default 1e-8] Absolute tolerance. Only used when check_exact is False.
  
  New in version 1.1.0.

**Notes**

Missing values are checked separately from valid values. A mask of missing values is computed for each and checked to match. The remaining all-valid values are cast to object dtype and checked.

### 3.15.3 Exceptions and warnings

<table>
<thead>
<tr>
<th>Exception</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>errors.AccessorRegistrationWarning</td>
<td>Warning for attribute conflicts in accessor registration.</td>
</tr>
<tr>
<td>errors.DtypeWarning</td>
<td>Warning raised when reading different dtypes in a column from a file.</td>
</tr>
<tr>
<td>errors.EmptyDataError</td>
<td>Exception that is thrown in <code>pd.read_csv</code> (by both the C and Python engines) when empty data or header is encountered.</td>
</tr>
<tr>
<td>errors.InvalidIndexError</td>
<td>Exception raised when attempting to use an invalid index key.</td>
</tr>
<tr>
<td>errors.MergeError</td>
<td>Error raised when problems arise during merging due to problems with input data.</td>
</tr>
</tbody>
</table>

continues on next page
### errors.NullFrequencyError
Error raised when a null freq attribute is used in an operation that needs a non-null frequency, particularly `DateTimeIndex.shift`, `TimedeltaIndex.shift`, `PeriodIndex.shift`.

### errors.NumbaUtilError
Error raised for unsupported Numba engine routines.

### errorsOutOfBoundsDatetime
Raised when encountering a timedelta value that cannot be represented as a timedelta64[ns].

### errorsOutOfBoundsTimedelta
Raised when encountering a timedelta value that cannot be represented as a timedelta64[ns].

### errors.ParserError
Exception that is raised by an error encountered in parsing file contents.

### errors.ParserWarning
Warning raised when reading a file that doesn’t use the default ‘c’ parser.

### errors.PerformanceWarning
Warning raised when there is a possible performance impact.

### errors.UnsortedIndexError
Error raised when attempting to get a slice of a MultiIndex, and the index has not been lexsorted.

### errors.UnsupportedFunctionCall
Exception raised when attempting to call a numpy function on a pandas object, but that function is not supported by the object e.g.

<table>
<thead>
<tr>
<th>Exception</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>pandas.errors.AccessorRegistrationWarning</td>
<td>Warning for attribute conflicts in accessor registration.</td>
</tr>
<tr>
<td>exception pandas.errors.AccessorRegistrationWarning</td>
<td></td>
</tr>
<tr>
<td>pandas.errors.DtypeWarning</td>
<td>Warning raised when reading different dtypes in a column from a file.</td>
</tr>
<tr>
<td>exception pandas.errors.DtypeWarning</td>
<td></td>
</tr>
<tr>
<td>raised for a dtype incompatibility. This can</td>
<td>raised when reading different dtypes in a column from a file.</td>
</tr>
<tr>
<td>happen whenever <code>read_csv</code> or <code>read_table</code></td>
<td>raised when reading different dtypes in a column(s) of a given CSV file.</td>
</tr>
<tr>
<td>encounter non-uniform dtypes in a column(s)</td>
<td></td>
</tr>
<tr>
<td>of a given CSV file.</td>
<td></td>
</tr>
<tr>
<td>See also:</td>
<td>raised for a dtype incompatibility. This can happen whenever <code>read_csv</code> or</td>
</tr>
<tr>
<td></td>
<td><code>read_table</code> encounter non-uniform dtypes in a column(s) of a given CSV</td>
</tr>
<tr>
<td></td>
<td>file.</td>
</tr>
<tr>
<td>Notes</td>
<td>raised for a dtype incompatibility. This can happen whenever <code>read_csv</code> or</td>
</tr>
<tr>
<td></td>
<td><code>read_table</code> encounter non-uniform dtypes in a column(s) of a given CSV</td>
</tr>
<tr>
<td></td>
<td>file.</td>
</tr>
</tbody>
</table>

This warning is issued when dealing with larger files because the dtype checking happens per chunk read.

Despite the warning, the CSV file is read with mixed types in a single column which will be an object type. See the examples below to better understand this issue.
Examples

This example creates and reads a large CSV file with a column that contains *int* and *str*.

```python
>>> df = pd.DataFrame({'a': ['1'] * 100000 + ['X'] * 100000 + ...
... ['1'] * 100000),
... 'b': ['b'] * 300000})
>>> df.to_csv('test.csv', index=False)
>>> df2 = pd.read_csv('test.csv')
... # DtypeWarning: Columns (0) have mixed types

Important to notice that *df2* will contain both *str* and *int* for the same input, ‘1’.

```python
>>> df2.iloc[262140, 0]
'1'
>>> type(df2.iloc[262140, 0])
<class 'str'>
>>> df2.iloc[262150, 0]
1
>>> type(df2.iloc[262150, 0])
<class 'int'>
```

One way to solve this issue is using the *dtype* parameter in the *read_csv* and *read_table* functions to explicit the conversion:

```python
>>> df2 = pd.read_csv('test.csv', sep=',', dtype={'a': str})

No warning was issued.

```python
>>> import os
>>> os.remove('test.csv')
```

**pandas.errors.EmptyDataError**

*exception pandas.errors.EmptyDataError*  
Exception that is thrown in *pd.read_csv* (by both the C and Python engines) when empty data or header is encountered.

**pandas.errors.InvalidIndexError**

*exception pandas.errors.InvalidIndexError*  
Exception raised when attempting to use an invalid index key.  
New in version 1.1.0.
pandas.errors.MergeError

exception pandas.errors.MergeError
Error raised when problems arise during merging due to problems with input data. Subclass of ValueError.

pandas.errors.NullFrequencyError

exception pandas.errors.NullFrequencyError
Error raised when a null freq attribute is used in an operation that needs a non-null frequency, particularly DatetimeIndex.shift, TimedeltaIndex.shift, PeriodIndex.shift.

pandas.errors.NumbaUtilError

exception pandas.errors.NumbaUtilError
Error raised for unsupported Numba engine routines.

pandas.errors.OutOfBoundsDatetime

exception pandas.errors.OutOfBoundsDatetime

pandas.errors.OutOfBoundsTimedelta

exception pandas.errors.OutOfBoundsTimedelta
Raised when encountering a timedelta value that cannot be represented as a timedelta64[ns].

pandas.errors.ParserError

exception pandas.errors.ParserError
Exception that is raised by an error encountered in parsing file contents.

This is a generic error raised for errors encountered when functions like read_csv or read_html are parsing contents of a file.

See also:
read_csv Read CSV (comma-separated) file into a DataFrame.
read_html Read HTML table into a DataFrame.

pandas.errors.ParserWarning

exception pandas.errors.ParserWarning
Warning raised when reading a file that doesn’t use the default ‘c’ parser.

Raised by pd.read_csv and pd.read_table when it is necessary to change parsers, generally from the default ‘c’ parser to ‘python’.

It happens due to a lack of support or functionality for parsing a particular attribute of a CSV file with the requested engine.

Currently, ‘c’ unsupported options include the following parameters:
1. sep other than a single character (e.g. regex separators)
2. skipfooter higher than 0
3. sep=None with delim_whitespace=False
The warning can be avoided by adding `engine='python'` as a parameter in `pd.read_csv` and `pd.read_table` methods.

See also:

**pd.read_csv**  Read CSV (comma-separated) file into DataFrame.

**pd.read_table**  Read general delimited file into DataFrame.

**Examples**

Using a `sep` in `pd.read_csv` other than a single character:

```python
>>> import io
>>> csv = '''a;b;c
... 1;1,8
... 1;2,1'''
>>> df = pd.read_csv(io.StringIO(csv), sep='[;,]')
... # ParserWarning: Falling back to the 'python' engine...
```

Adding `engine='python'` to `pd.read_csv` removes the Warning:

```python
>>> df = pd.read_csv(io.StringIO(csv), sep='[;,]', engine='python')
```

**pandas.errors.PerformanceWarning**

**exception** pandas.errors.PerformanceWarning  
Warning raised when there is a possible performance impact.

**pandas.errors.UnsortedIndexError**

**exception** pandas.errors.UnsortedIndexError  
Error raised when attempting to get a slice of a MultiIndex, and the index has not been lexsorted. Subclass of `KeyError`.

**pandas.errors.UnsupportedFunctionCall**

**exception** pandas.errors.UnsupportedFunctionCall  
Exception raised when attempting to call a numpy function on a pandas object, but that function is not supported by the object e.g. `np.cumsum(groupby_object)`.

### 3.15.4 Data types related functionality

| api.types.union_categoricals(to_union[, ...]) | Combine list-like of Categorical-like, unioning categories. |
| api.types.infer_dtype | Efficiently infer the type of a passed val, or list-like array of values. |
| api.types.pandas_dtype(dtype) | Convert input into a pandas only dtype object or a numpy dtype object. |
pandas.api.types.union_categoricals

\`pandas.api.types.union_categoricals\` \(\text{to}_\text{union},\text{sort}_\text{categories}=\text{False},\text{ignore}_\text{order}=\text{False}\)  
Combine list-like of Categorical-like, unioning categories.  
All categories must have the same dtype.  

**Parameters**  

- `to_union` [list-like] Categorical, CategoricalIndex, or Series with dtype='category'.  
- `sort_categories` [bool, default False] If true, resulting categories will be lexsorted, otherwise they will be ordered as they appear in the data.  
- `ignore_order` [bool, default False] If true, the ordered attribute of the Categoricals will be ignored. Results in an unordered categorical.  

**Returns**  

Categorical  

**Raises**  

- TypeError  
  - all inputs do not have the same dtype  
  - all inputs do not have the same ordered property  
  - all inputs are ordered and their categories are not identical  
  - `sort_categories=True` and Categoricals are ordered  
- ValueError  
  Empty list of categoricals passed  

**Notes**  

To learn more about categories, see link  

**Examples**  

```python  
>>> from pandas.api.types import union_categoricals  
```

If you want to combine categoricals that do not necessarily have the same categories, `union_categoricals` will combine a list-like of categoricals. The new categories will be the union of the categories being combined.

```python  
>>> a = pd.Categorical(['b', 'c'])  
>>> b = pd.Categorical(['a', 'b'])  
>>> union_categoricals([a, b])  
['b', 'c', 'a', 'b']  
Categories (3, object): ['b', 'c', 'a']  
```

By default, the resulting categories will be ordered as they appear in the `categories` of the data. If you want the categories to be lexsorted, use `sort_categories=True` argument.

```python  
>>> union_categoricals([a, b], sort_categories=True)  
['b', 'c', 'a', 'b']  
Categories (3, object): ['a', 'b', 'c']  
```

`union_categoricals` also works with the case of combining two categoricals of the same categories and order information (e.g. what you could also `append` for).
>>> a = pd.Categorical(["a", "b"], ordered=True)
>>> b = pd.Categorical(["a", "b", "a"], ordered=True)

union_categoricals([a, b])
['a', 'b', 'a', 'b', 'a']
Categories (2, object): ['a' < 'b']

Raises TypeError because the categories are ordered and not identical.

>>> a = pd.Categorical(["a", "b"], ordered=True)
>>> b = pd.Categorical(["a", "b", "c"], ordered=True)
>>> union_categoricals([a, b])
Traceback (most recent call last):
  ...          
TypeError: to union ordered Categoricals, all categories must be the same

New in version 0.20.0

Ordered categoricals with different categories or orderings can be combined by using the ignore_ordered=True argument.

>>> a = pd.Categorical(["a", "b", "c"], ordered=True)
>>> b = pd.Categorical(["c", "b", "a"], ordered=True)
>>> union_categoricals([a, b], ignore_order=True)
['a', 'b', 'c', 'c', 'b', 'a']
Categories (3, object): ['a', 'b', 'c']

union_categoricals also works with a CategoricalIndex, or Series containing categorical data, but note that the resulting array will always be a plain Categorical

>>> a = pd.Series(["b", "c"], dtype='category')
>>> b = pd.Series(["a", "b"], dtype='category')
>>> union_categoricals([a, b])
['b', 'c', 'a', 'b']
Categories (3, object): ['b', 'c', 'a']

pandas.api.types.infer_dtype

pandas.api.types.infer_dtype()

Efficiently infer the type of a passed val, or list-like array of values. Return a string describing the type.

Parameters

value [scalar, list, ndarray, or pandas type]

skipna [bool, default True] Ignore NaN values when inferring the type.

Returns

str Describing the common type of the input data.

Results can include:

- string
- bytes
- floating
- integer
- mixed-integer
mixed-integer-float  
decimal  
complex  
categorical  
boolean  
datetime64  
datetime  
date  
timedelta64  
timedelta  
time  
period  
mixed  

Raises  

TypeError If ndarray-like but cannot infer the dtype

Notes

- ‘mixed’ is the catchall for anything that is not otherwise specialized
- ‘mixed-integer-float’ are floats and integers
- ‘mixed-integer’ are integers mixed with non-integers

Examples

```python
>>> infer_dtype(['foo', 'bar'])
'string'

>>> infer_dtype(['a', np.nan, 'b'], skipna=True)
'string'

>>> infer_dtype(['a', np.nan, 'b'], skipna=False)
'mixed'

>>> infer_dtype(['b'foo', 'b'bar'])
'bytes'

>>> infer_dtype([1, 2, 3])
'integer'

>>> infer_dtype([1, 2, 3.5])
'mixed-integer-float'

>>> infer_dtype([1.0, 2.0, 3.5])
'floating'
```
>>> infer_dtypes(['a', 1])
'mixed-integer'

>>> infer_dtypes([Decimal(1), Decimal(2.0)])
'decimal'

>>> infer_dtypes([True, False])
'boolean'

>>> infer_dtypes([True, False, np.nan])
'mixed'

>>> infer_dtypes([pd.Timestamp('20130101')])
'datetime'

>>> infer_dtypes([datetime.date(2013, 1, 1)])
'date'

>>> infer_dtypes([np.datetime64('2013-01-01')])
'datetime64'

>>> infer_dtypes([datetime.timedelta(0, 1, 1)])
'timedelta'

>>> infer_dtypes(pd.Series(list('aabc')).astype('category'))
'categorical'

**pandas.api.types.pandas_dtype**

`pandas.api.types.pandas_dtype(dtpe)`

Convert input into a pandas only dtype object or a numpy dtype object.

**Parameters**

- `dtype` [object to be converted]

**Returns**

- `np.dtype` or a pandas dtype

**Raises**

- TypeError if not a dtype

**Dtype introspection**

- `api.types.is_bool_dtype(arr_or_dtype)`  
  Check whether the provided array or dtype is of a boolean dtype.

- `api.types.is_categorical_dtype(arr_or_dtype)`  
  Check whether an array-like or dtype is of the Categorical dtype.

- `api.types.is_complex_dtype(arr_or_dtype)`  
  Check whether the provided array or dtype is of a complex dtype.

**continues on next page**
Table 392 – continued from previous page

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>pandas.api.types.is_datetime64_any_dtype(arr_or_dtype)</td>
<td>Check whether the provided array or dtype is of the datetime64 dtype.</td>
</tr>
<tr>
<td>pandas.api.types.is_datetime64_dtype(arr_or_dtype)</td>
<td>Check whether an array-like or dtype is of the datetime64 dtype.</td>
</tr>
<tr>
<td>pandas.api.types.is_datetime64_ns_dtype(arr_or_dtype)</td>
<td>Check whether the provided array or dtype is of the datetime64[ns] dtype.</td>
</tr>
<tr>
<td>pandas.api.types.is_datetime64tz_dtype(arr_or_dtype)</td>
<td>Check whether an array-like or dtype is of a DatetimeTZDtype dtype.</td>
</tr>
<tr>
<td>pandas.api.types.is_extension_type(arr)</td>
<td>(DEPRECATED) Check whether an array-like is of a pandas extension class instance.</td>
</tr>
<tr>
<td>pandas.api.types.is_extension_array_dtype(arr_or_dtype)</td>
<td>Check if an object is a pandas extension array type.</td>
</tr>
<tr>
<td>pandas.api.types.is_float_dtype(arr_or_dtype)</td>
<td>Check whether the provided array or dtype is of a float dtype.</td>
</tr>
<tr>
<td>pandas.api.types.is_int64_dtype(arr_or_dtype)</td>
<td>Check whether the provided array or dtype is of the int64 dtype.</td>
</tr>
<tr>
<td>pandas.api.types.is_integer_dtype(arr_or_dtype)</td>
<td>Check whether the provided array or dtype is of an integer dtype.</td>
</tr>
<tr>
<td>pandas.api.types.is_interval_dtype(arr_or_dtype)</td>
<td>Check whether an array-like or dtype is of the Interval dtype.</td>
</tr>
<tr>
<td>pandas.api.types.is_numeric_dtype(arr_or_dtype)</td>
<td>Check whether the provided array or dtype is of a numeric dtype.</td>
</tr>
<tr>
<td>pandas.api.types.is_object_dtype(arr_or_dtype)</td>
<td>Check whether an array-like or dtype is of the object dtype.</td>
</tr>
<tr>
<td>pandas.api.types.is_period_dtype(arr_or_dtype)</td>
<td>Check whether an array-like or dtype is of the Period dtype.</td>
</tr>
<tr>
<td>pandas.api.types.is_signed_integer_dtype(arr_or_dtype)</td>
<td>Check whether the provided array or dtype is of a signed integer dtype.</td>
</tr>
<tr>
<td>pandas.api.types.is_string_dtype(arr_or_dtype)</td>
<td>Check whether the provided array or dtype is of the string dtype.</td>
</tr>
<tr>
<td>pandas.api.types.is_timedelta64_dtype(arr_or_dtype)</td>
<td>Check whether an array-like or dtype is of the timedelta64 dtype.</td>
</tr>
<tr>
<td>pandas.api.types.is_timedelta64_ns_dtype(arr_or_dtype)</td>
<td>Check whether the provided array or dtype is of the timedelta64[ns] dtype.</td>
</tr>
<tr>
<td>pandas.api.types.is_unsigned_integer_dtype(arr_or_dtype)</td>
<td>Check whether the provided array or dtype is of an unsigned integer dtype.</td>
</tr>
<tr>
<td>pandas.api.types.is_sparse(arr)</td>
<td>Check whether an array-like is a 1-D pandas sparse array.</td>
</tr>
</tbody>
</table>

**pandas.api.types.is_bool_dtype**

pandas.api.types.is_bool_dtype(arr_or_dtype)  
Check whether the provided array or dtype is of a boolean dtype.

**Parameters**

- **arr_or_dtype** [array-like] The array or dtype to check.

**Returns**

- **boolean** Whether or not the array or dtype is of a boolean dtype.
Notes

An ExtensionArray is considered boolean when the `_is_boolean` attribute is set to True.

Examples

```python
>>> is_bool_dtype(str)
False
>>> is_bool_dtype(int)
False
>>> is_bool_dtype(bool)
True
>>> is_bool_dtype(np.bool_)
True
>>> is_bool_dtype(np.array(['a', 'b']))
False
>>> is_bool_dtype(pd.Series([1, 2]))
False
>>> is_bool_dtype(np.array([True, False]))
True
>>> is_bool_dtype(pd.Categorical([True, False]))
True
>>> is_bool_dtype(pd.arrays.SparseArray([True, False]))
True
```

**pandas.api.types.is_categorical_dtype**

`pandas.api.types.is_categorical_dtype(arr_or_dtype)`

Check whether an array-like or dtype is of the Categorical dtype.

**Parameters**

- `arr_or_dtype` [array-like] The array-like or dtype to check.

**Returns**

- `boolean` Whether or not the array-like or dtype is of the Categorical dtype.

**Examples**

```python
>>> is_categorical_dtype(object)
False
>>> is_categorical_dtype(CategoricalDtype())
True
>>> is_categorical_dtype([1, 2, 3])
False
>>> is_categorical_dtype(pd.Categorical([1, 2, 3]))
True
>>> is_categorical_dtype(pd.CategoricalIndex([1, 2, 3]))
True
```
pandas.api.types.is_complex_dtype

pandas.api.types.is_complex_dtype(arr_or_dtype)
Check whether the provided array or dtype is of a complex dtype.

Parameters

arr_or_dtype [array-like] The array or dtype to check.

Returns

boolean Whether or not the array or dtype is of a complex dtype.

Examples

```python
>>> is_complex_dtype(str)
False
>>> is_complex_dtype(int)
False
>>> is_complex_dtype(np.complex_)
True
>>> is_complex_dtype(np.array(['a', 'b']))
False
>>> is_complex_dtype(pd.Series([1, 2]))
False
>>> is_complex_dtype(np.array([1 + 1j, 5]))
True
```

pandas.api.types.is_datetime64_any_dtype

pandas.api.types.is_datetime64_any_dtype(arr_or_dtype)
Check whether the provided array or dtype is of the datetime64 dtype.

Parameters

arr_or_dtype [array-like] The array or dtype to check.

Returns

bool Whether or not the array or dtype is of the datetime64 dtype.

Examples

```python
>>> is_datetime64_any_dtype(str)
False
>>> is_datetime64_any_dtype(int)
False
>>> is_datetime64_any_dtype(np.datetime64)  # can be tz-naive
True
>>> is_datetime64_any_dtype(DatetimeTZDtype("ns", "US/Eastern"))
True
>>> is_datetime64_any_dtype(np.array(['a', 'b']))
False
>>> is_datetime64_any_dtype(np.array([1, 2]))
False
>>> is_datetime64_any_dtype(np.array([], dtype="datetime64[ns]"))
```
pandas.api.types.is_datetime64_dtype

pandas.api.types.is_datetime64_dtype(arr_or_dtype)

Check whether an array-like or dtype is of the datetime64 dtype.

Parameters

arr_or_dtype [array-like] The array-like or dtype to check.

Returns

boolean Whether or not the array-like or dtype is of the datetime64 dtype.

Examples

```python
>>> is_datetime64_dtype(object)
False
>>> is_datetime64_dtype(np.datetime64)
True
>>> is_datetime64_dtype(np.array([], dtype=int))
False
>>> is_datetime64_dtype(np.array([], dtype=np.datetime64))
True
>>> is_datetime64_dtype([1, 2, 3])
False
```

pandas.api.types.is_datetime64_ns_dtype

pandas.api.types.is_datetime64_ns_dtype(arr_or_dtype)

Check whether the provided array or dtype is of the datetime64[ns] dtype.

Parameters

arr_or_dtype [array-like] The array or dtype to check.

Returns

bool Whether or not the array or dtype is of the datetime64[ns] dtype.

Examples

```python
>>> is_datetime64_ns_dtype(str)
False
>>> is_datetime64_ns_dtype(int)
False
>>> is_datetime64_ns_dtype(np.datetime64)  # no unit
False
>>> is_datetime64_ns_dtype(DatetimeTZDtype("ns", "US/Eastern"))
True
>>> is_datetime64_ns_dtype(np.array(['a', 'b']))
```

3.15. General utility functions
False
>>> is_datetime64_ns_dtype(np.array([1, 2]))
False
>>> is_datetime64_ns_dtype(np.array([], dtype="datetime64"))  # no unit
False
>>> is_datetime64_ns_dtype(np.array([], dtype="datetime64[ps]"))  # wrong unit
False
>>> is_datetime64_ns_dtype(pd.DatetimeIndex([1, 2, 3], dtype="datetime64[ns]"))
True

pandas.api.types.is_datetime64tz_dtype

pandas.api.types.is_datetime64tz_dtype(arr_or_dtype)
Check whether an array-like or dtype is of a DatetimeTZDtype dtype.

Parameters

arr_or_dtype [array-like] The array-like or dtype to check.

Returns

boolean Whether or not the array-like or dtype is of a DatetimeTZDtype dtype.

Examples

>>> is_datetime64tz_dtype(object)
False
>>> is_datetime64tz_dtype([1, 2, 3])
False
>>> is_datetime64tz_dtype(pd.DatetimeIndex([1, 2, 3]))  # tz-naive
False
>>> is_datetime64tz_dtype(pd.DatetimeIndex([1, 2, 3], tz="US/Eastern"))
True

>>> dtype = DatetimeTZDtype("ns", tz="US/Eastern")
>>> s = pd.Series([], dtype=dtype)
>>> is_datetime64tz_dtype(dtype)
True
>>> is_datetime64tz_dtype(s)
True

pandas.api.types.is_extension_type

pandas.api.types.is_extension_type(arr)
Check whether an array-like is of a pandas extension class instance.

Deprecated since version 1.0.0: Use is_extension_array_dtype instead.

Extension classes include categoricals, pandas sparse objects (i.e. classes represented within the pandas library and not ones external to it like scipy sparse matrices), and datetime-like arrays.

Parameters

arr [array-like] The array-like to check.

Returns
boolean  Whether or not the array-like is of a pandas extension class instance.

Examples

```python
>>> is_extension_type([1, 2, 3])
False
>>> is_extension_type(np.array([1, 2, 3]))
False
>>> cat = pd.Categorical([1, 2, 3])
>>> is_extension_type(cat)
True
>>> is_extension_type(pd.Series(cat))
True
>>> is_extension_type(pd.arrays.SparseArray([1, 2, 3]))
True
>>> from scipy.sparse import bsr_matrix
>>> is_extension_type(bsr_matrix([1, 2, 3]))
False
>>> is_extension_type(pd.DatetimeIndex([1, 2, 3]))
False
>>> is_extension_type(pd.DatetimeIndex([1, 2, 3], tz="US/Eastern"))
True
>>> dtype = DatetimeTZDtype("ns", tz="US/Eastern")
>>> s = pd.Series([], dtype=dtype)
>>> is_extension_type(s)
True
```

pandas.api.types.is_extension_array_dtype

pandas.api.types.is_extension_array_dtype(arr_or_dtype)
Check if an object is a pandas extension array type.

See the Use Guide for more.

Parameters:

arr_or_dtype [object] For array-like input, the .dtype attribute will be extracted.

Returns:

bool  Whether the arr_or_dtype is an extension array type.

Notes

This checks whether an object implements the pandas extension array interface. In pandas, this includes:

- Categorical
- Sparse
- Interval
- Period
- DatetimeArray
- TimedeltaArray

Third-party libraries may implement arrays or types satisfying this interface as well.
Examples

>>> from pandas.api.types import is_extension_array_dtype
>>> arr = pd.Categorical(['a', 'b'])
>>> is_extension_array_dtype(arr)
True
>>> is_extension_array_dtype(arr.dtype)
True

>>> arr = np.array(['a', 'b'])
>>> is_extension_array_dtype(arr.dtype)
False

pandas.api.types.is_float_dtype

pandas.api.types.is_float_dtype(arr_or_dtype)
Check whether the provided array or dtype is of a float dtype.
This function is internal and should not be exposed in the public API.

Parameters

arr_or_dtype [array-like] The array or dtype to check.

Returns

boolean Whether or not the array or dtype is of a float dtype.

Examples

>>> is_float_dtype(str)
False
>>> is_float_dtype(int)
False
>>> is_float_dtype(float)
True
>>> is_float_dtype(np.array(['a', 'b']))
False
>>> is_float_dtype(pd.Series([1, 2]))
False
>>> is_float_dtype(pd.Index([1, 2.]))
True

pandas.api.types.is_int64_dtype

pandas.api.types.is_int64_dtype(arr_or_dtype)
Check whether the provided array or dtype is of the int64 dtype.

Parameters

arr_or_dtype [array-like] The array or dtype to check.

Returns

boolean Whether or not the array or dtype is of the int64 dtype.
Notes

Depending on system architecture, the return value of `is_int64_dtype(int)` will be True if the OS uses 64-bit integers and False if the OS uses 32-bit integers.

Examples

```python
>>> is_int64_dtype(str)
False
>>> is_int64_dtype(np.int32)
False
>>> is_int64_dtype(np.int64)
True
>>> is_int64_dtype('int8')
False
>>> is_int64_dtype('Int8')
False
>>> is_int64_dtype(pd.Int64Dtype)
True
>>> is_int64_dtype(float)
False
>>> is_int64_dtype(np.uint64)  # unsigned
False
>>> is_int64_dtype(np.array(['a', 'b']))
False
>>> is_int64_dtype(np.array([1, 2], dtype=np.int64))
True
>>> is_int64_dtype(pd.Index([1, 2.]))  # float
False
>>> is_int64_dtype(np.array([1, 2], dtype=np.uint32))  # unsigned
False
```

**pandas.api.types.is_integer_dtype**

`pandas.api.types.is_integer_dtype(arr_or_dtype)`

Check whether the provided array or dtype is of an integer dtype.

Unlike in `in_any_int_dtype`, timedelta64 instances will return False.

Changed in version 0.24.0: The nullable Integer dtypes (e.g. pandas.Int64Dtype) are also considered as integer by this function.

**Parameters**

- `arr_or_dtype` [array-like] The array or dtype to check.

**Returns**

- `boolean` Whether or not the array or dtype is of an integer dtype and not an instance of timedelta64.
Examples

```python
>>> is_integer_dtype(str)
False
>>> is_integer_dtype(int)
True
>>> is_integer_dtype(float)
False
>>> is_integer_dtype(np.uint64)
True
>>> is_integer_dtype('int8')
True
>>> is_integer_dtype('Int8')
True
>>> is_integer_dtype(pd.Int8Dtype)
True
>>> is_integer_dtype(np.datetime64)
False
>>> is_integer_dtype(np.timedelta64)
False
>>> is_integer_dtype(np.array(['a', 'b']))
False
>>> is_integer_dtype(pd.Series([1, 2]))
True
>>> is_integer_dtype(np.array([], dtype=np.timedelta64))
False
>>> is_integer_dtype(pd.Index([1, 2.]))  # float  # float
False

pandas.api.types.is_interval_dtype

pandas.api.types.is_interval_dtype(arr_or_dtype)
Check whether an array-like or dtype is of the Interval dtype.
Parameters

arr_or_dtype  [array-like] The array-like or dtype to check.

Returns

boolean  Whether or not the array-like or dtype is of the Interval dtype.

Examples

```python
>>> is_interval_dtype(object)
False
>>> is_interval_dtype(IntervalDtype())
True
>>> is_interval_dtype([1, 2, 3])
False
>>> interval = pd.Interval(1, 2, closed="right")
>>> is_interval_dtype(interval)
False
>>> is_interval_dtype(pd.IntervalIndex([interval]))
True
```
pandas.api.types.is_numeric_dtype

**pandas.api.types.is_numeric_dtype(arr_or_dtype)**

Check whether the provided array or dtype is of a numeric dtype.

**Parameters**

- **arr_or_dtype** [array-like] The array or dtype to check.

**Returns**

- **boolean** Whether or not the array or dtype is of a numeric dtype.

**Examples**

```python
g>>> is_numeric_dtype(str)
False
g>>> is_numeric_dtype(int)
True
g>>> is_numeric_dtype(float)
True
g>>> is_numeric_dtype(np.uint64)
True
g>>> is_numeric_dtype(np.datetime64)
False
g>>> is_numeric_dtype(np.timedelta64)
False
g>>> is_numeric_dtype(np.array(['a', 'b']))
False
g>>> is_numeric_dtype(pd.Series([1, 2]))
True
g>>> is_numeric_dtype(pd.Index([1, 2.]))
True
g>>> is_numeric_dtype(np.array([], dtype=np.timedelta64))
False
```

pandas.api.types.is_object_dtype

**pandas.api.types.is_object_dtype(arr_or_dtype)**

Check whether an array-like or dtype is of the object dtype.

**Parameters**

- **arr_or_dtype** [array-like] The array-like or dtype to check.

**Returns**

- **boolean** Whether or not the array-like or dtype is of the object dtype.
Examples

```python
>>> is_object_dtype(object)
True
>>> is_object_dtype(int)
False
>>> is_object_dtype(np.array([], dtype=object))
True
>>> is_object_dtype(np.array([], dtype=int))
False
>>> is_object_dtype([1, 2, 3])
False
```

**pandas.api.types.is_period_dtype**

**pandas.api.types.is_period_dtype(arr_or_dtype)**

Check whether an array-like or dtype is of the Period dtype.

**Parameters**

- **arr_or_dtype** [array-like] The array-like or dtype to check.

**Returns**

- **boolean** Whether or not the array-like or dtype is of the Period dtype.

**Examples**

```python
>>> is_period_dtype(object)
False
>>> is_period_dtype(PeriodDtype(freq="D"))
True
>>> is_period_dtype([1, 2, 3])
False
>>> is_period_dtype(pd.Period("2017-01-01"))
False
>>> is_period_dtype(pd.PeriodIndex([], freq="A"))
True
```

**pandas.api.types.is_signed_integer_dtype**

**pandas.api.types.is_signed_integer_dtype(arr_or_dtype)**

Check whether the provided array or dtype is of a signed integer dtype.

Unlike in `in_any_int_dtype`, timedelta64 instances will return False.

Changed in version 0.24.0: The nullable Integer dtypes (e.g. pandas.Int64Dtype) are also considered as integer by this function.

**Parameters**

- **arr_or_dtype** [array-like] The array or dtype to check.

**Returns**

- **boolean** Whether or not the array or dtype is of a signed integer dtype and not an instance of timedelta64.
Examples

```python
>>> is_signed_integer_dtype(str)
False
>>> is_signed_integer_dtype(int)
True
>>> is_signed_integer_dtype(float)
False
>>> is_signed_integer_dtype(np.uint64)  # unsigned
False
>>> is_signed_integer_dtype('int8')
True
>>> is_signed_integer_dtype('Int8')
True
>>> is_signed_integer_dtype(pd.Int8Dtype)
True
>>> is_signed_integer_dtype(np.datetime64)
False
>>> is_signed_integer_dtype(np.timedelta64)
False
>>> is_signed_integer_dtype(np.array(['a', 'b']))
False
>>> is_signed_integer_dtype(pd.Series([1, 2]))
True
>>> is_signed_integer_dtype(np.array([], dtype=np.timedelta64))
False
>>> is_signed_integer_dtype(pd.Index([1, 2.]))  # float
False
>>> is_signed_integer_dtype(np.array([1, 2], dtype=np.uint32))  # unsigned
False
```

def pandas.api.types.is_string_dtype(arr_or_dtype):
    """Check whether the provided array or dtype is of the string dtype."
    """
    Parameters
    arr_or_dtype [array-like] The array or dtype to check.
    """
    """Returns"
    boolean Whether or not the array or dtype is of the string dtype.
    """

Examples

```python
>>> is_string_dtype(str)
True
>>> is_string_dtype(object)
True
>>> is_string_dtype(int)
False
>>> is_string_dtype(np.array(['a', 'b']))
True
```

(continues on next page)
is_string_dtype(pd.Series([1, 2]))
False

pandas.api.types.is_timedelta64_dtype

pandas.api.types.is_timedelta64_dtype(arr_or_dtype)
Check whether an array-like or dtype is of the timedelta64 dtype.

Parameters

arr_or_dtype [array-like] The array-like or dtype to check.

Returns

boolean Whether or not the array-like or dtype is of the timedelta64 dtype.

Examples

>>> is_timedelta64_dtype('object')
False
>>> is_timedelta64_dtype(np.timedelta64)
True
>>> is_timedelta64_dtype([1, 2, 3])
False
>>> is_timedelta64_dtype(pd.Series([], dtype="timedelta64[ns]")
True
>>> is_timedelta64_dtype('0 days')
False

pandas.api.types.is_timedelta64_ns_dtype

pandas.api.types.is_timedelta64_ns_dtype(arr_or_dtype)
Check whether the provided array or dtype is of the timedelta64[ns] dtype.

This is a very specific dtype, so generic ones like np.timedelta64 will return False if passed into this function.

Parameters

arr_or_dtype [array-like] The array or dtype to check.

Returns

boolean Whether or not the array or dtype is of the timedelta64[ns] dtype.

Examples

>>> is_timedelta64_ns_dtype(np.dtype('m8[ns]'))
True
>>> is_timedelta64_ns_dtype(np.dtype('m8[ps]')) # Wrong frequency
False
>>> is_timedelta64_ns_dtype(np.array([1, 2], dtype='m8[ns]'))
True
>>> is_timedelta64_ns_dtype(np.array([1, 2], dtype=np.timedelta64))
False
pandas.api.types.is_unsigned_integer_dtype

pandas.api.types.

is_unsigned_integer_dtype(arr_or_dtype)

Check whether the provided array or dtype is of an unsigned integer dtype.

Changed in version 0.24.0: The nullable Integer dtypes (e.g. pandas.UInt64Dtype) are also considered as integer by this function.

Parameters

arr_or_dtype [array-like] The array or dtype to check.

Returns

boolean Whether or not the array or dtype is of an unsigned integer dtype.

Examples

```python
>>> is_unsigned_integer_dtype(str)
False
>>> is_unsigned_integer_dtype(int)  # signed
False
>>> is_unsigned_integer_dtype(float)
False
>>> is_unsigned_integer_dtype(np.uint64)
True
>>> is_unsigned_integer_dtype('uint8')
True
>>> is_unsigned_integer_dtype('UInt8')
True
>>> is_unsigned_integer_dtype(pd.UInt8Dtype)
True
>>> is_unsigned_integer_dtype(np.array(['a', 'b']))
False
>>> is_unsigned_integer_dtype(pd.Series([1, 2]))  # signed
False
>>> is_unsigned_integer_dtype(pd.Index([1, 2.]))  # float
False
>>> is_unsigned_integer_dtype(np.array([1, 2], dtype=np.uint32))
True
```

pandas.api.types.is_sparse

pandas.api.types.

is_sparse(arr)

Check whether an array-like is a 1-D pandas sparse array.

Check that the one-dimensional array-like is a pandas sparse array. Returns True if it is a pandas sparse array, not another type of sparse array.

Parameters

arr [array-like] Array-like to check.

Returns

bool Whether or not the array-like is a pandas sparse array.
Examples

Returns *True* if the parameter is a 1-D pandas sparse array.

```python
>>> is_sparse(pd.arrays.SparseArray([0, 0, 1, 0]))
True
>>> is_sparse(pd.Series(pd.arrays.SparseArray([0, 0, 1, 0])))
True
```

Returns *False* if the parameter is not sparse.

```python
>>> is_sparse(np.array([0, 0, 1, 0]))
False
>>> is_sparse(pd.Series([0, 1, 0, 0]))
False
```

Returns *False* if the parameter is not a pandas sparse array.

```python
>>> from scipy.sparse import bsr_matrix
>>> is_sparse(bsr_matrix([0, 1, 0, 0]))
False
```

Returns *False* if the parameter has more than one dimension.

### Iterable introspection

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>api.types.is_dict_like(obj)</code></td>
<td>Check if the object is dict-like.</td>
</tr>
<tr>
<td><code>api.types.is_file_like(obj)</code></td>
<td>Check if the object is a file-like object.</td>
</tr>
<tr>
<td><code>api.types.is_list_like</code></td>
<td>Check if the object is list-like.</td>
</tr>
<tr>
<td><code>api.types.is_named_tuple(obj)</code></td>
<td>Check if the object is a named tuple.</td>
</tr>
<tr>
<td><code>api.types.is_iterator</code></td>
<td>Check if the object is an iterator.</td>
</tr>
</tbody>
</table>

### pandas.api.types.is_dict_like

`pandas.api.types.is_dict_like(obj)`

Check if the object is dict-like.

**Parameters**

- `obj` [The object to check]

**Returns**

- `is_dict_like` [bool] Whether `obj` has dict-like properties.
Examples

```python
>>> is_dict_like({1: 2})
True
>>> is_dict_like([1, 2, 3])
False
>>> is_dict_like(dict)
False
>>> is_dict_like(dict())
True
```

**pandas.api.types.is_file_like**

`pandas.api.types.is_file_like(obj)`

Check if the object is a file-like object.

For objects to be considered file-like, they must be an iterator AND have either a `read` and/or `write` method as an attribute.

Note: file-like objects must be iterable, but iterable objects need not be file-like.

**Parameters**

- `obj` [The object to check]

**Returns**

- `is_file_like` [bool] Whether `obj` has file-like properties.

Examples

```python
>>> import io
>>> buffer = io.StringIO("data")
>>> is_file_like(buffer)
True
>>> is_file_like([1, 2, 3])
False
```

**pandas.api.types.is_list_like**

`pandas.api.types.is_list_like()`

Check if the object is list-like.

Objects that are considered list-like are for example Python lists, tuples, sets, NumPy arrays, and Pandas Series.

Strings and datetime objects, however, are not considered list-like.

**Parameters**

- `obj` [object] Object to check.

- `allow_sets` [bool, default True] If this parameter is False, sets will not be considered list-like.

  New in version 0.24.0.

**Returns**

- `bool` Whether `obj` has list-like properties.
Examples

```python
>>> is_list_like([1, 2, 3])
True
>>> is_list_like([1, 2, 3])
True
>>> is_list_like(datetime(2017, 1, 1))
False
>>> is_list_like("foo")
False
>>> is_list_like(1)
False
>>> is_list_like(np.array([2]))
True
>>> is_list_like(np.array(2))
False
```

pandas.api.types.is_named_tuple

pandas.api.types.is_named_tuple(obj)
Check if the object is a named tuple.

Parameters

- **obj** [The object to check]

Returns

- **is_named_tuple** [bool] Whether *obj* is a named tuple.

Examples

```python
>>> from collections import namedtuple
>>> Point = namedtuple("Point", ["x", "y"])
>>> p = Point(1, 2)
>>> is_named_tuple(p)
True
>>> is_named_tuple((1, 2))
False
```

pandas.api.types.is_iterator

pandas.api.types.is_iterator()
Check if the object is an iterator.
This is intended for generators, not list-like objects.

Parameters

- **obj** [The object to check]

Returns

- **is_iter** [bool] Whether *obj* is an iterator.
Examples

```python
>>> is_iterator((x for x in []))
True
>>> is_iterator([1, 2, 3])
False
>>> is_iterator(datetime(2017, 1, 1))
False
>>> is_iterator("foo")
False
>>> is_iterator(1)
False
```

Scalar introspection

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>is_bool</code></td>
<td>Returns <code>bool</code></td>
</tr>
<tr>
<td><code>is_categorical</code></td>
<td>Check whether an array-like is a Categorical instance.</td>
</tr>
<tr>
<td><code>is_complex</code></td>
<td>Returns <code>bool</code></td>
</tr>
<tr>
<td><code>is_float</code></td>
<td>Returns <code>bool</code></td>
</tr>
<tr>
<td><code>is_hashable</code></td>
<td>Return <code>True</code> if <code>hash(obj)</code> will succeed, <code>False</code> otherwise.</td>
</tr>
<tr>
<td><code>is_integer</code></td>
<td>Returns <code>bool</code></td>
</tr>
<tr>
<td><code>is_interval</code></td>
<td>Check if the object is a number.</td>
</tr>
<tr>
<td><code>is_re</code></td>
<td>Check if the object is a regex pattern instance.</td>
</tr>
<tr>
<td><code>is_re_compilable</code></td>
<td>Check if the object can be compiled into a regex pattern instance.</td>
</tr>
</tbody>
</table>

`pandas.api.types.is_bool`

`pandas.api.types.is_bool()`

Returns `bool`
pandas.api.types.is_categorical

pandas.api.types.is_categorical(arr)
Check whether an array-like is a Categorical instance.

Parameters
arr [array-like] The array-like to check.

Returns
boolean Whether or not the array-like is of a Categorical instance.

Examples

```python
>>> is_categorical([1, 2, 3])
False
```

Categoricals, Series Categoricals, and CategoricalIndex will return True.

```python
>>> cat = pd.Categorical([1, 2, 3])
>>> is_categorical(cat)
True
>>> is_categorical(pd.Series(cat))
True
>>> is_categorical(pd.CategoricalIndex([1, 2, 3]))
True
```

pandas.api.types.is_complex

pandas.api.types.is_complex()
Returns
bool

pandas.api.types.is_float

pandas.api.types.is_float()
Returns
bool

pandas.api.types.is_hashable

pandas.api.types.is_hashable(obj)
Return True if hash(obj) will succeed, False otherwise.

Some types will pass a test against collections.abc.Hashable but fail when they are actually hashed with hash().

Distinguish between these and other types by trying the call to hash() and seeing if they raise TypeError.
Returns
bool
Examples

```python
>>> import collections
>>> a = ([],)
>>> isinstance(a, collections.abc.Hashable)
True
>>> is_hashable(a)
False
```

`pandas.api.types.is_integer`

`pandas.api.types.is_integer()`

Returns `bool`

`pandas.api.types.is_interval`

`pandas.api.types.is_interval()`

`pandas.api.types.is_number`

`pandas.api.types.is_number(obj)`

Check if the object is a number. Returns True when the object is a number, and False if is not.

Parameters:

- `obj` [any type] The object to check if is a number.

Returns

- `is_number` [bool] Whether `obj` is a number or not.

See also:

- `api.types.is_integer` Checks a subgroup of numbers.

Examples

```python
>>> pd.api.types.is_number(1)
True
>>> pd.api.types.is_number(7.15)
True
Booleans are valid because they are int subclass.

>>> pd.api.types.is_number(False)
True

>>> pd.api.types.is_number("foo")
False
>>> pd.api.types.is_number("5")
False
```
pandas.api.types.is_re

pandas.api.types.is_re(obj)
Check if the object is a regex pattern instance.
Parameters
    obj [The object to check]
Returns
    is_regex [bool] Whether \( \text{obj} \) is a regex pattern.

Examples

```python
>>> is_re(re.compile(".*"))
True
>>> is_re("foo")
False
```

pandas.api.types.is_re_compilable

pandas.api.types.is_re_compilable(obj)
Check if the object can be compiled into a regex pattern instance.
Parameters
    obj [The object to check]
Returns
    is_regex_compilable [bool] Whether \( \text{obj} \) can be compiled as a regex pattern.

Examples

```python
>>> is_re_compilable(".*")
True
>>> is_re_compilable(1)
False
```

pandas.api.types.is_scalar

pandas.api.types.is_scalar()
Parameters
    val [object] This includes:
    • numpy array scalar (e.g. np.int64)
    • Python builtin numerics
    • Python builtin byte arrays and strings
    • None
    • datetime.datetime
    • datetime.timedelta
• Period
• decimal.Decimal
• Interval
• DateOffset
• Fraction
• Number.

Returns

```
bool  Return True if given object is scalar.
```

Examples

```
>>> dt = datetime.datetime(2018, 10, 3)
>>> pd.api.types.is_scalar(dt)
True
```

```
>>> pd.api.types.is_scalar([2, 3])
False
```

```
>>> pd.api.types.is_scalar({0: 1, 2: 3})
False
```

```
>>> pd.api.types.is_scalar((0, 2))
False
```

pandas supports PEP 3141 numbers:

```
>>> from fractions import Fraction
>>> pd.api.types.is_scalar(Fraction(3, 5))
True
```

3.15.5 Bug report function

```
show_versions(as_json)
```

Provide useful information, important for bug reports.

```
pandas.show_versions(as_json=False)
```

Provide useful information, important for bug reports.

It comprises info about hosting operation system, pandas version, and versions of other installed relative packages.

Parameters

```
as_json [str or bool, default False]
```

- If False, outputs info in a human readable form to the console.
- If str, it will be considered as a path to a file. Info will be written to that file in JSON format.
3.16 Extensions

These are primarily intended for library authors looking to extend pandas objects.

<table>
<thead>
<tr>
<th>api.extensions.register_extension_dtype</th>
<th>Register an ExtensionType with pandas as class decorator.</th>
</tr>
</thead>
<tbody>
<tr>
<td>api.extensions.register_dataframe_accessor</td>
<td>Register a custom accessor on DataFrame objects.</td>
</tr>
<tr>
<td>api.extensions.register_series_accessor</td>
<td>Register a custom accessor on Series objects.</td>
</tr>
<tr>
<td>api.extensions.register_index_accessor</td>
<td>Register a custom accessor on Index objects.</td>
</tr>
<tr>
<td>api.extensions.ExtensionDtype()</td>
<td>A custom data type, to be paired with an ExtensionArray.</td>
</tr>
</tbody>
</table>

3.16.1 pandas.api.extensions.register_extension_dtype

pandas.api.extensions.register_extension_dtype(cls)

Register an ExtensionType with pandas as class decorator.

New in version 0.24.0.

This enables operations like \astype(name) for the name of the ExtensionDtype.

**Returns**

callable  A class decorator.

**Examples**

```python
>>> from pandas.api.extensions import register_extension_dtype
>>> from pandas.api.extensions import ExtensionDtype
>>> @register_extension_dtype
... class MyExtensionDtype(ExtensionDtype):
...     name = "myextension"
```

3.16.2 pandas.api.extensions.register_dataframe_accessor

pandas.api.extensions.register_dataframe_accessor(name)

Register a custom accessor on DataFrame objects.

**Parameters**

- **name** [str] Name under which the accessor should be registered. A warning is issued if this name conflicts with a preexisting attribute.

**Returns**

callable  A class decorator.

**See also:**

- register_dataframe_accessor  Register a custom accessor on DataFrame objects.
- register_series_accessor  Register a custom accessor on Series objects.
- register_index_accessor  Register a custom accessor on Index objects.
Notes

When accessed, your accessor will be initialized with the pandas object the user is interacting with. So the signature must be

```python
def __init__(self, pandas_object):  # noqa: E999
    ...
```

For consistency with pandas methods, you should raise an `AttributeError` if the data passed to your accessor has an incorrect dtype.

```python
>>> pd.Series(['a', 'b']).dt
Traceback (most recent call last):
...
AttributeError: Can only use .dt accessor with datetimelike values
```

Examples

In your library code:

```python
import pandas as pd

@pd.api.extensions.register_dataframe_accessor("geo")
class GeoAccessor:
    def __init__(self, pandas_obj):
        self._obj = pandas_obj

    @property
    def center(self):
        # return the geographic center point of this DataFrame
        lat = self._obj.latitude
        lon = self._obj.longitude
        return (float(lon.mean()), float(lat.mean()))

    def plot(self):
        # plot this array's data on a map, e.g., using Cartopy
        pass
```

Back in an interactive IPython session:

```python
In [1]: ds = pd.DataFrame({"longitude": np.linspace(0, 10),
...:                      "latitude": np.linspace(0, 20)})
In [2]: ds.geo.center
Out[2]: (5.0, 10.0)
In [3]: ds.geo.plot()  # plots data on a map
```
3.16.3 pandas.api.extensions.register_series_accessor

pandas.api.extensions.register_series_accessor(name)
Register a custom accessor on Series objects.

Parameters

name [str] Name under which the accessor should be registered. A warning is issued if this name conflicts with a preexisting attribute.

Returns
callable A class decorator.

See also:
register_dataframe_accessor Register a custom accessor on DataFrame objects.
register_series_accessor Register a custom accessor on Series objects.
register_index_accessor Register a custom accessor on Index objects.

Notes

When accessed, your accessor will be initialized with the pandas object the user is interacting with. So the signature must be

```python
def __init__(self, pandas_object): # noqa: E999 ...
```

For consistency with pandas methods, you should raise an AttributeError if the data passed to your accessor has an incorrect dtype.

```python
>>> pd.Series(['a', 'b']).dt
Traceback (most recent call last):
...
AttributeError: Can only use .dt accessor with datetimelike values
```

Examples

In your library code:

```python
import pandas as pd

@pd.api.extensions.register_dataframe_accessor("geo")
class GeoAccessor:
    def __init__(self, pandas_obj):
        self._obj = pandas_obj

    @property
def center(self):
        # return the geographic center point of this DataFrame
        lat = self._obj.latitude
        lon = self._obj.longitude
        return (float(lon.mean()), float(lat.mean()))

    def plot(self):
        # plot this array's data on a map, e.g., using Cartopy
        pass
```

Back in an interactive IPython session:
In [1]: ds = pd.DataFrame({"longitude": np.linspace(0, 10), ...:                     "latitude": np.linspace(0, 20)})
In [2]: ds.geo.center
Out[2]: (5.0, 10.0)
In [3]: ds.geo.plot()  # plots data on a map

3.16.4 pandas.api.extensions.register_index_accessor

pandas.api.extensions.register_index_accessor(name)

Register a custom accessor on Index objects.

Parameters

name [str] Name under which the accessor should be registered. A warning is issued if this name conflicts with a preexisting attribute.

Returns
callable A class decorator.

See also:

register_dataframe_accessor Register a custom accessor on DataFrame objects.
register_series_accessor Register a custom accessor on Series objects.
register_index_accessor Register a custom accessor on Index objects.

Notes

When accessed, your accessor will be initialized with the pandas object the user is interacting with. So the signature must be

```python
def __init__(self, pandas_object):  # noqa: E999
...```

For consistency with pandas methods, you should raise an AttributeError if the data passed to your accessor has an incorrect dtype.

```python
>>> pd.Series(['a', 'b']).dt
AttributeError: Can only use .dt accessor with datetimelike values
```

Examples

In your library code:

```python
import pandas as pd

@pd.api.extensions.register_dataframe_accessor("geo")
class GeoAccessor:
    def __init__(self, pandas_obj):
        self._obj = pandas_obj

    @property
def center(self):
        # return the geographic center point of this DataFrame
```

(continues on next page)
lat = self._obj.latitude
lon = self._obj.longitude
return (float(lon.mean()), float(lat.mean()))

def plot(self):
    # plot this array's data on a map, e.g., using Cartopy
    pass

Back in an interactive IPython session:

```
In [1]: ds = pd.DataFrame({"longitude": np.linspace(0, 10),
                      ...
                      "latitude": np.linspace(0, 20)})
In [2]: ds.geo.center
Out[2]: (5.0, 10.0)
In [3]: ds.geo.plot()  # plots data on a map
```

### 3.16.5 pandas.api.extensions.ExtensionDtype

class pandas.api.extensions.ExtensionDtype
A custom data type, to be paired with an ExtensionArray.

New in version 0.23.0.

See also:

- `extensions.register_extension_dtype`
- `extensions.ExtensionArray`

**Notes**

The interface includes the following abstract methods that must be implemented by subclasses:
- type
- name

The following attributes and methods influence the behavior of the dtype in pandas operations:
- _is_numeric
- _is_boolean
- _get_common_dtype

Optionally one can override `construct_array_type` for construction with the name of this dtype via the Registry.

See `extensions.register_extension_dtype()`.

- `construct_array_type`

The `na_value` class attribute can be used to set the default NA value for this type. `numpy.nan` is used by default.

ExtensionDtotypes are required to be hashable. The base class provides a default implementation, which relies on the `_metadata` class attribute. `_metadata` should be a tuple containing the strings that define your data type. For example, with `PeriodDtype` that’s the `freq` attribute.

**If you have a parametrized dtype you should set the `"_metadata"` class property.**

Ideally, the attributes in `_metadata` will match the parameters to your `ExtensionDtype.__init__` (if any). If any of the attributes in `_metadata` don’t implement the standard `__eq__` or `__hash__`, the default implementations here will not work.

Changed in version 0.24.0: Added `_metadata`, `__hash__`, and changed the default definition of `__eq__`. 
For interaction with Apache Arrow (pyarrow), a `__from_arrow__` method can be implemented: this method receives a pyarrow Array or ChunkedArray as only argument and is expected to return the appropriate pandas ExtensionArray for this dtype and the passed values:

```python
class ExtensionDtype:
    def __from_arrow__(
        self, array: Union[pyarrow.Array, pyarrow.ChunkedArray]
    ) -> ExtensionArray:
        ...
```

This class does not inherit from `abc.ABCMeta` for performance reasons. Methods and properties required by the interface raise `pandas.errors(AbstractMethodError` and no `register` method is provided for registering virtual subclasses.

**Attributes**

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>kind</td>
<td>A character code (one of 'biufcmMOSUV'), default ‘O’</td>
</tr>
<tr>
<td>na_value</td>
<td>Default NA value to use for this type.</td>
</tr>
<tr>
<td>name</td>
<td>A string identifying the data type.</td>
</tr>
<tr>
<td>names</td>
<td>Ordered list of field names, or None if there are no fields.</td>
</tr>
<tr>
<td>type</td>
<td>The scalar type for the array, e.g.</td>
</tr>
</tbody>
</table>

**pandas.api.extensions.ExtensionDtype.kind**

**property** `ExtensionDtype.kind`

A character code (one of ‘biufcmMOSUV’), default ‘O’

This should match the NumPy dtype used when the array is converted to an ndarray, which is probably ‘O’ for object if the extension type cannot be represented as a built-in NumPy type.

**See also:**

- `numpy.dtype.kind`

**pandas.api.extensions.ExtensionDtype.na_value**

**property** `ExtensionDtype.na_value`

Default NA value to use for this type.

This is used in e.g. ExtensionArray.take. This should be the user-facing “boxed” version of the NA value, not the physical NA value for storage. e.g. for JSONArray, this is an empty dictionary.
pandas.api.extensions.ExtensionDtype.name

**property** `ExtensionDtype.name`

A string identifying the data type.

Will be used for display in, e.g. `Series.dtype`.

pandas.api.extensions.ExtensionDtype.names

**property** `ExtensionDtype.names`

Ordered list of field names, or None if there are no fields.

This is for compatibility with NumPy arrays, and may be removed in the future.

pandas.api.extensions.ExtensionDtype.type

**property** `ExtensionDtype.type`

The scalar type for the array, e.g. `int`.

It’s expected `ExtensionArray[item]` returns an instance of `ExtensionDtype.type` for scalar `item`, assuming that value is valid (not NA). NA values do not need to be instances of `type`.

Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>construct_array_type()</code></td>
<td>Return the array type associated with this dtype.</td>
</tr>
<tr>
<td><code>construct_from_string(string)</code></td>
<td>Construct this type from a string.</td>
</tr>
<tr>
<td><code>is_dtype(dtype)</code></td>
<td>Check if we match <code>dtype</code>.</td>
</tr>
</tbody>
</table>

pandas.api.extensions.ExtensionDtype.construct_array_type

**classmethod** `ExtensionDtype.construct_array_type()`

Return the array type associated with this dtype.

Returns

`type`

pandas.api.extensions.ExtensionDtype.construct_from_string

**classmethod** `ExtensionDtype.construct_from_string(string)`

Construct this type from a string.

This is useful mainly for data types that accept parameters. For example, a period dtype accepts a frequency parameter that can be set as `period[H]` (where H means hourly frequency).

By default, in the abstract class, just the name of the type is expected. But subclasses can overwrite this method to accept parameters.

Parameters

- `string` [str] The name of the type, for example `category`.

Returns

`ExtensionDtype` Instance of the dtype.
Raises

**TypeError** If a class cannot be constructed from this ‘string’.

Examples

For extension dtypes with arguments the following may be an adequate implementation.

```python
>>> @classmethod
... def construct_from_string(cls, string):
...     pattern = re.compile(r"^my_type\[(?P<arg_name>.+)\]\$")
...     if match:
...         return cls(**match.groupdict())
...     else:
...         raise TypeError(
...             f"Cannot construct a '{cls.__name__}' from '{string}'"
...         )
```

---

**pandas.api.extensions.ExtensionDtype.is_dtype**

**classmethod** `ExtensionDtype.is_dtype(dtype)`

Check if we match ‘dtype’.

**Parameters**

- **dtype** [object] The object to check.

**Returns**

- **bool**

**Notes**

The default implementation is True if

1. `cls.construct_from_string(dtype)` is an instance of `cls`
2. `dtype` is an object and is an instance of `cls`
3. `dtype` has a `dtype` attribute, and any of the above conditions is true for `dtype.dtype`.

---

**3.16.6 pandas.api.extensions.ExtensionArray**

**class pandas.api.extensions.ExtensionArray**

Abstract base class for custom 1-D array types.

Pandas will recognize instances of this class as proper arrays with a custom type and will not attempt to coerce them to objects. They may be stored directly inside a `DataFrame` or `Series`.

New in version 0.23.0.
Notes

The interface includes the following abstract methods that must be implemented by subclasses:

- `_from_sequence`
- `_from_factorized`
- `__getitem__`
- `__len__`
- `__eq__`
- `dtype`
- `nbytes`
- `isna`
- `take`
- `copy`
- `_concat_same_type`

A default repr displaying the type, (truncated) data, length, and dtype is provided. It can be customized or replaced by by overriding:

- `__repr__`: A default repr for the ExtensionArray.
- `_formatter`: Print scalars inside a Series or DataFrame.

Some methods require casting the ExtensionArray to an ndarray of Python objects with `self.astype(object)`, which may be expensive. When performance is a concern, we highly recommend overriding the following methods:

- `fillna`
- `dropna`
- `unique`
- `factorize` / `_values_for_factorize`
- `argsort` / `_values_for_argsort`
- `searchsorted`

The remaining methods implemented on this class should be performant, as they only compose abstract methods. Still, a more efficient implementation may be available, and these methods can be overridden.

One can implement methods to handle array reductions.

- `reduce`

One can implement methods to handle parsing from strings that will be used in methods such as `pandas.io.parsers.read_csv`.

- `_from_sequence_of_strings`

This class does not inherit from `abc.ABCMeta` for performance reasons. Methods and properties required by the interface raise `pandas.errors(AbstractMethodError)` and no `register` method is provided for registering virtual subclasses.

ExtensionArrays are limited to 1 dimension.

They may be backed by none, one, or many NumPy arrays. For example, `pandas.Categorical` is an extension array backed by two arrays, one for codes and one for categories. An array of IPv6 address may be backed by a NumPy structured array with two fields, one for the lower 64 bits and one for the upper 64 bits. Or they may be backed by some other storage type, like Python lists. Pandas makes no assumptions on how the data are stored, just that it can be converted to a NumPy array. The ExtensionArray interface does not impose any rules on how this data is stored. However, currently, the backing data cannot be stored in attributes called `.values` or `._values` to ensure full compatibility with pandas internals. But other names as `.data`, `._data`, `._items`, ... can be freely used.

If implementing NumPy's `__array_ufunc__` interface, pandas expects that

1. You defer by returning `NotImplemented` when any Series are present in `inputs`. Pandas will extract the arrays and call the ufunc again.
2. You define a `_HANDLED_TYPES` tuple as an attribute on the class. Pandas inspect this to determine whether the ufunc is valid for the types present.

See NumPy universal functions for more.
By default, ExtensionArrays are not hashable. Immutable subclasses may override this behavior.

**Attributes**

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>dtype</code></td>
<td>An instance of ‘ExtensionDtype’.</td>
</tr>
<tr>
<td><code>nbytes</code></td>
<td>The number of bytes needed to store this object in memory.</td>
</tr>
<tr>
<td><code>ndim</code></td>
<td>Extension Arrays are only allowed to be 1-dimensional.</td>
</tr>
<tr>
<td><code>shape</code></td>
<td>Return a tuple of the array dimensions.</td>
</tr>
</tbody>
</table>

**Methods**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>argsort</code></td>
<td>Return the indices that would sort this array.</td>
</tr>
<tr>
<td><code>astype</code></td>
<td>Cast to a NumPy array with ‘dtype’.</td>
</tr>
<tr>
<td><code>copy</code></td>
<td>Return a copy of the array.</td>
</tr>
<tr>
<td><code>dropna</code></td>
<td>Return ExtensionArray without NA values.</td>
</tr>
<tr>
<td><code>factorize</code></td>
<td>Encode the extension array as an enumerated type.</td>
</tr>
<tr>
<td><code>fillna</code></td>
<td>Fill NA/NaN values using the specified method.</td>
</tr>
<tr>
<td><code>equals</code></td>
<td>Return if another array is equivalent to this array.</td>
</tr>
<tr>
<td><code>isna</code></td>
<td>A 1-D array indicating if each value is missing.</td>
</tr>
<tr>
<td><code>ravel</code></td>
<td>Return a flattened view on this array.</td>
</tr>
<tr>
<td><code>repeat</code></td>
<td>Repeat elements of a ExtensionArray.</td>
</tr>
<tr>
<td><code>searchsorted</code></td>
<td>Find indices where elements should be inserted to maintain order.</td>
</tr>
<tr>
<td><code>shift</code></td>
<td>Shift values by desired number.</td>
</tr>
</tbody>
</table>

continues on next page
Table 401 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>take</code></td>
<td>Take elements from an array.</td>
</tr>
<tr>
<td><code>unique()</code></td>
<td>Compute the ExtensionArray of unique values.</td>
</tr>
<tr>
<td><code>view</code></td>
<td>Return a view on the array.</td>
</tr>
<tr>
<td><code>_concat_same_type</code></td>
<td>Concatenate multiple array of this dtype.</td>
</tr>
<tr>
<td><code>_formatter</code></td>
<td>Formatting function for scalar values.</td>
</tr>
<tr>
<td><code>_from_factorized</code></td>
<td>Reconstruct an ExtensionArray after factorization.</td>
</tr>
<tr>
<td><code>_from_sequence</code></td>
<td>Construct a new ExtensionArray from a sequence of scalars.</td>
</tr>
<tr>
<td><code>_from_sequence_of_strings</code></td>
<td>Construct a new ExtensionArray from a sequence of strings.</td>
</tr>
<tr>
<td><code>_reduce</code></td>
<td>Return a scalar result of performing the reduction operation.</td>
</tr>
<tr>
<td><code>_values_for_argsort</code></td>
<td>Return values for sorting.</td>
</tr>
<tr>
<td><code>_values_for_factorize</code></td>
<td>Return an array and missing value suitable for factorization.</td>
</tr>
</tbody>
</table>

**pandas.api.extensions.ExtensionArray.argsort**

ExtensionArray.argsort (ascending=True, kind='quicksort', *args, **kwargs)

Return the indices that would sort this array.

**Parameters**

- `ascending` [bool, default True] Whether the indices should result in an ascending or descending sort.
- `*args, **kwargs`: Passed through to numpy.argsort().

**Returns**

- `ndarray`: Array of indices that sort self. If NaN values are contained, NaN values are placed at the end.

**See also:**

- numpy.argsort: Sorting implementation used internally.

**pandas.api.extensions.ExtensionArray.astype**

ExtensionArray.astype (dtype, copy=True)

Cast to a NumPy array with 'dtype'.

**Parameters**

- `dtype` [str or dtype] Typecode or data-type to which the array is cast.
- `copy` [bool, default True] Whether to copy the data, even if not necessary. If False, a copy is made only if the old dtype does not match the new dtype.

**Returns**

- `array`: NumPy ndarray with ‘dtype’ for its dtype.
pandas.api.extensions.ExtensionArray.copy

ExtensionArray.copy()
Return a copy of the array.

Returns
ExtensionArray

pandas.api.extensions.ExtensionArray.dropna

ExtensionArray.dropna()
Return ExtensionArray without NA values.

Returns
valid [ExtensionArray]

pandas.api.extensions.ExtensionArray.factorize

ExtensionArray.factorize(na_sentinel=-1)
Encode the extension array as an enumerated type.

Parameters
na_sentinel [int, default -1] Value to use in the codes array to indicate missing values.

Returns
codes [ndarray] An integer NumPy array that’s an indexer into the original ExtensionArray.
uniques [ExtensionArray] An ExtensionArray containing the unique values of self.

Note: uniques will not contain an entry for the NA value of the ExtensionArray if there are any missing values present in self.

See also:
factorize Top-level factorize method that dispatches here.

Notes

pandas.factorize() offers a sort keyword as well.
**pandas.api.extensions.ExtensionArrayfillna**

`ExtensionArray.fillna(value=None, method=None, limit=None)`  
Fill NA/NaN values using the specified method.

**Parameters**

- **value** [scalar, array-like] If a scalar value is passed it is used to fill all missing values. Alternatively, an array-like `value` can be given. It’s expected that the array-like have the same length as `self`.
- **method** [{'backfill', 'bfill', 'pad', 'ffill', None}, default None] Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill gap.
- **limit** [int, default None] If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled.

**Returns**

- `ExtensionArray` With NA/NaN filled.

**pandas.api.extensions.ExtensionArray.equals**

`ExtensionArray.equals(other)`  
Return if another array is equivalent to this array.

Equivalent means that both arrays have the same shape and dtype, and all values compare equal. Missing values in the same location are considered equal (in contrast with normal equality).

**Parameters**

- **other** [ExtensionArray] Array to compare to this Array.

**Returns**

- boolean Whether the arrays are equivalent.

**pandas.api.extensions.ExtensionArray.isna**

`ExtensionArray.isna()`  
A 1-D array indicating if each value is missing.

**Returns**

- `na_values` [Union[np.ndarray, ExtensionArray]] In most cases, this should return a NumPy ndarray. For exceptional cases like SparseArray, where returning an ndarray would be expensive, an ExtensionArray may be returned.
Notes

If returning an ExtensionArray, then

- `na_values._is_boolean` should be `True`
- `na_values` should implement `ExtensionArray._reduce()`
- `na_values.any` and `na_values.all` should be implemented

**pandas.api.extensions.ExtensionArray.ravel**

*ExtensionArray.ravel (order='C')*

Return a flattened view on this array.

**Parameters**


**Returns**

- `ExtensionArray`

**Notes**

- Because ExtensionArrays are 1D-only, this is a no-op.
- The “order” argument is ignored, is for compatibility with NumPy.

**pandas.api.extensions.ExtensionArray.repeat**

*ExtensionArray.repeat (repeats, axis=None)*

Repeat elements of a ExtensionArray.

Returns a new ExtensionArray where each element of the current ExtensionArray is repeated consecutively a given number of times.

**Parameters**

- `repeats` [int or array of ints] The number of repetitions for each element. This should be a non-negative integer. Repeating 0 times will return an empty ExtensionArray.
- `axis` [None] Must be None. Has no effect but is accepted for compatibility with numpy.

**Returns**

- `repeated_array` [ExtensionArray] Newly created ExtensionArray with repeated elements.

See also:

- `Series.repeat` Equivalent function for Series.
- `Index.repeat` Equivalent function for Index.
- `numpy.repeat` Similar method for `numpy.ndarray`.

- `ExtensionArray.take` Take arbitrary positions.
Examples

```python
>>> cat = pd.Categorical(['a', 'b', 'c'])
>>> cat
['a', 'b', 'c']
Categories (3, object): ['a', 'b', 'c']

>>> cat.repeat(2)
['a', 'a', 'b', 'b', 'c', 'c']
Categories (3, object): ['a', 'b', 'c']

>>> cat.repeat([1, 2, 3])
['a', 'b', 'b', 'c', 'c', 'c']
Categories (3, object): ['a', 'b', 'c']
```

```
pandas.api.extensions.ExtensionArray.searchsorted

ExtensionArray.searchsorted(value, side='left', sorter=None)

Find indices where elements should be inserted to maintain order.

New in version 0.24.0.

Find the indices into a sorted array `self` (a) such that, if the corresponding elements in `value` were inserted before the indices, the order of `self` would be preserved.

Assuming that `self` is sorted:

<table>
<thead>
<tr>
<th><code>side</code></th>
<th>returned index i satisfies</th>
</tr>
</thead>
<tbody>
<tr>
<td>left</td>
<td>self[i-1] &lt; value &lt;= self[i]</td>
</tr>
<tr>
<td>right</td>
<td>self[i-1] &lt;= value &lt; self[i]</td>
</tr>
</tbody>
</table>

Parameters

- **value** [array_like] Values to insert into `self`.
- **side** [{‘left’, ‘right’}, optional] If ‘left’, the index of the first suitable location found is given. If ‘right’, return the last such index. If there is no suitable index, return either 0 or N (where N is the length of `self`).
- **sorter** [1-D array_like, optional] Optional array of integer indices that sort array a into ascending order. They are typically the result of argsort.

Returns

- **array of ints** Array of insertion points with the same shape as `value`.

See also:

- `numpy.searchsorted` Similar method from NumPy.
```
pandas.api.extensions.ExtensionArray.shift

ExtensionArray.shift(periods=1, fill_value=None)
Shift values by desired number.
Newly introduced missing values are filled with self.dtype.na_value.
New in version 0.24.0.

Parameters

- **periods** [int, default 1] The number of periods to shift. Negative values are allowed for shifting backwards.
- **fill_value** [object, optional] The scalar value to use for newly introduced missing values. The default is self.dtype.na_value.

New in version 0.24.0.

Returns

ExtensionArray Shifted.

Notes

- If self is empty or periods is 0, a copy of self is returned.
- If periods > len(self), then an array of size len(self) is returned, with all values filled with self.dtype.na_value.

pandas.api.extensions.ExtensionArray.take

ExtensionArray.take(indices, allow_fill=False, fill_value=None)
Take elements from an array.

Parameters

- **indices** [sequence of int] Indices to be taken.
- **allow_fill** [bool, default False] How to handle negative values in indices.
  - False: negative values in indices indicate positional indices from the right (the default). This is similar to numpy.take().
  - True: negative values in indices indicate missing values. These values are set to fill_value. Any other other negative values raise a ValueError.
- **fill_value** [any, optional] Fill value to use for NA-indices when allow_fill is True. This may be None, in which case the default NA value for the type, self.dtype.na_value, is used.

For many ExtensionArrays, there will be two representations of fill_value: a user-facing “boxed” scalar, and a low-level physical NA value. fill_value should be the user-facing version, and the implementation should handle translating that to the physical version for processing the take if necessary.

Returns

ExtensionArray

Raises
**IndexError**  When the indices are out of bounds for the array.

**ValueError**  When *indices* contains negative values other than -1 and *allow_fill* is True.

See also:

numpy.take

api.extensions.take

Notes

ExtensionArray.take is called by Series.__getitem__, .loc, iloc, when *indices* is a sequence of values. Additionally, it’s called by Series.reindex(), or any other method that causes realignment, with a fill_value.

Examples

Here’s an example implementation, which relies on casting the extension array to object dtype. This uses the helper method pandas.api.extensions.take().

```python

def take(self, indices, allow_fill=False, fill_value=None):
    from pandas.core.algorithms import take

    # If the ExtensionArray is backed by an ndarray, then
    # just pass that here instead of coercing to object.
    data = self.astype(object)

    if allow_fill and fill_value is None:
        fill_value = self.dtype.na_value

    # fill value should always be translated from the scalar
    # type for the array, to the physical storage type for
    # the data, before passing to take.

    result = take(data, indices, fill_value=fill_value,
                  allow_fill=allow_fill)
    return self._from_sequence(result, dtype=self.dtype)
```

pandas.api.extensions.ExtensionArray.unique

ExtensionArray.unique()

Compute the ExtensionArray of unique values.

Returns

uniques  [ExtensionArray]
pandas.api.extensions.ExtensionArray.view

ExtensionArray.view(dtype=None)
Return a view on the array.

Parameters

dtype  [str, np.dtype, or ExtensionDtype, optional] Default None.

Returns

ExtensionArray or np.ndarray A view on the ExtensionArray’s data.

pandas.api.extensions.ExtensionArray._concat_same_type

classmethod ExtensionArray._concat_same_type(to_concat)
Concatenate multiple array of this dtype.

Parameters

to_concat  [sequence of this type]

Returns

ExtensionArray

pandas.api.extensions.ExtensionArray._formatter

ExtensionArray._formatter(boxed=False)
Formatting function for scalar values.
This is used in the default ‘__repr__’. The returned formatting function receives instances of your scalar type.

Parameters

boxed  [bool, default False] An indicated for whether or not your array is being printed within a Series, DataFrame, or Index (True), or just by itself (False). This may be useful if you want scalar values to appear differently within a Series versus on its own (e.g. quoted or not).

Returns

Callable[[Any], str] A callable that gets instances of the scalar type and returns a string. By default, repr() is used when boxed=False and str() is used when boxed=True.

pandas.api.extensions.ExtensionArray._from_factorized

classmethod ExtensionArray._from_factorized(values, original)
Reconstruct an ExtensionArray after factorization.

Parameters

values  [ndarray] An integer ndarray with the factorized values.

original  [ExtensionArray] The original ExtensionArray that factorize was called on.

See also:
factorize

ExtensionArray.factorize

pandas.api.extensions.ExtensionArray._from_sequence

classmethod ExtensionArray._from_sequence(scalars, dtype=None, copy=False)
Construct a new ExtensionArray from a sequence of scalars.

Parameters

- **scalars** [Sequence] Each element will be an instance of the scalar type for this array,
  cls.dtype.type or be converted into this type in this method.
- **dtype** [dtype, optional] Construct for this particular dtype. This should be a Dtype
  compatible with the ExtensionArray.
- **copy** [bool, default False] If True, copy the underlying data.

Returns

- ExtensionArray

pandas.api.extensions.ExtensionArray._from_sequence_of_strings

classmethod ExtensionArray._from_sequence_of_strings(strings, dtype=None, copy=False)
Construct a new ExtensionArray from a sequence of strings.

New in version 0.24.0.

Parameters

- **strings** [Sequence] Each element will be an instance of the scalar type for this array,
  cls.dtype.type.
- **dtype** [dtype, optional] Construct for this particular dtype. This should be a Dtype
  compatible with the ExtensionArray.
- **copy** [bool, default False] If True, copy the underlying data.

Returns

- ExtensionArray

pandas.api.extensions.ExtensionArray._reduce

ExtensionArray._reduce(name, skipna=True, **kwargs)
Return a scalar result of performing the reduction operation.

Parameters

- **name** [str] Name of the function, supported values are: { any, all, min, max, sum,
  mean, median, prod, std, var, sem, kurt, skew }.
- **skipna** [bool, default True] If True, skip NaN values.
- ****kwarg Additional keyword arguments passed to the reduction function. Currently,
  ddo is the only supported kwarg.

Returns
### pandas.api.extensions.ExtensionArray._values_for_argsort

**ExtensionArray._values_for_argsort()**

Return values for sorting.

**Returns**

- **ndarray**: The transformed values should maintain the ordering between values within the array.

**See also:**

*ExtensionArray.argsort*

### pandas.api.extensions.ExtensionArray._values_for_factorize

**ExtensionArray._values_for_factorize()**

Return an array and missing value suitable for factorization.

**Returns**

- **values** [ndarray]: An array suitable for factorization. This should maintain order and be a supported dtype (Float64, Int64, UInt64, String, Object). By default, the extension array is cast to object dtype.
- **na_value** [object]: The value in values to consider missing. This will be treated as NA in the factorization routines, so it will be coded as `na_sentinel` and not included in uniques. By default, `np.nan` is used.

**Notes**

The values returned by this method are also used in `pandas.util.hash_pandas_object()`.

### 3.16.7 pandas.arrays.PandasArray

**class pandas.arrays.PandasArray(values, copy=False)**

A pandas ExtensionArray for NumPy data.

New in version 0.24.0.

This is mostly for internal compatibility, and is not especially useful on its own.

**Parameters**

- **values** [ndarray]: The NumPy ndarray to wrap. Must be 1-dimensional.
- **copy** [bool, default False]: Whether to copy values.
Attributes

None

Methods

None

Additionally, we have some utility methods for ensuring your object behaves correctly.

\[\text{api.indexers.check_array_indexer(array, indexer)}\]

Check if \textit{indexer} is a valid array indexer for \textit{array}.

3.16.8 pandas.api.indexers.check_array_indexer

\texttt{pandas.api.indexers.check_array_indexer} \texttt{(array, indexer)}

Check if \textit{indexer} is a valid array indexer for \textit{array}.

For a boolean mask, \textit{array} and \textit{indexer} are checked to have the same length. The dtype is validated, and if it is an integer or boolean ExtensionArray, it is checked if there are missing values present, and it is converted to the appropriate numpy array. Other dtypes will raise an error.

Non-array indexers (integer, slice, Ellipsis, tuples, ..) are passed through as is.

New in version 1.0.0.

Parameters

- \texttt{array} \ [array-like] The array that is being indexed (only used for the length).
- \texttt{indexer} \ [array-like or list-like] The array-like that’s used to index. List-like input that is not yet a numpy array or an ExtensionArray is converted to one. Other input types are passed through as is.

Returns

- \texttt{numpy.ndarray} The validated indexer as a numpy array that can be used to index.

Raises

- \texttt{IndexError} When the lengths don’t match.
- \texttt{ValueError} When \textit{indexer} cannot be converted to a numpy ndarray to index (e.g. presence of missing values).

See also:

- \texttt{api.types.is_bool_dtype} Check if \textit{key} is of boolean dtype.
Examples

When checking a boolean mask, a boolean ndarray is returned when the arguments are all valid.

```python
>>> mask = pd.array([True, False])
>>> arr = pd.array([1, 2])
>>> pd.api.indexers.check_array_indexer(arr, mask)
array([True, False])
```

An IndexError is raised when the lengths don’t match.

```python
>>> mask = pd.array([True, False, True])
>>> pd.api.indexers.check_array_indexer(arr, mask)
Traceback (most recent call last):
  ...
IndexError: Boolean index has wrong length: 3 instead of 2.
```

NA values in a boolean array are treated as False.

```python
>>> mask = pd.array([True, pd.NA])
>>> pd.api.indexers.check_array_indexer(arr, mask)
array([True, False])
```

A numpy boolean mask will get passed through (if the length is correct):

```python
>>> mask = np.array([True, False])
>>> pd.api.indexers.check_array_indexer(arr, mask)
array([True, False])
```

Similarly for integer indexers, an integer ndarray is returned when it is a valid indexer, otherwise an error is (for integer indexers, a matching length is not required):

```python
>>> indexer = pd.array([0, 2], dtype="Int64")
>>> arr = pd.array([1, 2, 3])
>>> pd.api.indexers.check_array_indexer(arr, indexer)
array([0, 2])
```

```python
>>> indexer = pd.array([0, pd.NA], dtype="Int64")
>>> pd.api.indexers.check_array_indexer(arr, indexer)
Traceback (most recent call last):
  ...
ValueError: Cannot index with an integer indexer containing NA values
```

For non-integer/boolean dtypes, an appropriate error is raised:

```python
>>> indexer = np.array([0., 2.], dtype="float64")
>>> pd.api.indexers.check_array_indexer(arr, indexer)
Traceback (most recent call last):
  ...
IndexError: arrays used as indices must be of integer or boolean type
```

The sentinel `pandas.api.extensions.no_default` is used as the default value in some methods. Use an is comparison to check if the user provides a non-default value.
4.1 Contributing to pandas

Table of contents:

• Where to start?
• Bug reports and enhancement requests
• Working with the code
  – Version control, Git, and GitHub
  – Getting started with Git
  – Forking
  – Creating a development environment
    • Using a Docker container
    • Installing a C compiler
    • Creating a Python environment
    • Creating a Python environment (pip)
  – Creating a branch
• Contributing to the documentation
  – About the pandas documentation
  – Updating a pandas docstring
  – How to build the pandas documentation
    • Requirements
    • Building the documentation
    • Building master branch documentation
• Contributing to the code base
  – Code standards
  – Optional dependencies
    • C (cpplint)
All contributions, bug reports, bug fixes, documentation improvements, enhancements, and ideas are welcome.

If you are brand new to pandas or open-source development, we recommend going through the GitHub “issues” tab to find issues that interest you. There are a number of issues listed under Docs and good first issue where you could start out. Once you’ve found an interesting issue, you can return here to get your development environment setup.

When you start working on an issue, it’s a good idea to assign the issue to yourself, so nobody else duplicates the work on it. GitHub restricts assigning issues to maintainers of the project only. In most projects, and until recently in pandas, contributors added a comment letting others know they are working on an issue. While this is ok, you need to check each issue individually, and it’s not possible to find the unassigned ones.

For this reason, we implemented a workaround consisting of adding a comment with the exact text `take`. When you do
it, a GitHub action will automatically assign you the issue (this will take seconds, and may require refreshing the page to see it). By doing this, it’s possible to filter the list of issues and find only the unassigned ones.

So, a good way to find an issue to start contributing to pandas is to check the list of unassigned good first issues and assign yourself one you like by writing a comment with the exact text `take`.

If for whatever reason you are not able to continue working with the issue, please try to unassign it, so other people know it’s available again. You can check the list of assigned issues, since people may not be working in them anymore. If you want to work on one that is assigned, feel free to kindly ask the current assignee if you can take it (please allow at least a week of inactivity before considering work in the issue discontinued).

Feel free to ask questions on the mailing list or on Gitter.

### 4.1.2 Bug reports and enhancement requests

Bug reports are an important part of making pandas more stable. Having a complete bug report will allow others to reproduce the bug and provide insight into fixing. See this stackoverflow article and this blogpost for tips on writing a good bug report.

Trying the bug-producing code out on the master branch is often a worthwhile exercise to confirm the bug still exists. It is also worth searching existing bug reports and pull requests to see if the issue has already been reported and/or fixed.

Bug reports must:

1. Include a short, self-contained Python snippet reproducing the problem. You can format the code nicely by using GitHub Flavored Markdown:

```python
>>> from pandas import DataFrame
>>> df = DataFrame(...)
...```

2. Include the full version string of pandas and its dependencies. You can use the built-in function:

```python
>>> import pandas as pd
>>> pd.show_versions()
```

3. Explain why the current behavior is wrong/not desired and what you expect instead.

The issue will then show up to the pandas community and be open to comments/ideas from others.

### 4.1.3 Working with the code

Now that you have an issue you want to fix, enhancement to add, or documentation to improve, you need to learn how to work with GitHub and the pandas code base.
Version control, Git, and GitHub

To the new user, working with Git is one of the more daunting aspects of contributing to pandas. It can very quickly become overwhelming, but sticking to the guidelines below will help keep the process straightforward and mostly trouble free. As always, if you are having difficulties please feel free to ask for help.

The code is hosted on GitHub. To contribute you will need to sign up for a free GitHub account. We use Git for version control to allow many people to work together on the project.

Some great resources for learning Git:

- the GitHub help pages.
- the NumPy’s documentation.
- Matthew Brett’s Pydagogue.

Getting started with Git

GitHub has instructions for installing git, setting up your SSH key, and configuring git. All these steps need to be completed before you can work seamlessly between your local repository and GitHub.

Forking

You will need your own fork to work on the code. Go to the pandas project page and hit the Fork button. You will want to clone your fork to your machine:

```bash
git clone https://github.com/your-user-name/pandas.git pandas-yourname
cd pandas-yourname
git remote add upstream https://github.com/pandas-dev/pandas.git
```

This creates the directory `pandas-yourname` and connects your repository to the upstream (main project) `pandas` repository.

Note that performing a shallow clone (with `--depth=N`, for some N greater or equal to 1) might break some tests and features as `pd.show_versions()` as the version number cannot be computed anymore.

Creating a development environment

To test out code changes, you’ll need to build pandas from source, which requires a C compiler and Python environment. If you’re making documentation changes, you can skip to Contributing to the documentation but you won’t be able to build the documentation locally before pushing your changes.

Using a Docker container

Instead of manually setting up a development environment, you can use Docker to automatically create the environment with just several commands. Pandas provides a DockerFile in the root directory to build a Docker image with a full pandas development environment.

Even easier, you can use the DockerFile to launch a remote session with Visual Studio Code, a popular free IDE, using the `.devcontainer.json` file. See https://code.visualstudio.com/docs/remote/containers for details.
Installing a C compiler

Pandas uses C extensions (mostly written using Cython) to speed up certain operations. To install pandas from source, you need to compile these C extensions, which means you need a C compiler. This process depends on which platform you’re using.

**Windows**


**Mac OS**

Information about compiler installation can be found here: https://devguide.python.org/setup/#macos

**Unix**

Some Linux distributions will come with a pre-installed C compiler. To find out which compilers (and versions) are installed on your system:

```bash
# for Debian/Ubuntu:
dpkg --list | grep compiler
# for Red Hat/RHEL/CentOS/Fedora:
yum list installed | grep -i --color compiler
```

GCC (GNU Compiler Collection), is a widely used compiler, which supports C and a number of other languages. If GCC is listed as an installed compiler nothing more is required. If no C compiler is installed (or you wish to install a newer version) you can install a compiler (GCC in the example code below) with:

```bash
# for recent Debian/Ubuntu:
sudo apt install build-essential
# for Red Hat/RHEL/CentOS/Fedora
yum groupinstall "Development Tools"
```

For other Linux distributions, consult your favourite search engine for compiler installation instructions.

Let us know if you have any difficulties by opening an issue or reaching out on Gitter.

Creating a Python environment

Now that you have a C compiler, create an isolated pandas development environment:

- Install either Anaconda or miniconda
- Make sure your conda is up to date (conda update conda)
- Make sure that you have cloned the repository
- cd to the pandas source directory

We’ll now kick off a three-step process:

1. Install the build dependencies
2. Build and install pandas
3. Install the optional dependencies
# Create and activate the build environment
conda env create -f environment.yml
conda activate pandas-dev

# or with older versions of Anaconda:
source activate pandas-dev

# Build and install pandas
python setup.py build_ext --inplace -j 4
python -m pip install -e . --no-build-isolation --no-use-pep517

At this point you should be able to import pandas from your locally built version:

```
$ python  # start an interpreter
>>> import pandas
0.22.0.dev0+29.g4ad6d4d74
```

This will create the new environment, and not touch any of your existing environments, nor any existing Python installation.

To view your environments:

```
conda info -e
```

To return to your root environment:

```
conda deactivate
```

See the full conda docs here.

### Creating a Python environment (pip)

If you aren’t using conda for your development environment, follow these instructions. You’ll need to have at least Python 3.6.1 installed on your system.

#### Unix/Mac OS with virtualenv

```
# Create a virtual environment
# Use an ENV_DIR of your choice. We’ll use ~/virtualenvs/pandas-dev
# Any parent directories should already exist
python3 -m venv ~/virtualenvs/pandas-dev

# Activate the virtualenv
. ~/virtualenvs/pandas-dev/bin/activate

# Install the build dependencies
python -m pip install -r requirements-dev.txt

# Build and install pandas
python setup.py build_ext --inplace -j 4
python -m pip install -e . --no-build-isolation --no-use-pep517
```

#### Unix/Mac OS with pyenv

Consult the docs for setting up pyenv here.
# Create a virtual environment
# Use an ENV_DIR of your choice. We'll use ~/Users/<yourname>/.pyenv/versions/pandas-dev

pyenv virtualenv <version> <name-to-give-it>

# For instance:
pyenv virtualenv 3.7.6 pandas-dev

# Activate the virtualenv
pyenv activate pandas-dev

# Now install the build dependencies in the cloned pandas repo
python -m pip install -r requirements-dev.txt

# Build and install pandas
python setup.py build_ext --inplace -j 4
python -m pip install -e . --no-build-isolation --no-use-pep517

Windows

Below is a brief overview on how to set-up a virtual environment with Powershell under Windows. For details please refer to the official virtualenv user guide

Use an ENV_DIR of your choice. We'll use ~\virtualenvs\pandas-dev where '~' is the folder pointed to by either $env:USERPROFILE (Powershell) or %USERPROFILE% (cmd.exe) environment variable. Any parent directories should already exist.

# Create a virtual environment
python -m venv $env:USERPROFILE\virtualenvs\pandas-dev

# Activate the virtualenv. Use activate.bat for cmd.exe
~\virtualenvs\pandas-dev\Scripts\Activate.ps1

# Install the build dependencies
python -m pip install -r requirements-dev.txt

# Build and install pandas
python setup.py build_ext --inplace -j 4
python -m pip install -e . --no-build-isolation --no-use-pep517

Creating a branch

You want your master branch to reflect only production-ready code, so create a feature branch for making your changes. For example:

git branch shiny-new-feature
git checkout shiny-new-feature

The above can be simplified to:

git checkout -b shiny-new-feature

This changes your working directory to the shiny-new-feature branch. Keep any changes in this branch specific to one bug or feature so it is clear what the branch brings to pandas. You can have many shiny-new-features and switch in between them using the git checkout command.
When creating this branch, make sure your master branch is up to date with the latest upstream master version. To update your local master branch, you can do:

```
git checkout master
git pull upstream master --ff-only
```

When you want to update the feature branch with changes in master after you created the branch, check the section on updating a PR.

### 4.1.4 Contributing to the documentation

Contributing to the documentation benefits everyone who uses pandas. We encourage you to help us improve the documentation, and you don’t have to be an expert on pandas to do so! In fact, there are sections of the docs that are worse off after being written by experts. If something in the docs doesn’t make sense to you, updating the relevant section after you figure it out is a great way to ensure it will help the next person.

**Documentation:**

- About the pandas documentation
- Updating a pandas docstring
- How to build the pandas documentation
  - Requirements
  - Building the documentation
  - Building master branch documentation

**About the pandas documentation**

The documentation is written in **reStructuredText**, which is almost like writing in plain English, and built using **Sphinx**. The Sphinx Documentation has an excellent introduction to reST. Review the Sphinx docs to perform more complex changes to the documentation as well.

Some other important things to know about the docs:

- The pandas documentation consists of two parts: the docstrings in the code itself and the docs in this folder `doc/`.
  
  The docstrings provide a clear explanation of the usage of the individual functions, while the documentation in this folder consists of tutorial-like overviews per topic together with some other information (what’s new, installation, etc).

- The docstrings follow a pandas convention, based on the **Numpy Docstring Standard**. Follow the **pandas docstring guide** for detailed instructions on how to write a correct docstring.
**pandas docstring guide**

**About docstrings and standards**

A Python docstring is a string used to document a Python module, class, function or method, so programmers can understand what it does without having to read the details of the implementation.

Also, it is a common practice to generate online (html) documentation automatically from docstrings. Sphinx serves this purpose.

The next example gives an idea of what a docstring looks like:

```python
def add(num1, num2):
    
    """
    Add up two integer numbers.
    
    This function simply wraps the `+` operator, and does not do anything interesting, except for illustrating what the docstring of a very simple function looks like.
    
    Parameters
    ----------
    num1 : int
        First number to add
    num2 : int
        Second number to add
    
    Returns
    -------
    int
        The sum of `num1` and `num2`
    
    See Also
    --------
    subtract : Subtract one integer from another
    
    Examples
    --------
    >>> add(2, 2)
    4
    >>> add(25, 0)
    25
    >>> add(10, -10)
    0
    """
    return num1 + num2
```

Some standards regarding docstrings exist, which make them easier to read, and allow them be easily exported to other formats such as html or pdf.

The first conventions every Python docstring should follow are defined in PEP-257.

As PEP-257 is quite broad, other more specific standards also exist. In the case of pandas, the numpy docstring convention is followed. These conventions are explained in this document:

- `numpydoc docstring guide` (which is based in the original Guide to NumPy/SciPy documentation)

`numpydoc` is a Sphinx extension to support the numpy docstring convention.

---

4.1. Contributing to pandas
The standard uses reStructuredText (reST). reStructuredText is a markup language that allows encoding styles in plain text files. Documentation about reStructuredText can be found in:

- Sphinx reStructuredText primer
- Quick reStructuredText reference
- Full reStructuredText specification

pandas has some helpers for sharing docstrings between related classes, see *Sharing docstrings*.

The rest of this document will summarize all the above guidelines, and will provide additional conventions specific to the pandas project.

**Writing a docstring**

**General rules**

Docstrings must be defined with three double-quotes. No blank lines should be left before or after the docstring. The text starts in the next line after the opening quotes. The closing quotes have their own line (meaning that they are not at the end of the last sentence).

On rare occasions reST styles like bold text or italics will be used in docstrings, but is it common to have inline code, which is presented between backticks. The following are considered inline code:

- The name of a parameter
- Python code, a module, function, built-in, type, literal... (e.g. `os, list, numpy.abs, datetime.date, True`)
- A pandas class (in the form `:class:`*pandas.Series* `)
- A pandas method (in the form `:meth:`*pandas.Series.sum* `)
- A pandas function (in the form `:func:`*pandas.to_datetime* `)

**Note:** To display only the last component of the linked class, method or function, prefix it with ~. For example, `:class:`~pandas.Series` will link to pandas.Series but only display the last part, Series as the link text. See Sphinx cross-referencing syntax for details.

**Good:**

```python
def add_values(arr):
    ""
    Add the values in `arr`.

    This is equivalent to Python `sum` of :meth:`pandas.Series.sum`.

    Some sections are omitted here for simplicity.
    ""
    return sum(arr)
```

**Bad:**

```python
def func():
    """Some function.
```
With several mistakes in the docstring.

It has a blank like after the signature `def func():`.

The text 'Some function' should go in the line after the opening quotes of the docstring, not in the same line.

There is a blank line between the docstring and the first line of code `foo = 1`.

The closing quotes should be in the next line, not in this one.""

```python
foo = 1
bar = 2
return foo + bar
```

Section 1: short summary

The short summary is a single sentence that expresses what the function does in a concise way.

The short summary must start with a capital letter, end with a dot, and fit in a single line. It needs to express what the object does without providing details. For functions and methods, the short summary must start with an infinitive verb.

Good:

```python
def astype(dtype):
    ""
    Cast Series type.

    This section will provide further details.
    ""
    pass
```

Bad:

```python
def astype(dtype):
    ""
    Casts Series type.

    Verb in third-person of the present simple, should be infinitive.
    ""
    pass
```

```python
def astype(dtype):
    ""
    Method to cast Series type.

    Does not start with verb.
    ""
    pass
```

(continues on next page)
Section 2: extended summary

The extended summary provides details on what the function does. It should not go into the details of the parameters, or discuss implementation notes, which go in other sections.

A blank line is left between the short summary and the extended summary. Every paragraph in the extended summary ends with a dot.

The extended summary should provide details on why the function is useful and their use cases, if it is not too generic.

Section 3: parameters

The details of the parameters will be added in this section. This section has the title “Parameters”, followed by a line with a hyphen under each letter of the word “Parameters”. A blank line is left before the section title, but not after, and not between the line with the word “Parameters” and the one with the hyphens.

After the title, each parameter in the signature must be documented, including *args and **kwargs, but not self.

The parameters are defined by their name, followed by a space, a colon, another space, and the type (or types). Note that the space between the name and the colon is important. Types are not defined for *args and **kwargs, but must be defined for all other parameters. After the parameter definition, it is required to have a line with the parameter description, which is indented, and can have multiple lines. The description must start with a capital letter, and finish with a dot.
For keyword arguments with a default value, the default will be listed after a comma at the end of the type. The exact form of the type in this case will be “int, default 0”. In some cases it may be useful to explain what the default argument means, which can be added after a comma “int, default -1, meaning all cpus”.

In cases where the default value is None, meaning that the value will not be used. Instead of “str, default None”, it is preferred to write “str, optional”. When None is a value being used, we will keep the form “str, default None”. For example, in `df.to_csv(compression=)`, None is not a value being used, but means that compression is optional, and no compression is being used if not provided. In this case we will use `str, optional`. Only in cases like `func(value=None)` and None is being used in the same way as 0 or foo would be used, then we will specify “str, int or None, default None”.

**Good:**

```python
class Series:
    def plot(self, kind, color='blue', **kwargs):
        ""
        Generate a plot.
        Render the data in the Series as a matplotlib plot of the specified kind.

        Parameters
        ----------
        kind : str
            Kind of matplotlib plot.
        color : str, default 'blue'
            Color name or rgb code.
        **kwargs
            These parameters will be passed to the matplotlib plotting function.
        ""
        pass
```

**Bad:**

```python
class Series:
    def plot(self, kind, **kwargs):
        ""
        Generate a plot.
        Render the data in the Series as a matplotlib plot of the specified kind.

        Note the blank line between the parameters title and the first parameter. Also, note that after the name of the parameter `kind` and before the colon, a space is missing.

        Also, note that the parameter descriptions do not start with a capital letter, and do not finish with a dot.

        Finally, the `**kwargs` parameter is missing.

        Parameters
        ----------
        kind: str
            kind of matplotlib plot
        ""
```

(continues on next page)
Parameter types

When specifying the parameter types, Python built-in data types can be used directly (the Python type is preferred to the more verbose string, integer, boolean, etc):

- int
- float
- str
- bool

For complex types, define the subtypes. For `dict` and `tuple`, as more than one type is present, we use the brackets to help read the type (curly brackets for `dict` and normal brackets for `tuple`):

- list of int
- dict of {str : int}
- tuple of (str, int, int)
- tuple of (str,)
- set of str

In case where there are just a set of values allowed, list them in curly brackets and separated by commas (followed by a space). If the values are ordinal and they have an order, list them in this order. Otherwise, list the default value first, if there is one:

- {0, 10, 25}
- {'simple', 'advanced'}
- {'low', 'medium', 'high'}
- {'cat', 'dog', 'bird'}

If the type is defined in a Python module, the module must be specified:

- datetime.date
- datetime.datetime
- decimal.Decimal

If the type is in a package, the module must be also specified:

- numpy.ndarray
- scipy.sparse.coo_matrix

If the type is a pandas type, also specify pandas except for `Series` and `DataFrame`:

- Series
- DataFrame
- pandas.Index
- pandas.Categorical
- pandas.arrays.SparseArray
If the exact type is not relevant, but must be compatible with a numpy array, array-like can be specified. If any type that can be iterated is accepted, iterable can be used:

- array-like
- iterable

If more than one type is accepted, separate them by commas, except the last two types, that need to be separated by the word ‘or’:

- int or float
- float, decimal.Decimal or None
- str or list of str

If None is one of the accepted values, it always needs to be the last in the list.

For axis, the convention is to use something like:

- axis: {0 or ‘index’, 1 or ‘columns’, None}, default None

Section 4: returns or yields

If the method returns a value, it will be documented in this section. Also if the method yields its output.

The title of the section will be defined in the same way as the “Parameters”. With the names “Returns” or “Yields” followed by a line with as many hyphens as the letters in the preceding word.

The documentation of the return is also similar to the parameters. But in this case, no name will be provided, unless the method returns or yields more than one value (a tuple of values).

The types for “Returns” and “Yields” are the same as the ones for the “Parameters”. Also, the description must finish with a dot.

For example, with a single value:

```python
def sample():
    """
    Generate and return a random number.
    The value is sampled from a continuous uniform distribution between 0 and 1.
    Returns
    -------
    float
    Random number generated.
    """
    return np.random.random()
```

With more than one value:

```python
import string

def random_letters():
    """
    Generate and return a sequence of random letters.
    The length of the returned string is also random, and is also returned.
    """
    return string.ascii_letters
```

(continues on next page)
Returns
-------
length : int
  Length of the returned string.
letters : str
  String of random letters.

""
length = np.random.randint(1, 10)
letters = ''.join(np.random.choice(string.ascii_lowercase)
               for i in range(length))
return length, letters

If the method yields its value:

def sample_values():
    ""
    Generate an infinite sequence of random numbers.
    
The values are sampled from a continuous uniform distribution between
0 and 1.
    ""
    Yields
    ------
    float
      Random number generated.
    ""
    while True:
        yield np.random.random()

Section 5: see also

This section is used to let users know about pandas functionality related to the one being documented. In rare
cases, if no related methods or functions can be found at all, this section can be skipped.

An obvious example would be the head() and tail() methods. As tail() does the equivalent as head() but at the
end of the Series or DataFrame instead of at the beginning, it is good to let the users know about it.

To give an intuition on what can be considered related, here there are some examples:

- loc and iloc, as they do the same, but in one case providing indices and in the other positions
- max and min, as they do the opposite
- iterrows, itertuples and items, as it is easy that a user looking for the method to iterate over
columns ends up in the method to iterate over rows, and vice-versa
- fillna and dropna, as both methods are used to handle missing values
- read_csv and to_csv, as they are complementary
- merge and join, as one is a generalization of the other
- astype and pandas.to_datetime, as users may be reading the documentation of astype to know
how to cast as a date, and the way to do it is with pandas.to_datetime
- where is related to numpy.where, as its functionality is based on it
When deciding what is related, you should mainly use your common sense and think about what can be useful for the users reading the documentation, especially the less experienced ones.

When relating to other libraries (mainly numpy), use the name of the module first (not an alias like np). If the function is in a module which is not the main one, like scipy.sparse, list the full module (e.g. scipy.sparse.coo_matrix).

This section has a header, “See Also” (note the capital S and A), followed by the line with hyphens and preceded by a blank line.

After the header, we will add a line for each related method or function, followed by a space, a colon, another space, and a short description that illustrates what this method or function does, why is it relevant in this context, and what the key differences are between the documented function and the one being referenced. The description must also end with a dot.

Note that in “Returns” and “Yields”, the description is located on the line after the type. In this section, however, it is located on the same line, with a colon in between. If the description does not fit on the same line, it can continue onto other lines which must be further indented.

For example:

```python
class Series:
    def head(self):
        """Return the first 5 elements of the Series.
        This function is mainly useful to preview the values of the Series without displaying the whole of it.
        """
        Returns
        ------
        Series
        Subset of the original series with the 5 first values.

        See Also
        -------
        Series.tail : Return the last 5 elements of the Series.
        Series.iloc : Return a slice of the elements in the Series, which can also be used to return the first or last n.
        """
        return self.iloc[:5]
```

**Section 6: notes**

This is an optional section used for notes about the implementation of the algorithm, or to document technical aspects of the function behavior.

Feel free to skip it, unless you are familiar with the implementation of the algorithm, or you discover some counter-intuitive behavior while writing the examples for the function.

This section follows the same format as the extended summary section.
Section 7: examples

This is one of the most important sections of a docstring, despite being placed in the last position, as often people understand concepts better by example than through accurate explanations.

Examples in docstrings, besides illustrating the usage of the function or method, must be valid Python code, that returns the given output in a deterministic way, and that can be copied and run by users.

Examples are presented as a session in the Python terminal. >>> is used to present code. … is used for code continuing from the previous line. Output is presented immediately after the last line of code generating the output (no blank lines in between). Comments describing the examples can be added with blank lines before and after them.

The way to present examples is as follows:

1. Import required libraries (except numpy and pandas)
2. Create the data required for the example
3. Show a very basic example that gives an idea of the most common use case
4. Add examples with explanations that give an idea of the most common use case

A simple example could be:

```python
class Series:

    def head(self, n=5):
        
        #
        # Return the first elements of the Series.
        #
        # This function is mainly useful to preview the values of the
        # Series without displaying all of it.
        #
        Parameters
        #
        # n : int
        #     Number of values to return.
        #
        Return
        #
        pandas.Series
        #     Subset of the original series with the n first values.
        #
        See Also
        #
        # tail : Return the last n elements of the Series.
        #
        Examples
        #
        >>> s = pd.Series(['Ant', 'Bear', 'Cow', 'Dog', 'Falcon',...
        #                    'Lion', 'Monkey', 'Rabbit', 'Zebra'])
        >>> s.head()
        0  Ant
        1  Bear
        2  Cow
        3  Dog
        4  Falcon
        dtype: object
```

(continues on next page)
With the `n` parameter, we can change the number of returned rows:

```python
>>> s.head(n=3)
0   Ant
1  Bear
2   Cow
dtype: object
```

```
""
return self.iloc[:n]
""
```

The examples should be as concise as possible. In cases where the complexity of the function requires long examples, it is recommended to use blocks with headers in bold. Use double star ** to make a text bold, like in **this example**.

**Conventions for the examples**

Code in examples is assumed to always start with these two lines which are not shown:

```python
import numpy as np
import pandas as pd
```

Any other module used in the examples must be explicitly imported, one per line (as recommended in PEP 8#imports) and avoiding aliases. Avoid excessive imports, but if needed, imports from the standard library go first, followed by third-party libraries (like matplotlib).

When illustrating examples with a single `Series` use the name `s`, and if illustrating with a single `DataFrame` use the name `df`. For indices, `idx` is the preferred name. If a set of homogeneous `Series` or `DataFrame` is used, name them `s1, s2, s3`.. or `df1, df2, df3`.. If the data is not homogeneous, and more than one structure is needed, name them with something meaningful, for example `df_main` and `df_to_join`.

Data used in the example should be as compact as possible. The number of rows is recommended to be around 4, but make it a number that makes sense for the specific example. For example in the `head` method, it requires to be higher than 5, to show the example with the default values. If doing the `mean`, we could use something like `[1, 2, 3]`, so it is easy to see that the value returned is the mean.

For more complex examples (grouping for example), avoid using data without interpretation, like a matrix of random numbers with columns A, B, C, D... And instead use a meaningful example, which makes it easier to understand the concept. Unless required by the example, use names of animals, to keep examples consistent. And numerical properties of them.

When calling the method, keywords arguments `head(n=3)` are preferred to positional arguments `head(3)`.

**Good:**

```python
class Series:
    
def mean(self):
        ""
        Compute the mean of the input.
        ""
        Examples
        -------
        >>> s = pd.Series([1, 2, 3])
        >>> s.mean()
        2
        ""
```
```python
deffillna(self, value):
    """
    Replace missing values by 'value'.
    
    Examples
    --------
    >>> s = pd.Series([1, np.nan, 3])
    >>> s.fillna(0)
    [1, 0, 3]
    """
    pass

def groupby_mean(self):
    """
    Group by index and return mean.
    
    Examples
    --------
    >>> s = pd.Series([380., 370., 24., 26],
    ...                 name='max_speed',
    ...                 index=['falcon', 'falcon', 'parrot', 'parrot'])
    >>> s.groupby_mean()
    index
    falcon     375.0
    parrot     25.0
    Name: max_speed, dtype: float64
    """
    pass

def contains(self, pattern, case_sensitive=True, na=numpy.nan):
    """
    Return whether each value contains 'pattern'.
    
    In this case, we are illustrating how to use sections, even
    if the example is simple enough and does not require them.
    
    Examples
    --------
    >>> s = pd.Series('Antelope', 'Lion', 'Zebra', np.nan)
    >>> s.contains(pattern='a')
    0 False
    1 False
    2  True
    3    NaN
    dtype: bool
    **Case sensitivity**
    
    With 'case_sensitive' set to 'False' we can match 'a' with both
    'a' and 'A':
    
    >>> s.contains(pattern='a', case_sensitive=False)
    0    True
    1   False
    ```
2  True
3  NaN
dtype: bool

**Missing values**

We can fill missing values in the output using the `na` parameter:

```python
>>> s.contains(pattern='a', na=False)
0   False
1   False
2    True
3   False
dtype: bool
```

Bad:

```python
def method(foo=None, bar=None):
    ""
    A sample DataFrame method.

    Do not import numpy and pandas.

    Try to use meaningful data, when it makes the example easier
to understand.

    Try to avoid positional arguments like in `df.method(1)`. They
can be all right if previously defined with a meaningful name,
like in `present_value(interest_rate)`, but avoid them otherwise.

    When presenting the behavior with different parameters, do not place
all the calls one next to the other. Instead, add a short sentence
explaining what the example shows.

    Examples
    --------
    >>> import numpy as np
    >>> import pandas as pd
    >>> df = pd.DataFrame(np.random.randn(3, 3),
                       columns=('a', 'b', 'c'))
    >>> df.method(1)
    21
    >>> df.method(bar=14)
    123
    ""
```

pass
Tips for getting your examples pass the doctests

Getting the examples pass the doctests in the validation script can sometimes be tricky. Here are some attention points:

- Import all needed libraries (except for pandas and numpy, those are already imported as import pandas as pd and import numpy as np) and define all variables you use in the example.

- Try to avoid using random data. However random data might be OK in some cases, like if the function you are documenting deals with probability distributions, or if the amount of data needed to make the function result meaningful is too much, such that creating it manually is very cumbersome. In those cases, always use a fixed random seed to make the generated examples predictable. Example:

```python
>>> np.random.seed(42)
>>> df = pd.DataFrame({'normal': np.random.normal(100, 5, 20)})
```

- If you have a code snippet that wraps multiple lines, you need to use ‘...’ on the continued lines:

```python
>>> df = pd.DataFrame([[1, 2, 3], [4, 5, 6]], index=['a', 'b', 'c'],
                    columns=['A', 'B'])
```

- If you want to show a case where an exception is raised, you can do:

```python
>>> pd.to_datetime(['712-01-01'])
```

```
OutOfBoundsDatetime: Out of bounds nanosecond timestamp: 712-01-01 00:00:00
```

It is essential to include the “Traceback (most recent call last):”, but for the actual error only the error name is sufficient.

- If there is a small part of the result that can vary (e.g. a hash in an object representation), you can use ... to represent this part.

If you want to show that s.plot() returns a matplotlib AxesSubplot object, this will fail the doctest

```python
>>> s.plot()
<matplotlib.axes._subplots.AxesSubplot at 0x7efd0c0b0690>
```

However, you can do (notice the comment that needs to be added)

```python
>>> s.plot()
<matplotlib.axes._subplots.AxesSubplot at ...>
```

Plots in examples

There are some methods in pandas returning plots. To render the plots generated by the examples in the documentation, the .. plot:: directive exists.

To use it, place the next code after the “Examples” header as shown below. The plot will be generated automatically when building the documentation.
Examples
--------
.. plot::
   :context: close-figs
   >>> s = pd.Series([1, 2, 3])
   >>> s.plot()
   ""
   pass

Sharing docstrings

pandas has a system for sharing docstrings, with slight variations, between classes. This helps us keep docstrings consistent, while keeping things clear for the user reading. It comes at the cost of some complexity when writing.

Each shared docstring will have a base template with variables, like `{klass}`. The variables filled in later on using the `doc` decorator. Finally, docstrings can also be appended to with the `doc` decorator.

In this example, we’ll create a parent docstring normally (this is like `pandas.core.generic.NDFrame`). Then we’ll have two children (like `pandas.core.series.Series` and `pandas.core.frame.DataFrame`). We’ll substitute the class names in this docstring.

class Parent:
    @doc(klass="Parent")
    def my_function(self):
        """Apply my function to {klass}."""
        ...

class ChildA(Parent):
    @doc(Parent.my_function, klass="ChildA")
    def my_function(self):
        ...

class ChildB(Parent):
    @doc(Parent.my_function, klass="ChildB")
    def my_function(self):
        ...

The resulting docstrings are

```python
>>> print(Parent.my_function.__doc__)
Apply my function to Parent.
>>> print(ChildA.my_function.__doc__)
Apply my function to ChildA.
>>> print(ChildB.my_function.__doc__)
Apply my function to ChildB.
```

Notice:

1. We “append” the parent docstring to the children docstrings, which are initially empty.

Our files will often contain a module-level `_shared_doc_kwargs` with some common substitution values (things like `klass`, `axes`, etc).
You can substitute and append in one shot with something like

```python
@doc(template, **_shared_doc_kwargs)
def my_function(self):
    ...
```

where `template` may come from a module-level `_shared_docs` dictionary mapping function names to docstrings. Wherever possible, we prefer using `doc`, since the docstring-writing processes is slightly closer to normal.

See `pandas.core.generic.NDFrame.fillna` for an example template, and `pandas.core.series.Series.fillna` and `pandas.core.generic.frame.fillna` for the filled versions.

- The tutorials make heavy use of the `ipython` directive `sphinx` extension. This directive lets you put code in the documentation which will be run during the doc build. For example:

```python
.. ipython:: python
   :columns: 1

   x = 2
   x**3
```

will be rendered as:

```
In [1]: x = 2
In [2]: x**3
Out[2]: 8
```

Almost all code examples in the docs are run (and the output saved) during the doc build. This approach means that code examples will always be up to date, but it does make the doc building a bit more complex.

- Our API documentation files in `doc/source/reference` house the auto-generated documentation from the docstrings. For classes, there are a few subtleties around controlling which methods and attributes have pages auto-generated.

We have two autosummary templates for classes.

1. `_templates/autosummary/class.rst`. Use this when you want to automatically generate a page for every public method and attribute on the class. The `Attributes` and `Methods` sections will be automatically added to the class’ rendered documentation by numpydoc. See `DataFrame` for an example.

2. `_templates/autosummary/class_without_autosummary`. Use this when you want to pick a subset of methods / attributes to auto-generate pages for. When using this template, you should include an `Attributes` and `Methods` section in the class docstring. See `CategoricalIndex` for an example.

Every method should be included in a `toctree` in one of the documentation files in `doc/source/reference`, else `Sphinx` will emit a warning.

---

**Note:** The `.rst` files are used to automatically generate Markdown and HTML versions of the docs. For this reason, please *do not* edit `CONTRIBUTING.md` directly, but instead make any changes to `doc/source/development/contributing.rst`. Then, to generate `CONTRIBUTING.md`, use `pandoc` with the following command:

```bash
pandoc doc/source/development/contributing.rst -t markdown_github > CONTRIBUTING.md
```

The utility script `scripts/validate_docstrings.py` can be used to get a csv summary of the API documentation. And also validate common errors in the docstring of a specific class, function or method. The summary
also compares the list of methods documented in the files in doc/source/reference (which is used to generate the API Reference page) and the actual public methods. This will identify methods documented in doc/source/reference that are not actually class methods, and existing methods that are not documented in doc/source/reference.

**Updating a pandas docstring**

When improving a single function or method’s docstring, it is not necessarily needed to build the full documentation (see next section). However, there is a script that checks a docstring (for example for the DataFrame.mean method):

```
python scripts/validate_docstrings.py pandas.DataFrame.mean
```

This script will indicate some formatting errors if present, and will also run and test the examples included in the docstring. Check the pandas docstring guide for a detailed guide on how to format the docstring.

The examples in the docstring (‘doctests’) must be valid Python code, that in a deterministic way returns the presented output, and that can be copied and run by users. This can be checked with the script above, and is also tested on Travis. A failing doctest will be a blocker for merging a PR. Check the examples section in the docstring guide for some tips and tricks to get the doctests passing.

When doing a PR with a docstring update, it is good to post the output of the validation script in a comment on github.

**How to build the pandas documentation**

**Requirements**

First, you need to have a development environment to be able to build pandas (see the docs on creating a development environment above).

**Building the documentation**

So how do you build the docs? Navigate to your local doc/ directory in the console and run:

```
python make.py html
```

Then you can find the HTML output in the folder doc/build/html/.

The first time you build the docs, it will take quite a while because it has to run all the code examples and build all the generated docstring pages. In subsequent evocations, sphinx will try to only build the pages that have been modified.

If you want to do a full clean build, do:

```
python make.py clean
python make.py html
```

You can tell make.py to compile only a single section of the docs, greatly reducing the turn-around time for checking your changes.

```
# omit autosummary and API section
python make.py clean
python make.py --no-api
```

```
# compile the docs with only a single section, relative to the "source" folder.
# For example, compiling only this guide (doc/source/development/contributing.rst)
```

(continues on next page)
For comparison, a full documentation build may take 15 minutes, but a single section may take 15 seconds. Subsequent builds, which only process portions you have changed, will be faster.

You can also specify to use multiple cores to speed up the documentation build:

```
python make.py html --num-jobs 4
```

Open the following file in a web browser to see the full documentation you just built:

```
doc/build/html/index.html
```

And you’ll have the satisfaction of seeing your new and improved documentation!

### Building master branch documentation

When pull requests are merged into the pandas `master` branch, the main parts of the documentation are also built by Travis-CI. These docs are then hosted here, see also the *Continuous Integration* section.

#### 4.1.5 Contributing to the code base

**Code Base:**

- **Code standards**
- **Optional dependencies**
  - C (cpplint)
  - Python (PEP8 / black)
  - Import formatting
  - Pre-commit
  - Backwards compatibility
- **Type hints**
  - Style guidelines
  - pandas-specific types
  - Validating type hints
- **Testing with continuous integration**
- **Test-driven development/code writing**
  - Writing tests
  - Transitioning to pytest
- Using pytest
- Using hypothesis
- Testing warnings
  - Running the test suite
  - Running the performance test suite
  - Documenting your code

Code standards

Writing good code is not just about what you write. It is also about how you write it. During Continuous Integration testing, several tools will be run to check your code for stylistic errors. Generating any warnings will cause the test to fail. Thus, good style is a requirement for submitting code to pandas.

There is a tool in pandas to help contributors verify their changes before contributing them to the project:

```bash
./ci/code_checks.sh
```

The script verifies the linting of code files, it looks for common mistake patterns (like missing spaces around sphinx directives that make the documentation not being rendered properly) and it also validates the doctests. It is possible to run the checks independently by using the parameters lint, patterns and doctests (e.g. ./ci/code_checks.sh lint).

In addition, because a lot of people use our library, it is important that we do not make sudden changes to the code that could have the potential to break a lot of user code as a result, that is, we need it to be as backwards compatible as possible to avoid mass breakages.

Additional standards are outlined on the pandas code style guide

Optional dependencies

Optional dependencies (e.g. matplotlib) should be imported with the private helper pandas.compat._optional.import_optional_dependency. This ensures a consistent error message when the dependency is not met.

All methods using an optional dependency should include a test asserting that an ImportError is raised when the optional dependency is not found. This test should be skipped if the library is present.

All optional dependencies should be documented in Optional dependencies and the minimum required version should be set in the pandas.compat._optional.VERSIONS dict.

C (cpplint)

pandas uses the Google standard. Google provides an open source style checker called cpplint, but we use a fork of it that can be found here. Here are some of the more common cpplint issues:

- we restrict line-length to 80 characters to promote readability
- every header file must include a header guard to avoid name collisions if re-included

Continuous Integration will run the cpplint tool and report any stylistic errors in your code. Therefore, it is helpful before submitting code to run the check yourself:
pandas: powerful Python data analysis toolkit, Release 1.1.1

You can also run this command on an entire directory if necessary:

```bash
cpplint --extensions=c,h --headers=h --filter=-readability/casting,-runtime/int,--build/include_subdir modified-c-directory
```

To make your commits compliant with this standard, you can install the ClangFormat tool, which can be downloaded here. To configure, in your home directory, run the following command:

```bash
clang-format style=google --dump-config > .clang-format
```

Then modify the file to ensure that any indentation width parameters are at least four. Once configured, you can run the tool as follows:

```bash
clang-format modified-c-file
```

This will output what your file will look like if the changes are made, and to apply them, run the following command:

```bash
clang-format -i modified-c-file
```

To run the tool on an entire directory, you can run the following analogous commands:

```bash
clang-format modified-c-directory/*.c modified-c-directory/*.h
```

```bash
clang-format -i modified-c-directory/*.c modified-c-directory/*.h
```

Do note that this tool is best-effort, meaning that it will try to correct as many errors as possible, but it may not correct all of them. Thus, it is recommended that you run `cpplint` to double check and make any other style fixes manually.

**Python (PEP8 / black)**

pandas follows the PEP8 standard and uses Black and Flake8 to ensure a consistent code format throughout the project.

Continuous Integration will run those tools and report any stylistic errors in your code. Therefore, it is helpful before submitting code to run the check yourself:

```bash
black pandas
git diff upstream/master -u -- "*.py" | flake8 --diff
```

to auto-format your code. Additionally, many editors have plugins that will apply black as you edit files.

You should use a black version >= 19.10b0 as previous versions are not compatible with the pandas codebase.

If you wish to run these checks automatically, we encourage you to use pre-commits instead.

One caveat about `git diff upstream/master -u -- "*.py" | flake8 --diff`: this command will catch any stylistic errors in your changes specifically, but be beware it may not catch all of them. For example, if you delete the only usage of an imported function, it is stylistically incorrect to import an unused function. However, style-checking the diff will not catch this because the actual import is not part of the diff. Thus, for completeness, you should run this command, though it may take longer:

```bash
git diff upstream/master --name-only -- "*.py" | xargs -r flake8
```

Note that on OSX, the `-r` flag is not available, so you have to omit it and run this slightly modified command:
Windows does not support the `xargs` command (unless installed for example via the MinGW toolchain), but one can imitate the behaviour as follows:

```bash
for /f %i in ('git diff upstream/master --name-only -- "*.py"') do flake8 %i
```

This will get all the files being changed by the PR (and ending with .py), and run `flake8` on them, one after the other.

Note that these commands can be run analogously with `black`.

### Import formatting

pandas uses `isort` to standardise import formatting across the codebase.

A guide to import layout as per pep8 can be found [here](#).

A summary of our current import sections (in order):

- Future
- Python Standard Library
- Third Party
  - `pandas._libs`, `pandas.compat`, `pandas.util._*`, `pandas.errors` (largely not dependent on `pandas.core`)
  - `pandas.core.dtypes` (largely not dependent on the rest of `pandas.core`)
  - `Rest of pandas.core.*`
- Non-core `pandas.io`, `pandas.plotting`, `pandas.tseries`
- Local application/library specific imports

Imports are alphabetically sorted within these sections.

As part of Continuous Integration checks we run:

```bash
isort --check-only pandas
```

to check that imports are correctly formatted as per the `setup.cfg`.

If you see output like the below in Continuous Integration checks:

```
Check import format using isort
ERROR: /home/travis/build/pandas-dev/pandas/pandas/io/pytables.py Imports are incorrectly sorted
Check import format using isort DONE
The command "ci/code_checks.sh" exited with 1
```

You should run:

```bash
isort pandas/io/pytables.py
```

to automatically format imports correctly. This will modify your local copy of the files.

Alternatively, you can run a command similar to what was suggested for `black` and `flake8` right above:
git diff upstream/master --name-only -- "*.py" | xargs -r isort

Where similar caveats apply if you are on OSX or Windows.
You can then verify the changes look ok, then git commit and push.

Pre-commit

You can run many of these styling checks manually as we have described above. However, we encourage you to use pre-commit hooks instead to automatically run black, flake8, isort when you make a git commit. This can be done by installing pre-commit:

```
pip install pre-commit
```

and then running:

```
pre-commit install
```

from the root of the pandas repository. Now all of the styling checks will be run each time you commit changes without your needing to run each one manually. In addition, using this pre-commit hook will also allow you to more easily remain up-to-date with our code checks as they change.

Note that if needed, you can skip these checks with git commit --no-verify.

Backwards compatibility

Please try to maintain backward compatibility. pandas has lots of users with lots of existing code, so don’t break it if at all possible. If you think breakage is required, clearly state why as part of the pull request. Also, be careful when changing method signatures and add deprecation warnings where needed. Also, add the deprecated sphinx directive to the deprecated functions or methods.

If a function with the same arguments as the one being deprecated exist, you can use the pandas.util._decorators.deprecate:

```
from pandas.util._decorators import deprecate

deprecated('old_func', 'new_func', '1.1.0')
```

Otherwise, you need to do it manually:

```
import warnings

def old_func():
    """Summary of the function.
    .. deprecated:: 1.1.0
        Use new_func instead.
    ""
    warnings.warn('Use new_func instead.', FutureWarning, stacklevel=2)
    new_func()

def new_func():
    pass
```
You’ll also need to

1. Write a new test that asserts a warning is issued when calling with the deprecated argument
2. Update all of pandas existing tests and code to use the new argument

See Testing warnings for more.

Type hints

pandas strongly encourages the use of PEP 484 style type hints. New development should contain type hints and pull requests to annotate existing code are accepted as well!

Style guidelines

Types imports should follow the from typing import ... convention. So rather than

```python
import typing
primes: typing.List[int] = []
```

You should write

```python
from typing import List, Optional, Union
primes: List[int] = []
```

Optional should be used where applicable, so instead of

```python
maybe_primes: List[Union[int, None]] = []
```

You should write

```python
maybe_primes: List[Optional[int]] = []
```

In some cases in the code base classes may define class variables that shadow builtins. This causes an issue as described in Mypy 1775. The defensive solution here is to create an unambiguous alias of the builtin and use that without your annotation. For example, if you come across a definition like

```python
class SomeClass1:
    str = None
```

The appropriate way to annotate this would be as follows

```python
str_type = str
```

```python
class SomeClass2:
    str: str_type = None
```

In some cases you may be tempted to use cast from the typing module when you know better than the analyzer. This occurs particularly when using custom inference functions. For example

```python
from typing import cast
from pandas.core.dtypes.common import is_number
```
The limitation here is that while a human can reasonably understand that `is_number` would catch the `int` and `float` types mypy cannot make that same inference just yet (see mypy #5206. While the above works, the use of `cast` is strongly discouraged. Where applicable a refactor of the code to appease static analysis is preferable.

With custom types and inference this is not always possible so exceptions are made, but every effort should be exhausted to avoid `cast` before going down such paths.

### pandas-specific types

Commonly used types specific to pandas will appear in `pandas_typing` and you should use these where applicable. This module is private for now but ultimately this should be exposed to third party libraries who want to implement type checking against pandas.

For example, quite a few functions in pandas accept a `dtype` argument. This can be expressed as a string like "object", a numpy.dtype like `np.int64` or even a pandas ExtensionDtype like `pd.CategoricalDtype`. Rather than burden the user with having to constantly annotate all of those options, this can simply be imported and reused from the `pandas_typing` module.

```python
from pandas._typing import Dtype

def as_type(dtype: Dtype) -> ...:
    ...
```

This module will ultimately house types for repeatedly used concepts like “path-like”, “array-like”, “numeric”, etc... and can also hold aliases for commonly appearing parameters like `axis`. Development of this module is active so be sure to refer to the source for the most up to date list of available types.

### Validating type hints

pandas uses `mypy` to statically analyze the code base and type hints. After making any change you can ensure your type hints are correct by running

```
mypy pandas
```
Testing with continuous integration

The pandas test suite will run automatically on Travis-CI and Azure Pipelines continuous integration services, once your pull request is submitted. However, if you wish to run the test suite on a branch prior to submitting the pull request, then the continuous integration services need to be hooked to your GitHub repository. Instructions are here for Travis-CI and Azure Pipelines.

A pull-request will be considered for merging when you have an all ‘green’ build. If any tests are failing, then you will get a red ‘X’, where you can click through to see the individual failed tests. This is an example of a green build.

Note: Each time you push to your fork, a new run of the tests will be triggered on the CI. You can enable the auto-cancel feature, which removes any non-currently-running tests for that same pull-request, for Travis-CI here.

Test-driven development/code writing

pandas is serious about testing and strongly encourages contributors to embrace test-driven development (TDD). This development process “relies on the repetition of a very short development cycle: first the developer writes an (initially failing) automated test case that defines a desired improvement or new function, then produces the minimum amount of code to pass that test.” So, before actually writing any code, you should write your tests. Often the test can be taken from the original GitHub issue. However, it is always worth considering additional use cases and writing corresponding tests.

Adding tests is one of the most common requests after code is pushed to pandas. Therefore, it is worth getting in the habit of writing tests ahead of time so this is never an issue.

Like many packages, pandas uses pytest and the convenient extensions in numpy.testing.

Note: The earliest supported pytest version is 5.0.1.
Writing tests

All tests should go into the tests subdirectory of the specific package. This folder contains many current examples of tests, and we suggest looking to these for inspiration. If your test requires working with files or network connectivity, there is more information on the testing page of the wiki.

The pandas._testing module has many special assert functions that make it easier to make statements about whether Series or DataFrame objects are equivalent. The easiest way to verify that your code is correct is to explicitly construct the result you expect, then compare the actual result to the expected correct result:

```python
def test_pivot(self):
    data = {
        'index' : ['A', 'B', 'C', 'C', 'B', 'A'],
        'columns' : ['One', 'One', 'One', 'Two', 'Two', 'Two'],
        'values' : [1., 2., 3., 3., 2., 1.]
    }

    frame = DataFrame(data)
    pivoted = frame.pivot(index='index', columns='columns', values='values')

    expected = DataFrame({
        'One' : {'A' : 1., 'B' : 2., 'C' : 3.},
        'Two' : {'A' : 1., 'B' : 2., 'C' : 3.}
    })

    assert_frame_equal(pivoted, expected)
```

Please remember to add the Github Issue Number as a comment to a new test. E.g. “# brief comment, see GH#28907”

Transitioning to pytest

pandas existing test structure is mostly class-based, meaning that you will typically find tests wrapped in a class.

```python
class TestReallyCoolFeature:
    pass
```

Going forward, we are moving to a more functional style using the pytest framework, which offers a richer testing framework that will facilitate testing and developing. Thus, instead of writing test classes, we will write test functions like this:

```python
def test_really_cool_feature():
    pass
```

Using pytest

Here is an example of a self-contained set of tests that illustrate multiple features that we like to use.

- functional style: tests are like test_* and only take arguments that are either fixtures or parameters
- pytest.mark can be used to set metadata on test functions, e.g. skip or xfail.
- using parametrize: allow testing of multiple cases
- to set a mark on a parameter, pytest.param(..., marks=...) syntax should be used
- fixture, code for object construction, on a per-test basis
• using bare `assert` for scalars and truth-testing

• `tm.assert_series_equal` (and its counter part `tm.assert_frame_equal`), for pandas object comparisons.

• the typical pattern of constructing an expected and comparing versus the result

We would name this file `test_cool_feature.py` and put in an appropriate place in the `pandas/tests/` structure.

```python
import pytest
import numpy as np
import pandas as pd

@pytest.mark.parametrize('dtype', ['int8', 'int16', 'int32', 'int64'])
def test_dtypes(dtype):
    assert str(np.dtype(dtype)) == dtype

@pytest.mark.parametrize('dtype', ['float32', pytest.param('int16', marks=pytest.mark.skip),
                                     pytest.param('int32', marks=pytest.mark.xfail(reason='to show how it works'))])
def test_mark(dtype):
    assert str(np.dtype(dtype)) == 'float32'

@ pytest.fixture
def series():
    return pd.Series([1, 2, 3])

@ pytest.fixture(params=['int8', 'int16', 'int32', 'int64'])
def dtype(request):
    return request.param

def test_series(series, dtype):
    result = series.astype(dtype)
    assert result.dtype == dtype

    expected = pd.Series([1, 2, 3], dtype=dtype)
    tm.assert_series_equal(result, expected)
```

A test run of this yields

```bash
((pandas) bash-3.2$ pytest test_cool_feature.py -v
=========================== test session starts ===========================
platform darwin -- Python 3.6.2, pytest-3.6.0, py-1.4.31, pluggy-0.4.0
collected 11 items
tester.py::test_dtypes[int8] PASSED
tester.py::test_dtypes[int16] PASSED
tester.py::test_dtypes[int32] PASSED
tester.py::test_dtypes[int64] PASSED
tester.py::test_mark[float32] PASSED
tester.py::test_mark[int16] SKIPPED
tester.py::test_mark[int32] xfail
(continues on next page)
```

4.1. Contributing to pandas 2459
Tests that we have parametrized are now accessible via the test name, for example we could run these with `-k int8` to sub-select only those tests which match `int8`.

```
((pandas) bash-3.2$ pytest test_cool_feature.py -v -k int8
=========================== test session starts ===========================
platform darwin -- Python 3.6.2, pytest-3.6.0, py-1.4.31, pluggy-0.4.0
collected 11 items

test_cool_feature.py::test_dtypes[int8] PASSED

test_cool_feature.py::test_series[int8] PASSED
```

Using hypothesis

Hypothesis is a library for property-based testing. Instead of explicitly parametrizing a test, you can describe all valid inputs and let Hypothesis try to find a failing input. Even better, no matter how many random examples it tries, Hypothesis always reports a single minimal counterexample to your assertions - often an example that you would never have thought to test.

See Getting Started with Hypothesis for more of an introduction, then refer to the Hypothesis documentation for details.

```
import json
from hypothesis import given, strategies as st

any_json_value = st.deferred(lambda: st.one_of(
    st.none(), st.booleans(), st.floats(allow_nan=False), st.text(),
    st.lists(any_json_value), st.dictionaries(st.text(), any_json_value)
))

given(value=any_json_value)

def test_json_roundtrip(value):
    result = json.loads(json.dumps(value))
    assert value == result
```

This test shows off several useful features of Hypothesis, as well as demonstrating a good use-case: checking properties that should hold over a large or complicated domain of inputs.

To keep the Pandas test suite running quickly, parametrized tests are preferred if the inputs or logic are simple, with Hypothesis tests reserved for cases with complex logic or where there are too many combinations of options or subtle interactions to test (or think of!) all of them.
Testing warnings

By default, one of pandas CI workers will fail if any unhandled warnings are emitted.

If your change involves checking that a warning is actually emitted, use `tm.assert_produces_warning(ExpectedWarning)`.

```python
import pandas._testing as tm

df = pd.DataFrame()
with tm.assert_produces_warning(FutureWarning):
    df.some_operation()
```

We prefer this to the `pytest.warns` context manager because ours checks that the warning’s stacklevel is set correctly. The stacklevel is what ensures the user’s file name and line number is printed in the warning, rather than something internal to pandas. It represents the number of function calls from user code (e.g. `df.some_operation()`) to the function that actually emits the warning. Our linter will fail the build if you use `pytest.warns` in a test.

If you have a test that would emit a warning, but you aren’t actually testing the warning itself (say because it’s going to be removed in the future, or because we’re matching a 3rd-party library’s behavior), then use `pytest.mark.filterwarnings` to ignore the error.

```python
@pytest.mark.filterwarnings("ignore:msg:category")
def test_thing(self):
    ...
```

If the test generates a warning of class `category` whose message starts with `msg`, the warning will be ignored and the test will pass.

If you need finer-grained control, you can use Python’s usual `warnings` module to control whether a warning is ignored / raised at different places within a single test.

```python
with warnings.catch_warnings():
    warnings.simplefilter("ignore", FutureWarning)
    # Or use warnings.filterwarnings(...)  
```

Alternatively, consider breaking up the unit test.

Running the test suite

The tests can then be run directly inside your Git clone (without having to install pandas) by typing:

```bash
pytest pandas
```

The tests suite is exhaustive and takes around 20 minutes to run. Often it is worth running only a subset of tests first around your changes before running the entire suite.

The easiest way to do this is with:

```bash
pytest pandas/path/to/test.py -k regex_matching_test_name
```

Or with one of the following constructs:

```bash
pytest pandas/tests/[test-module].py
pytest pandas/tests/[test-module].py::[TestClass]
pytest pandas/tests/[test-module].py::[TestClass]:[test_method]
```
Using pytest-xdist, one can speed up local testing on multicore machines. To use this feature, you will need to install pytest-xdist via:

```
pip install pytest-xdist
```

Two scripts are provided to assist with this. These scripts distribute testing across 4 threads.

On Unix variants, one can type:

```
test_fast.sh
```

On Windows, one can type:

```
test_fast.bat
```

This can significantly reduce the time it takes to locally run tests before submitting a pull request.

For more, see the pytest documentation.

Furthermore one can run

```
pd.test()
```

with an imported pandas to run tests similarly.

### Running the performance test suite

Performance matters and it is worth considering whether your code has introduced performance regressions. pandas is in the process of migrating to asv benchmarks to enable easy monitoring of the performance of critical pandas operations. These benchmarks are all found in the pandas/asv_bench directory, and the test results can be found here.

To use all features of asv, you will need either conda or virtualenv. For more details please check the asv installation webpage.

To install asv:

```
pip install git+https://github.com/spacetelescope/asv
```

If you need to run a benchmark, change your directory to asv_bench/ and run:

```
asv continuous -f 1.1 upstream/master HEAD
```

You can replace HEAD with the name of the branch you are working on, and report benchmarks that changed by more than 10%. The command uses conda by default for creating the benchmark environments. If you want to use virtualenv instead, write:

```
asv continuous -f 1.1 -E virtualenv upstream/master HEAD
```

The -E virtualenv option should be added to all asv commands that run benchmarks. The default value is defined in asv.conf.json.

Running the full test suite can take up to one hour and use up to 3GB of RAM. Usually it is sufficient to paste only a subset of the results into the pull request to show that the committed changes do not cause unexpected performance regressions. You can run specific benchmarks using the -b flag, which takes a regular expression. For example, this will only run tests from a pandas/asv_bench/benchmarks/groupby.py file:
If you want to only run a specific group of tests from a file, you can do it using . as a separator. For example:

```
asv continuous -f 1.1 upstream/master HEAD -b ^groupby
```

will only run the GroupByMethods benchmark defined in groupby.py.

You can also run the benchmark suite using the version of pandas already installed in your current Python environment. This can be useful if you do not have virtualenv or conda, or are using the setup.py develop approach discussed above; for the in-place build you need to set PYTHONPATH, e.g. PYTHONPATH="$PWD/.." asv [remaining arguments]. You can run benchmarks using an existing Python environment by:

```
asv run -e -E existing
```

or, to use a specific Python interpreter:

```
asv run -e -E existing:python3.6
```

This will display stderr from the benchmarks, and use your local python that comes from your $PATH.

Information on how to write a benchmark and how to use asv can be found in the asv documentation.

### Documenting your code

Changes should be reflected in the release notes located in doc/source/whatsnew/vx.y.z.rst. This file contains an ongoing change log for each release. Add an entry to this file to document your fix, enhancement or (unavoidable) breaking change. Make sure to include the GitHub issue number when adding your entry (using :issue:`1234` where 1234 is the issue/pull request number).

If your code is an enhancement, it is most likely necessary to add usage examples to the existing documentation. This can be done following the section regarding documentation above. Further, to let users know when this feature was added, the versionadded directive is used. The sphinx syntax for that is:

```
.. versionadded:: 1.1.0
```

This will put the text New in version 1.1.0 wherever you put the sphinx directive. This should also be put in the docstring when adding a new function or method (example) or a new keyword argument (example).

#### 4.1.6 Contributing your changes to pandas

### Committing your code

Keep style fixes to a separate commit to make your pull request more readable.

Once you’ve made changes, you can see them by typing:

```
git status
```

If you have created a new file, it is not being tracked by git. Add it by typing:

```
git add path/to/file-to-be-added.py
```

Doing ‘git status’ again should give something like:
Finally, commit your changes to your local repository with an explanatory message. pandas uses a convention for commit message prefixes and layout. Here are some common prefixes along with general guidelines for when to use them:

- **ENH**: Enhancement, new functionality
- **BUG**: Bug fix
- **DOC**: Additions/updates to documentation
- **TST**: Additions/updates to tests
- **BLD**: Updates to the build process/scripts
- **PERF**: Performance improvement
- **TYP**: Type annotations
- **CLN**: Code cleanup

The following defines how a commit message should be structured. Please reference the relevant GitHub issues in your commit message using GH1234 or #1234. Either style is fine, but the former is generally preferred:

- a subject line with < 80 chars.
- One blank line.
- Optionally, a commit message body.

Now you can commit your changes in your local repository:

```
git commit -m
```

### Pushing your changes

When you want your changes to appear publicly on your GitHub page, push your forked feature branch’s commits:

```
git push origin shiny-new-feature
```

Here `origin` is the default name given to your remote repository on GitHub. You can see the remote repositories:

```
git remote -v
```

If you added the upstream repository as described above you will see something like:

```
origin git@github.com:yourname/pandas.git (fetch)
origin git@github.com:yourname/pandas.git (push)
upstream git://github.com/pandas-dev/pandas.git (fetch)
upstream git://github.com/pandas-dev/pandas.git (push)
```

Now your code is on GitHub, but it is not yet a part of the pandas project. For that to happen, a pull request needs to be submitted on GitHub.
Review your code

When you’re ready to ask for a code review, file a pull request. Before you do, once again make sure that you have followed all the guidelines outlined in this document regarding code style, tests, performance tests, and documentation. You should also double check your branch changes against the branch it was based on:

1. Navigate to your repository on GitHub – [https://github.com/your-user-name/pandas](https://github.com/your-user-name/pandas)
2. Click on Branches
3. Click on the Compare button for your feature branch
4. Select the base and compare branches, if necessary. This will be master and shiny-new-feature, respectively.

Finally, make the pull request

If everything looks good, you are ready to make a pull request. A pull request is how code from a local repository becomes available to the GitHub community and can be looked at and eventually merged into the master version. This pull request and its associated changes will eventually be committed to the master branch and available in the next release. To submit a pull request:

1. Navigate to your repository on GitHub
2. Click on the Pull Request button
3. You can then click on Commits and Files Changed to make sure everything looks okay one last time
4. Write a description of your changes in the Preview Discussion tab
5. Click Send Pull Request.

This request then goes to the repository maintainers, and they will review the code.

Updating your pull request

Based on the review you get on your pull request, you will probably need to make some changes to the code. In that case, you can make them in your branch, add a new commit to that branch, push it to GitHub, and the pull request will be automatically updated. Pushing them to GitHub again is done by:

```
git push origin shiny-new-feature
```

This will automatically update your pull request with the latest code and restart the Continuous Integration tests.

Another reason you might need to update your pull request is to solve conflicts with changes that have been merged into the master branch since you opened your pull request.

To do this, you need to “merge upstream master” in your branch:

```
git checkout shiny-new-feature
git fetch upstream
git merge upstream/master
```

If there are no conflicts (or they could be fixed automatically), a file with a default commit message will open, and you can simply save and quit this file.

If there are merge conflicts, you need to solve those conflicts. See for example at [https://help.github.com/articles/resolving-a-merge-conflict-using-the-command-line/](https://help.github.com/articles/resolving-a-merge-conflict-using-the-command-line/) for an explanation on how to do this. Once the conflicts are merged and the files where the conflicts were solved are added, you can run `git commit` to save those fixes.
If you have uncommitted changes at the moment you want to update the branch with master, you will need to `stash` them prior to updating (see the `stash docs`). This will effectively store your changes and they can be reapplied after updating.

After the feature branch has been update locally, you can now update your pull request by pushing to the branch on GitHub:

```
git push origin shiny-new-feature
```

**Delete your merged branch (optional)**

Once your feature branch is accepted into upstream, you’ll probably want to get rid of the branch. First, merge upstream master into your branch so git knows it is safe to delete your branch:

```
git fetch upstream
git checkout master
git merge upstream/master
```

Then you can do:

```
git branch -d shiny-new-feature
```

Make sure you use a lower-case `-d`, or else git won’t warn you if your feature branch has not actually been merged. The branch will still exist on GitHub, so to delete it there do:

```
git push origin --delete shiny-new-feature
```

### 4.1.7 Tips for a successful pull request

If you have made it to the *Review your code* phase, one of the core contributors may take a look. Please note however that a handful of people are responsible for reviewing all of the contributions, which can often lead to bottlenecks.

To improve the chances of your pull request being reviewed, you should:

- **Reference an open issue** for non-trivial changes to clarify the PR’s purpose
- **Ensure you have appropriate tests**. These should be the first part of any PR
- **Keep your pull requests as simple as possible**. Larger PRs take longer to review
- **Ensure that CI is in a green state**. Reviewers may not even look otherwise
- **Keep Updating your pull request**, either by request or every few days

### 4.2 pandas code style guide

**Table of contents:**

- Patterns
  - Using `foo.__class__`
- String formatting
4.2.1 Patterns

Using `foo.__class__`

pandas uses `type(foo)` instead of `foo.__class__` as it is making the code more readable. For example:

Good:

```python
foo = "bar"
type(foo)
```

Bad:

```python
foo = "bar"
foo.__class__
```

4.2.2 String formatting

Concatenated strings

Using f-strings

pandas uses f-strings formatting instead of `%' and `.format()` string formaters.

The convention of using f-strings on a string that is concatenated over several lines, is to prefix only the lines containing values which need to be interpreted.

For example:

Good:

```python
foo = "old_function"
bar = "new_function"

my_warning_message = {
    f"Warning, {foo} is deprecated, "
    "please use the new and way better "
    f"{bar}"}
```
Bad:

```python
foo = "old_function"
bar = "new_function"

my_warning_message = {
    f"Warning, {foo} is deprecated, "
    f"please use the new and way better "
    f"{bar}"}
```

White spaces

Only put white space at the end of the previous line, so there is no whitespace at the beginning of the concatenated string.

For example:

Good:

```python
example_string = {
    "Some long concatenated string, 
    "with good placement of the 
    "whitespaces"
}
```

Bad:

```python
example_string = {
    "Some long concatenated string,"
    " with bad placement of the"
    " whitespaces"
}
```

Representation function (aka ‘repr()’)

pandas uses ‘repr()’ instead of ‘%r’ and ‘!r’.

The use of ‘repr()’ will only happen when the value is not an obvious string.

For example:

Good:

```python
value = str
f"Unknown received value, got: {repr(value)}"
```

Good:

```python
value = str
f"Unknown received type, got: '{type(value).__name__}'"
```
4.2.3 Imports (aim for absolute)

In Python 3, absolute imports are recommended. Using absolute imports, doing something like `import string` will import the string module rather than `string.py` in the same directory. As much as possible, you should try to write out absolute imports that show the whole import chain from top-level pandas.

Explicit relative imports are also supported in Python 3 but it is not recommended to use them. Implicit relative imports should never be used and are removed in Python 3.

For example:

```python
# preferred
import pandas.core.common as com

# not preferred
from .common import test_base

# wrong
from common import test_base
```

4.2.4 Miscellaneous

Reading from a url

Good:

```python
from pandas.io.common import urlopen
with urlopen('http://www.google.com') as url:
    raw_text = url.read()
```

4.3 pandas maintenance

This guide is for pandas’ maintainers. It may also be interesting to contributors looking to understand the pandas development process and what steps are necessary to become a maintainer.

The main contributing guide is available at `Contributing to pandas`.

4.3.1 Roles

pandas uses two levels of permissions: `triage` and `core` team members.

Triage members can label and close issues and pull requests.

Core team members can label and close issues and pull request, and can merge pull requests.

GitHub publishes the full list of permissions.
4.3.2 Tasks

pandas is largely a volunteer project, so these tasks shouldn’t be read as “expectations” of triage and maintainers. Rather, they’re general descriptions of what it means to be a maintainer.

- Triage newly filed issues (see Issue triage)
- Review newly opened pull requests
- Respond to updates on existing issues and pull requests
- Drive discussion and decisions on stalled issues and pull requests
- Provide experience / wisdom on API design questions to ensure consistency and maintainability
- Project organization (run / attend developer meetings, represent pandas)

https://matthewrocklin.com/blog/2019/05/18/maintainer may be interesting background reading.

4.3.3 Issue triage

Here’s a typical workflow for triaging a newly opened issue.

1. Thank the reporter for opening an issue

   The issue tracker is many people’s first interaction with the pandas project itself, beyond just using the library. As such, we want it to be a welcoming, pleasant experience.

2. Is the necessary information provided?

   Ideally reporters would fill out the issue template, but many don’t. If crucial information (like the version of pandas they used), is missing feel free to ask for that and label the issue with “Needs info”. The report should follow the guidelines in Bug reports and enhancement requests. You may want to link to that if they didn’t follow the template.

   Make sure that the title accurately reflects the issue. Edit it yourself if it’s not clear.

3. Is this a duplicate issue?

   We have many open issues. If a new issue is clearly a duplicate, label the new issue as “Duplicate” assign the milestone “No Action”, and close the issue with a link to the original issue. Make sure to still thank the reporter, and encourage them to chime in on the original issue, and perhaps try to fix it.

   If the new issue provides relevant information, such as a better or slightly different example, add it to the original issue as a comment or an edit to the original post.

4. Is the issue minimal and reproducible?

   For bug reports, we ask that the reporter provide a minimal reproducible example. See https://matthewrocklin.com/blog/work/2018/02/28/minimal-bug-reports for a good explanation. If the example is not reproducible, or if it’s clearly not minimal, feel free to ask the reporter if they can provide and example or simplify the provided one. Do acknowledge that writing minimal reproducible examples is hard work. If the reporter is struggling, you can try to write one yourself and we’ll edit the original post to include it.

   If a reproducible example can’t be provided, add the “Needs info” label.

   If a reproducible example is provided, but you see a simplification, edit the original post with your simpler reproducible example.

5. Is this a clearly defined feature request?

   Generally, pandas prefers to discuss and design new features in issues, before a pull request is made. Encourage the submitter to include a proposed API for the new feature. Having them write a full docstring is a good way to pin down specifics.
We’ll need a discussion from several pandas maintainers before deciding whether the proposal is in scope for pandas.

6. **Is this a usage question?**

   We prefer that usage questions are asked on StackOverflow with the pandas tag. [https://stackoverflow.com/questions/tagged/pandas](https://stackoverflow.com/questions/tagged/pandas)

   If it’s easy to answer, feel free to link to the relevant documentation section, let them know that in the future this kind of question should be on StackOverflow, and close the issue.

7. **What labels and milestones should I add?**

   Apply the relevant labels. This is a bit of an art, and comes with experience. Look at similar issues to get a feel for how things are labeled.

   If the issue is clearly defined and the fix seems relatively straightforward, label the issue as “Good first issue”.

   Typically, new issues will be assigned the “Contributions welcome” milestone, unless it’s know that this issue should be addressed in a specific release (say because it’s a large regression).

**4.3.4 Closing issues**

Be delicate here: many people interpret closing an issue as us saying that the conversation is over. It’s typically best to give the reporter some time to respond or self-close their issue if it’s determined that the behavior is not a bug, or the feature is out of scope. Sometimes reporters just go away though, and we’ll close the issue after the conversation has died.

**4.3.5 Reviewing pull requests**

Anybody can review a pull request: regular contributors, triagers, or core-team members. Here are some guidelines to check.

- Tests should be in a sensible location.
- New public APIs should be included somewhere in `doc/source/reference/`.
- New / changed API should use the `versionadded` or `versionchanged` directives in the docstring.
- User-facing changes should have a `whatsnew` in the appropriate file.
- Regression tests should reference the original GitHub issue number like `# GH-1234`.

**4.3.6 Cleaning up old issues**

Every open issue in pandas has a cost. Open issues make finding duplicates harder, and can make it harder to know what needs to be done in pandas. That said, closing issues isn’t a goal on its own. Our goal is to make pandas the best it can be, and that’s best done by ensuring that the quality of our open issues is high.

Occasionally, bugs are fixed but the issue isn’t linked to in the Pull Request. In these cases, comment that “This has been fixed, but could use a test.” and label the issue as “Good First Issue” and “Needs Test”.

If an older issue doesn’t follow our issue template, edit the original post to include a minimal example, the actual output, and the expected output. Uniformity in issue reports is valuable.

If an older issue lacks a reproducible example, label it as “Needs Info” and ask them to provide one (or write one yourself if possible). If one isn’t provide reasonably soon, close it according to the policies in "Closing issues."
4.3.7 Cleaning up old pull requests

Occasionally, contributors are unable to finish off a pull request. If some time has passed (two weeks, say) since the last review requesting changes, gently ask if they’re still interested in working on this. If another two weeks or so passes with no response, thank them for their work and close the pull request. Comment on the original issue that “There’s a stalled PR at #1234 that may be helpful.”, and perhaps label the issue as “Good first issue” if the PR was relatively close to being accepted.

Additionally, core-team members can push to contributors branches. This can be helpful for pushing an important PR across the line, or for fixing a small merge conflict.

4.3.8 Becoming a pandas maintainer

The full process is outlined in our governance documents. In summary, we’re happy to give triage permissions to anyone who shows interest by being helpful on the issue tracker.

The current list of core-team members is at https://github.com/pandas-dev/pandas-governance/blob/master/people.md

4.4 Internals

This section will provide a look into some of pandas internals. It’s primarily intended for developers of pandas itself.

4.4.1 Indexing

In pandas there are a few objects implemented which can serve as valid containers for the axis labels:

- **Index**: the generic “ordered set” object, an ndarray of object dtype assuming nothing about its contents. The labels must be hashable (and likely immutable) and unique. Populates a dict of label to location in Cython to do \(O(1)\) lookups.
- **Int64Index**: a version of Index highly optimized for 64-bit integer data, such as time stamps
- **Float64Index**: a version of Index highly optimized for 64-bit float data
- **MultiIndex**: the standard hierarchical index object
- **DatetimeIndex**: An Index object with `Timestamp` boxed elements (impl are the int64 values)
- **TimedeltaIndex**: An Index object with `Timedelta` boxed elements (impl are the int64 values)
- **PeriodIndex**: An Index object with Period elements

There are functions that make the creation of a regular index easy:

- **date_range**: fixed frequency date range generated from a time rule or DateOffset. An ndarray of Python datetime objects
- **period_range**: fixed frequency date range generated from a time rule or DateOffset. An ndarray of Period objects, representing timespans

The motivation for having an Index class in the first place was to enable different implementations of indexing. This means that it’s possible for you, the user, to implement a custom Index subclass that may be better suited to a particular application than the ones provided in pandas.

From an internal implementation point of view, the relevant methods that an Index must define are one or more of the following (depending on how incompatible the new object internals are with the Index functions):

- **get_loc**: returns an “indexer” (an integer, or in some cases a slice object) for a label
• **slice_locs**: returns the “range” to slice between two labels
• **get_indexer**: Computes the indexing vector for reindexing / data alignment purposes. See the source / docstrings for more on this
• **get_indexer_non_unique**: Computes the indexing vector for reindexing / data alignment purposes when the index is non-unique. See the source / docstrings for more on this
• **reindex**: Does any pre-conversion of the input index then calls **get_indexer**
• **union, intersection**: computes the union or intersection of two Index objects
• **insert**: Inserts a new label into an Index, yielding a new object
• **delete**: Delete a label, yielding a new object
• **drop**: Deletes a set of labels
• **take**: Analogous to ndarray.take

**MultiIndex**

Internally, the MultiIndex consists of a few things: the levels, the integer codes (until version 0.24 named labels), and the level names:

```
In [1]: index = pd.MultiIndex.from_product([[range(3), ['one', 'two']],
                                           names=['first', 'second'])

In [2]: index
Out[2]:
MultiIndex([(0, 'one'),
            (0, 'two'),
            (1, 'one'),
            (1, 'two'),
            (2, 'one'),
            (2, 'two')],
           names=['first', 'second'])

In [3]: index.levels
Out[3]: FrozenList([[0, 1, 2], ['one', 'two']])

In [4]: index.codes
Out[4]: FrozenList([[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]])

In [5]: index.names
Out[5]: FrozenList(['first', 'second'])
```

You can probably guess that the codes determine which unique element is identified with that location at each layer of the index. It’s important to note that sortedness is determined **solely** from the integer codes and does not check (or care) whether the levels themselves are sorted. Fortunately, the constructors from_tuples and from_arrays ensure that this is true, but if you compute the levels and codes yourself, please be careful.
pandas: powerful Python data analysis toolkit, Release 1.1.1

Values

pandas extends NumPy’s type system with custom types, like Categorical or datetimes with a timezone, so we have multiple notions of “values”. For 1-D containers (Index classes and Series) we have the following convention:

- cls._values refers is the “best possible” array. This could be an ndarray or ExtensionArray.

So, for example, Series[category]._values is a Categorical.

4.4.2 Subclassing pandas data structures

This section has been moved to Subclassing pandas data structures.

4.5 Extending pandas

While pandas provides a rich set of methods, containers, and data types, your needs may not be fully satisfied. pandas offers a few options for extending pandas.

4.5.1 Registering custom accessors

Libraries can use the decorators pandas.api.extensions.register_dataframe_accessor(), pandas.api.extensions.register_series_accessor(), and pandas.api.extensions.register_index_accessor(), to add additional “namespaces” to pandas objects. All of these follow a similar convention: you decorate a class, providing the name of attribute to add. The class’s __init__ method gets the object being decorated. For example:

```python
@pd.api.extensions.register_dataframe_accessor("geo")
class GeoAccessor:
    def __init__(self, pandas_obj):
        self._validate(pandas_obj)
        self._obj = pandas_obj

    @staticmethod
    def _validate(obj):
        # verify there is a column latitude and a column longitude
        if 'latitude' not in obj.columns or 'longitude' not in obj.columns:
            raise AttributeError("Must have 'latitude' and 'longitude'.")

    @property
    def center(self):
        # return the geographic center point of this DataFrame
        lat = self._obj.latitude
        lon = self._obj.longitude
        return (float(lon.mean()), float(lat.mean()))

    def plot(self):
        # plot this array's data on a map, e.g., using Cartopy
        pass
```

Now users can access your methods using the geo namespace:
>>> ds = pd.DataFrame({'longitude': np.linspace(0, 10),
...     'latitude': np.linspace(0, 20)})

>>> ds.geo.center
(5.0, 10.0)

>>> ds.geo.plot()
# plots data on a map

This can be a convenient way to extend pandas objects without subclassing them. If you write a custom accessor, make a pull request adding it to our ecosystem page.

We highly recommend validating the data in your accessor's `__init__`. In our GeoAccessor, we validate that the data contains the expected columns, raising an `AttributeError` when the validation fails. For a Series accessor, you should validate the `dtype` if the accessor applies only to certain dtypes.

### 4.5.2 Extension types

New in version 0.23.0.

---

**Warning:** The `pandas.api.extensions.ExtensionDtype` and `pandas.api.extensions.ExtensionArray` APIs are new and experimental. They may change between versions without warning.

---

pandas defines an interface for implementing data types and arrays that extend NumPy's type system. pandas itself uses the extension system for some types that aren't built into NumPy (categorical, period, interval, datetime with timezone).

Libraries can define a custom array and data type. When pandas encounters these objects, they will be handled properly (i.e. not converted to an ndarray of objects). Many methods like `pandas.isna()` will dispatch to the extension type's implementation.

If you're building a library that implements the interface, please publicize it on ecosystem.extensions.

The interface consists of two classes.

**ExtensionDtype**

An `pandas.api.extensions.ExtensionDtype` is similar to a `numpy.dtype` object. It describes the data type. Implementors are responsible for a few unique items like the name.

One particularly important item is the `type` property. This should be the class that is the scalar type for your data. For example, if you were writing an extension array for IP Address data, this might be `ipaddress.IPv4Address`.

See the `extension dtype source` for interface definition.

New in version 0.24.0.

`pandas.api.extension.ExtensionDtype` can be registered to pandas to allow creation via a string dtype name. This allows one to instantiate `Series` and `.astype()` with a registered string name, for example `'category'` is a registered string accessor for the `CategoricalDtype`.

See the `extension dtype dtypes` for more on how to register dtypes.
ExtensionArray

This class provides all the array-like functionality. ExtensionArrays are limited to 1 dimension. An ExtensionArray is linked to an ExtensionDtype via the dtype attribute.

pandas makes no restrictions on how an extension array is created via its __new__ or __init__, and puts no restrictions on how you store your data. We do require that your array be convertible to a NumPy array, even if this is relatively expensive (as it is for Categorical).

They may be backed by none, one, or many NumPy arrays. For example, pandas.Categorical is an extension array backed by two arrays, one for codes and one for categories. An array of IPv6 addresses may be backed by a NumPy structured array with two fields, one for the lower 64 bits and one for the upper 64 bits. Or they may be backed by some other storage type, like Python lists.

See the extension array source for the interface definition. The docstrings and comments contain guidance for properly implementing the interface.

ExtensionArray operator support

New in version 0.24.0.

By default, there are no operators defined for the class ExtensionArray. There are two approaches for providing operator support for your ExtensionArray:

1. Define each of the operators on your ExtensionArray subclass.

2. Use an operator implementation from pandas that depends on operators that are already defined on the underlying elements (scalars) of the ExtensionArray.

Note: Regardless of the approach, you may want to set __array_priority__ if you want your implementation to be called when involved in binary operations with NumPy arrays.

For the first approach, you define selected operators, e.g., __add__, __le__, etc. that you want your ExtensionArray subclass to support.

The second approach assumes that the underlying elements (i.e., scalar type) of the ExtensionArray have the individual operators already defined. In other words, if your ExtensionArray named MyExtensionArray is implemented so that each element is an instance of the class MyExtensionElement, then if the operators are defined for MyExtensionElement, the second approach will automatically define the operators for MyExtensionArray.

A mixin class, ExtensionScalarOpsMixin supports this second approach. If developing an ExtensionArray subclass, for example MyExtensionArray, can simply include ExtensionScalarOpsMixin as a parent class of MyExtensionArray, and then call the methods _add_arithmetic_ops() and/or _add_comparison_ops() to hook the operators into your MyExtensionArray class, as follows:

```python
from pandas.api.extensions import ExtensionArray, ExtensionScalarOpsMixin

class MyExtensionArray(ExtensionArray, ExtensionScalarOpsMixin):
    pass

MyExtensionArray._add_arithmetic_ops()
MyExtensionArray._add_comparison_ops()
```
Note: Since pandas automatically calls the underlying operator on each element one-by-one, this might not be as performant as implementing your own version of the associated operators directly on the ExtensionArray.

For arithmetic operations, this implementation will try to reconstruct a new ExtensionArray with the result of the element-wise operation. Whether or not that succeeds depends on whether the operation returns a result that’s valid for the ExtensionArray. If an ExtensionArray cannot be reconstructed, an ndarray containing the scalars returned instead.

For ease of implementation and consistency with operations between pandas and NumPy ndarrays, we recommend not handling Series and Indexes in your binary ops. Instead, you should detect these cases and return `NotImplemented`. When pandas encounters an operation like `op(Series, ExtensionArray)`, pandas will

1. unbox the array from the Series(Series.array)
2. call `result = op(values, ExtensionArray)`
3. re-box the result in a Series

NumPy universal functions

`Series` implements `__array_ufunc__`. As part of the implementation, pandas unboxes the ExtensionArray from the Series, applies the ufunc, and re-boxes it if necessary.

If applicable, we highly recommend that you implement `__array_ufunc__` in your extension array to avoid coercion to an ndarray. See the numpy documentation for an example.

As part of your implementation, we require that you defer to pandas when a pandas container (Series, DataFrame, Index) is detected in inputs. If any of those is present, you should return `NotImplemented`. pandas will take care of unboxing the array from the container and re-calling the ufunc with the unwrapped input.

Testing extension arrays

We provide a test suite for ensuring that your extension arrays satisfy the expected behavior. To use the test suite, you must provide several pytest fixtures and inherit from the base test class. The required fixtures are found in https://github.com/pandas-dev/pandas/blob/master/pandas/tests/extension/conftest.py.

To use a test, subclass it:

```python
from pandas.tests.extension import base

class TestConstructors(base.BaseConstructorsTests):
    pass
```

See https://github.com/pandas-dev/pandas/blob/master/pandas/tests/extension/base/__init__.py for a list of all the tests available.
Compatibility with Apache Arrow

An ExtensionArray can support conversion to/from pyarrow arrays (and thus support for example serialization to the Parquet file format) by implementing two methods: ExtensionArray.__arrow_array__ and ExtensionDtype.__from_arrow__.

The ExtensionArray.__arrow_array__ ensures that pyarrow knows how to convert the specific extension array into a pyarrow.Array (also when included as a column in a pandas DataFrame):

```python
class MyExtensionArray(ExtensionArray):
    ...
    def __arrow_array__(self, type=None):
        # convert the underlying array values to a pyarrow Array
        import pyarrow
        return pyarrow.array(..., type=type)
```

The ExtensionDtype.__from_arrow__ method then controls the conversion back from pyarrow to a pandas ExtensionArray. This method receives a pyarrow Array or ChunkedArray as only argument and is expected to return the appropriate pandas ExtensionArray for this dtype and the passed values:

```python
class ExtensionDtype:
    ...
    def __from_arrow__(self, array: pyarrow.Array/ChunkedArray) -> ExtensionArray:
        ...
```

See more in the Arrow documentation.

Those methods have been implemented for the nullable integer and string extension dtypes included in pandas, and ensure roundtrip to pyarrow and the Parquet file format.

4.5.3 Subclassing pandas data structures

**Warning:** There are some easier alternatives before considering subclassing pandas data structures.

1. Extensible method chains with `pipe`
2. Use composition. See here.
3. Extending by registering an accessor
4. Extending by extension type

This section describes how to subclass pandas data structures to meet more specific needs. There are two points that need attention:

1. Override constructor properties.
2. Define original properties

**Note:** You can find a nice example in geopandas project.
Override constructor properties

Each data structure has several constructor properties for returning a new data structure as the result of an operation. By overriding these properties, you can retain subclasses through pandas data manipulations.

There are 3 constructor properties to be defined:

- `_constructor`: Used when a manipulation result has the same dimensions as the original.
- `_constructor_sliced`: Used when a manipulation result has one lower dimension(s) as the original, such as DataFrame single columns slicing.
- `_constructor_expanddim`: Used when a manipulation result has one higher dimension as the original, such as Series.to_frame()

Following table shows how pandas data structures define constructor properties by default.

<table>
<thead>
<tr>
<th>Property Attributes</th>
<th>Series</th>
<th>DataFrame</th>
</tr>
</thead>
<tbody>
<tr>
<td>_constructor</td>
<td>Series</td>
<td>DataFrame</td>
</tr>
<tr>
<td>_constructor_sliced</td>
<td>NotImplementedError</td>
<td>Series</td>
</tr>
<tr>
<td>_constructor_expanddim</td>
<td>DataFrame</td>
<td>NotImplementedError</td>
</tr>
</tbody>
</table>

Below example shows how to define SubclassedSeries and SubclassedDataFrame overriding constructor properties.

```python
class SubclassedSeries(pd.Series):
    @property
    def _constructor(self):
        return SubclassedSeries

    @property
    def _constructor_expanddim(self):
        return SubclassedDataFrame

class SubclassedDataFrame(pd.DataFrame):
    @property
    def _constructor(self):
        return SubclassedDataFrame

    @property
    def _constructor_sliced(self):
        return SubclassedSeries

>>> s = SubclassedSeries([1, 2, 3])
>>> type(s)
<class '__main__.SubclassedSeries'>

>>> to_framed = s.to_frame()
>>> type(to_framed)
<class '__main__.SubclassedDataFrame'>

>>> df = SubclassedDataFrame({'A': [1, 2, 3], 'B': [4, 5, 6], 'C': [7, 8, 9]})
>>> df
   A  B  C
0  1  4  7
```

(continues on next page)
Define original properties

To let original data structures have additional properties, you should let pandas know what properties are added. pandas maps unknown properties to data names overriding __getattr__. Defining original properties can be done in one of 2 ways:

1. Define _internal_names and _internal_names_set for temporary properties which WILL NOT be passed to manipulation results.
2. Define _metadata for normal properties which will be passed to manipulation results.

Below is an example to define two original properties, “internal_cache” as a temporary property and “added_property” as a normal property

```python
class SubclassedDataFrame2(pd.DataFrame):
    # temporary properties
    _internal_names = pd.DataFrame._internal_names + ['internal_cache']
    _internal_names_set = set(_internal_names)

    # normal properties
    _metadata = ['added_property']

    def __constructor__(self):
        return SubclassedDataFrame2

>>> df = SubclassedDataFrame2({'A': [1, 2, 3], 'B': [4, 5, 6], 'C': [7, 8, 9]})
>>> df
```
A  B  C
0 1 4 7
1 2 5 8
2 3 6 9

```python
>>> df.internal_cache = 'cached'
>>> df.added_property = 'property'

>>> df.internal_cache
cached
>>> df.added_property
property

# properties defined in _internal_names is reset after manipulation
>>> df[['A', 'B']].internal_cache
AttributeError: 'SubclassedDataFrame2' object has no attribute 'internal_cache'

# properties defined in _metadata are retained
>>> df[['A', 'B']].added_property
property
```

4.5.4 Plotting backends

Starting in 0.25 pandas can be extended with third-party plotting backends. The main idea is letting users select a plotting backend different than the provided one based on Matplotlib. For example:

```python
>>> pd.set_option('plotting.backend', 'backend.module')
>>> pd.Series([1, 2, 3]).plot()
```

This would be more or less equivalent to:

```python
>>> import backend.module
>>> backend.module.plot(pd.Series([1, 2, 3]))
```

The backend module can then use other visualization tools (Bokeh, Altair,...) to generate the plots.

Libraries implementing the plotting backend should use entry points to make their backend discoverable to pandas. The key is "pandas_plotting_backends". For example, pandas registers the default "matplotlib" backend as follows.

```
# in setup.py
setup(
    ...,
    entry_points={
        "pandas_plotting_backends": [
            "matplotlib = pandas:plotting._matplotlib",
        ],
    },
)
```

More information on how to implement a third-party plotting backend can be found at https://github.com/pandas-dev/pandas/blob/master/pandas/plotting/__init__.py#L1.

4.5. Extending pandas
4.6 Developer

This section will focus on downstream applications of pandas.

4.6.1 Storing pandas DataFrame objects in Apache Parquet format

The Apache Parquet format provides key-value metadata at the file and column level, stored in the footer of the Parquet file:

```python
5: optional list<KeyValue> key_value_metadata
```

where `KeyValue` is

```python
struct KeyValue {
  1: required string key
  2: optional string value
}
```

So that a `pandas.DataFrame` can be faithfully reconstructed, we store a pandas metadata key in the `FileMetaData` with the value stored as:

```python
{'index_columns': [descr0, descr1, ...],
 'column_indexes': [ci0, ci1, ..., ciN],
 'columns': [c0, c1, ...],
 'pandas_version': $VERSION,
 'creator': {
   'library': $LIBRARY,
   'version': $LIBRARY_VERSION
 }}
```

The “descriptor” values `descr0` in the 'index_columns' field are strings (referring to a column) or dictionaries with values as described below.

The `c0/ci0` and so forth are dictionaries containing the metadata for each column, including the index columns. This has JSON form:

```json
{ 'name': column_name,
  'field_name': parquet_column_name,
  'pandas_type': pandas_type,
  'numpy_type': numpy_type,
  'metadata': metadata }
```

See below for the detailed specification for these.

Index metadata descriptors

`RangeIndex` can be stored as metadata only, not requiring serialization. The descriptor format for these as is follows:

```python
index = pd.RangeIndex(0, 10, 2)
{'kind': 'range',
 'name': index.name,
 'start': index.start,
 'stop': index.stop,
 'step': index.step}
```

2482 Chapter 4. Development
Other index types must be serialized as data columns along with the other DataFrame columns. The metadata for these is a string indicating the name of the field in the data columns, for example '__index_level_0__'.

If an index has a non-None name attribute, and there is no other column with a name matching that value, then the index.name value can be used as the descriptor. Otherwise (for unnamed indexes and ones with names colliding with other column names) a disambiguating name with pattern matching __index_level__\d+__ should be used.

In cases of named indexes as data columns, name attribute is always stored in the column descriptors as above.

**Column metadata**

- **pandas_type** is the logical type of the column, and is one of:
  - Boolean: 'bool'
  - Integers: 'int8', 'int16', 'int32', 'int64', 'uint8', 'uint16', 'uint32', 'uint64'
  - Floats: 'float16', 'float32', 'float64'
  - Date and Time Types: 'datetime', 'datetimetz', 'timedelta'
  - String: 'unicode', 'bytes'
  - Categorical: 'categorical'
  - Other Python objects: 'object'

- The **numpy_type** is the physical storage type of the column, which is the result of \str\(\text{dtype}\) for the underlying NumPy array that holds the data. So for datetimetz this is \text{datetime64[ns]} and for categorical, it may be any of the supported integer categorical types.

- The metadata field is None except for:
  - datetimetz: {'timezone': zone, 'unit': 'ns'}, e.g. {'timezone': 'America/New_York', 'unit': 'ns'}. The 'unit' is optional, and if omitted it is assumed to be nanoseconds.
  - categorical: {'num_categories': K, 'ordered': is_ordered, 'type': $\text{STYPE}$}
    - Here 'type' is optional, and can be a nested pandas type specification here (but not categorical)
  - unicode: {'encoding': encoding}
    - The encoding is optional, and if not present is UTF-8
  - object: {'encoding': encoding}. Objects can be serialized and stored in BYTE_ARRAY Parquet columns. The encoding can be one of:
    - 'pickle'
    - 'bson'
    - 'json'
  - timedelta: {'unit': 'ns'}. The 'unit' is optional, and if omitted it is assumed to be nanoseconds.
    - This metadata is optional altogether

For types other than these, the 'metadata' key can be omitted. Implementations can assume None if the key is not present.

As an example of fully-formed metadata:
4.7 Policies

4.7.1 Version policy

Changed in version 1.0.0.

pandas uses a loose variant of semantic versioning (SemVer) to govern deprecations, API compatibility, and version numbering.

A pandas release number is made up of `MAJOR.MINOR.PATCH`.
API breaking changes should only occur in major releases. These changes will be documented, with clear guidance on what is changing, why it's changing, and how to migrate existing code to the new behavior.

Whenever possible, a deprecation path will be provided rather than an outright breaking change.

pandas will introduce deprecations in minor releases. These deprecations will preserve the existing behavior while emitting a warning that provide guidance on:

- How to achieve similar behavior if an alternative is available
- The pandas version in which the deprecation will be enforced.

We will not introduce new deprecations in patch releases.

Deprecations will only be enforced in major releases. For example, if a behavior is deprecated in pandas 1.2.0, it will continue to work, with a warning, for all releases in the 1.x series. The behavior will change and the deprecation removed in the next next major release (2.0.0).

Note: pandas will sometimes make behavior changing bug fixes, as part of minor or patch releases. Whether or not a change is a bug fix or an API-breaking change is a judgement call. We’ll do our best, and we invite you to participate in development discussion on the issue tracker or mailing list.

These policies do not apply to features marked as experimental in the documentation. pandas may change the behavior of experimental features at any time.

### 4.7.2 Python support

Pandas will only drop support for specific Python versions (e.g. 3.6.x, 3.7.x) in pandas major releases.

### 4.8 Roadmap

This page provides an overview of the major themes in pandas’ development. Each of these items requires a relatively large amount of effort to implement. These may be achieved more quickly with dedicated funding or interest from contributors.

An item being on the roadmap does not mean that it will necessarily happen, even with unlimited funding. During the implementation period we may discover issues preventing the adoption of the feature.

Additionally, an item not being on the roadmap does not exclude it from inclusion in pandas. The roadmap is intended for larger, fundamental changes to the project that are likely to take months or years of developer time. Smaller-scoped items will continue to be tracked on our issue tracker.

See Roadmap evolution for proposing changes to this document.

### 4.8.1 Extensibility

Pandas extension types allow for extending NumPy types with custom data types and array storage. Pandas uses extension types internally, and provides an interface for third-party libraries to define their own custom data types.

Many parts of pandas still unintentionally convert data to a NumPy array. These problems are especially pronounced for nested data.

We'd like to improve the handling of extension arrays throughout the library, making their behavior more consistent with the handling of NumPy arrays. We'll do this by cleaning up pandas’ internals and adding new methods to the extension array interface.
4.8.2 String data type

Currently, pandas stores text data in an `object`-dtype NumPy array. The current implementation has two primary drawbacks: First, `object`-dtype is not specific to strings: any Python object can be stored in an `object`-dtype array, not just strings. Second: this is not efficient. The NumPy memory model isn’t especially well-suited to variable width text data.

To solve the first issue, we propose a new extension type for string data. This will initially be opt-in, with users explicitly requesting `dtype="string"`. The array backing this string dtype may initially be the current implementation: an `object`-dtype NumPy array of Python strings.

To solve the second issue (performance), we’ll explore alternative in-memory array libraries (for example, Apache Arrow). As part of the work, we may need to implement certain operations expected by pandas users (for example the algorithm used in `Series.str.upper`). That work may be done outside of pandas.

4.8.3 Apache Arrow interoperability

Apache Arrow is a cross-language development platform for in-memory data. The Arrow logical types are closely aligned with typical pandas use cases.

We’d like to provide better-integrated support for Arrow memory and data types within pandas. This will let us take advantage of its I/O capabilities and provide for better interoperability with other languages and libraries using Arrow.

4.8.4 Block manager rewrite

We’d like to replace pandas current internal data structures (a collection of 1 or 2-D arrays) with a simpler collection of 1-D arrays.

Pandas internal data model is quite complex. A DataFrame is made up of one or more 2-dimensional “blocks”, with one or more blocks per dtype. This collection of 2-D arrays is managed by the BlockManager.

The primary benefit of the BlockManager is improved performance on certain operations (construction from a 2D array, binary operations, reductions across the columns), especially for wide DataFrames. However, the BlockManager substantially increases the complexity and maintenance burden of pandas.

By replacing the BlockManager we hope to achieve

- Substantially simpler code
- Easier extensibility with new logical types
- Better user control over memory use and layout
- Improved micro-performance
- Option to provide a C / Cython API to pandas’ internals

See these design documents for more.
4.8.5 Decoupling of indexing and internals

The code for getting and setting values in pandas’ data structures needs refactoring. In particular, we must clearly separate code that converts keys (e.g., the argument to `DataFrame.loc`) to positions from code that uses these positions to get or set values. This is related to the proposed BlockManager rewrite. Currently, the BlockManager sometimes uses label-based, rather than position-based, indexing. We propose that it should only work with positional indexing, and the translation of keys to positions should be entirely done at a higher level.

Indexing is a complicated API with many subtleties. This refactor will require care and attention. More details are discussed at https://github.com/pandas-dev/pandas/wiki/(Tentative)-rules-for-restructuring-indexing-code

4.8.6 Numba-accelerated operations

Numba is a JIT compiler for Python code. We’d like to provide ways for users to apply their own Numba-jitted functions where pandas accepts user-defined functions (for example, `Series.apply()`, `DataFrame.apply()`, `DataFrame.applymap()`, and in groupby and window contexts). This will improve the performance of user-defined-functions in these operations by staying within compiled code.

4.8.7 Documentation improvements

We’d like to improve the content, structure, and presentation of the pandas documentation. Some specific goals include

- Overhaul the HTML theme with a modern, responsive design (GH15556)
- Improve the “Getting Started” documentation, designing and writing learning paths for users different back-grounds (e.g. brand new to programming, familiar with other languages like R, already familiar with Python).
- Improve the overall organization of the documentation and specific subsections of the documentation to make navigation and finding content easier.

4.8.8 Performance monitoring

pandas uses airspeed velocity to monitor for performance regressions. ASV itself is a fabulous tool, but requires some additional work to be integrated into an open source project’s workflow.

The asv-runner organization, currently made up of pandas maintainers, provides tools built on top of ASV. We have a physical machine for running a number of project’s benchmarks, and tools managing the benchmark runs and reporting on results.

We’d like to fund improvements and maintenance of these tools to

- Be more stable. Currently, they’re maintained on the nights and weekends when a maintainer has free time.
- Tune the system for benchmarks to improve stability, following https://pyperf.readthedocs.io/en/latest/system.html
- Build a GitHub bot to request ASV runs before a PR is merged. Currently, the benchmarks are only run nightly.
4.8.9 Roadmap evolution

pandas continues to evolve. The direction is primarily determined by community interest. Everyone is welcome to review existing items on the roadmap and to propose a new item.

Each item on the roadmap should be a short summary of a larger design proposal. The proposal should include

1. Short summary of the changes, which would be appropriate for inclusion in the roadmap if accepted.
2. Motivation for the changes.
3. An explanation of why the change is in scope for pandas.
4. Detailed design: Preferably with example-usage (even if not implemented yet) and API documentation
5. API Change: Any API changes that may result from the proposal.

That proposal may then be submitted as a GitHub issue, where the pandas maintainers can review and comment on the design. The pandas mailing list should be notified of the proposal.

When there’s agreement that an implementation would be welcome, the roadmap should be updated to include the summary and a link to the discussion issue.

4.9 Developer meetings

We hold regular developer meetings on the second Wednesday of each month at 18:00 UTC. These meetings and their minutes are open to the public. All are welcome to join.

4.9.1 Minutes

The minutes of past meetings are available in this Google Document.

4.9.2 Calendar

This calendar shows all the developer meetings.

You can subscribe to this calendar with the following links:

- iCal
- Google calendar

Additionally, we’ll sometimes have one-off meetings on specific topics. These will be published on the same calendar.
This is the list of changes to pandas between each release. For full details, see the commit logs. For install and upgrade instructions, see Installation.

5.1 Version 1.1

5.1.1 What’s new in 1.1.1 (August 20, 2020)

These are the changes in pandas 1.1.1. See Release notes for a full changelog including other versions of pandas.

Fixed regressions

- Fixed regression in CategoricalIndex.format() where, when stringified scalars had different lengths, the shorter string would be right-filled with spaces, so it had the same length as the longest string (GH35439)
- Fixed regression in Series.truncate() when trying to truncate a single-element series (GH35544)
- Fixed regression where DataFrame.to_numpy() would raise a RuntimeError for mixed dtypes when converting to str (GH35455)
- Fixed regression where read_csv() would raise a ValueError when pandas.options.mode.use_inf_as_na was set to True (GH35493)
- Fixed regression where pandas.testing.assert_series_equal() would raise an error when non-numeric dtypes were passed with check_exact=True (GH35446)
- Fixed regression in .groupby(...).rolling(…) where column selection was ignored (GH35486)
- Fixed regression where DataFrame.interpolate() would raise a TypeError when the DataFrame was empty (GH35598)
- Fixed regression in DataFrame.shift() with axis=1 and heterogeneous dtypes (GH35488)
- Fixed regression in DataFrame.diff() with read-only data (GH35559)
- Fixed regression in .groupby(...).rolling(…) where a segfault would occur with center=True and an odd number of values (GH35552)
- Fixed regression in DataFrame.apply() where functions that altered the input in-place only operated on a single row (GH35462)
- Fixed regression in DataFrame.reset_index() would raise a ValueError on empty DataFrame with a MultiIndex with a datetime64 dtype level (GH35606, GH35657)
pandas: powerful Python data analysis toolkit, Release 1.1.1

- Fixed regression where `pandas.merge_asof()` would raise a `UnboundLocalError` when `left_index`, `right_index` and `tolerance` were set (GH3558)
- Fixed regression in `.groupby(..).rolling(..)` where a custom `BaseIndexer` would be ignored (GH35557)
- Fixed regression in `DataFrame.replace()` and `Series.replace()` where compiled regular expressions would be ignored during replacement (GH35680)
- Fixed regression in `aggregate()` where a list of functions would produce the wrong results if at least one of the functions did not aggregate (GH35490)
- Fixed memory usage issue when instantiating large `pandas.arrays.StringArray` (GH35499)

**Bug fixes**

- Bug in `Styler` whereby `cell_ids` argument had no effect due to other recent changes (GH35588) (GH35663)
- Bug in `pandas.testing.assert_series_equal()` and `pandas.testing.assert_frame_equal()` where extension dtypes were not ignored when `check_dtypes` was set to `False` (GH35715)
- Bug in `to_timedelta()` fails when `arg` is a `Series` with `Int64` dtype containing null values (GH35574)
- Bug in `.groupby(..).rolling(..)` where passing `closed` with column selection would raise a `ValueError` (GH35549)
- Bug in `DataFrame` constructor failing to raise `ValueError` in some cases when `data` and `index` have mismatched lengths (GH33437)

**Contributors**

A total of 20 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Ali McMaster
- Daniel Saxton
- Eric Goddard +
- Fangchen Li
- Isaac Virshup
- Joris Van den Bossche
- Kevin Sheppard
- Matthew Roeschke
- MeeseeksMachine +
- Pandas Development Team
- Richard Shadrach
- Simon Hawkins
- Terji Petersen
- Tom Augspurger
5.1.2 What’s new in 1.1.0 (July 28, 2020)

These are the changes in pandas 1.1.0. See Release notes for a full changelog including other versions of pandas.

Enhancements

KeyErrors raised by loc specify missing labels

Previously, if labels were missing for a .loc call, a KeyError was raised stating that this was no longer supported. Now the error message also includes a list of the missing labels (max 10 items, display width 80 characters). See GH34272.

All dtypes can now be converted to StringDtype

Previously, declaring or converting to StringDtype was in general only possible if the data was already only str or nan-like (GH31204). StringDtype now works in all situations where astype(str) or dtype=str work:

For example, the below now works:

```python
In [1]: ser = pd.Series([1, "abc", np.nan], dtype="string")
In [2]: ser
Out[2]:
0 1
1 abc
2 <NA>
Length: 3, dtype: string
In [3]: ser[0]
Out[3]: '1'
In [4]: pd.Series([1, 2, np.nan], dtype="Int64").astype("string")
Out[4]:
0 1
1 2
2 <NA>
Length: 3, dtype: string
```
Non-monotonic PeriodIndex Partial String Slicing

`PeriodIndex` now supports partial string slicing for non-monotonic indexes, mirroring `DatetimeIndex` behavior (GH31096)

For example:

```python
In [5]: dti = pd.date_range("2014-01-01", periods=30, freq="30D")
In [6]: pi = dti.to_period("D")
In [7]: ser_monotonic = pd.Series(np.arange(30), index=pi)
In [8]: shuffler = list(range(0, 30, 2)) + list(range(1, 31, 2))
In [9]: ser = ser_monotonic[shuffler]

In [10]: ser
Out[10]:
2014-01-01 0
2014-03-02 2
2014-05-01 4
2014-06-30 6
2014-08-29 8
...  
2015-09-23 21
2015-11-22 23
2016-01-21 25
2016-03-21 27
2016-05-20 29
Freq: D, Length: 30, dtype: int64

In [11]: ser["2014"]
Out[11]:
2014-01-01 0
2014-03-02 2
2014-05-01 4
2014-06-30 6
2014-08-29 8
2014-10-28 10
2014-12-27 12
2014-01-31 1
2014-04-01 3
2014-05-31 5
2014-07-30 7
2014-09-28 9
2014-11-27 11
Freq: D, Length: 13, dtype: int64

In [12]: ser.loc["May 2015"]
Out[12]:
2015-05-26 17
Freq: D, Length: 1, dtype: int64
```
Comparing two DataFrame or two Series and summarizing the differences

We’ve added DataFrame.compare() and Series.compare() for comparing two DataFrame or two Series (GH30429)

```python
In [13]: df = pd.DataFrame(
      ....:     {
      ....:         "col1": ["a", "a", "b", "b", "a"],
      ....:         "col2": [1.0, 2.0, 3.0, np.nan, 5.0],
      ....:         "col3": [1.0, 2.0, 3.0, 4.0, 5.0]
      ....:     },
      ....:     columns=["col1", "col2", "col3"],
      ....: )

In [14]: df
Out[14]:
   col1 col2 col3
0    a    1.0    1.0
1    a    2.0    2.0
2    b    3.0    3.0
3    b   NaN    4.0
4    a    5.0    5.0
5 rows x 3 columns

In [15]: df2 = df.copy()

In [16]: df2.loc[0, 'col1'] = 'c'

In [17]: df2.loc[2, 'col3'] = 4.0

In [18]: df2
Out[18]:
   col1 col2 col3
0    c    1.0    1.0
1    a    2.0    2.0
2    b    3.0    4.0
3    b   NaN    4.0
4    a    5.0    5.0
5 rows x 3 columns

In [19]: df.compare(df2)
Out[19]:
       col1       col3
self          other       self       other
0    a         c    NaN       NaN
2  NaN        NaN      3.0       4.0

[2 rows x 4 columns]
```

See User Guide for more details.
Allow NA in groupby key

With `groupby`, we’ve added a `dropna` keyword to `DataFrame.groupby()` and `Series.groupby()` in order to allow NA values in group keys. Users can define `dropna` to `False` if they want to include NA values in groupby keys. The default is set to `True` for `dropna` to keep backwards compatibility (GH3729).

```python
In [20]: df_list = [[1, 2, 3], [1, None, 4], [2, 1, 3], [1, 2, 2]]
In [21]: df_dropna = pd.DataFrame(df_list, columns=['a', 'b', 'c'])
In [22]: df_dropna
Out[22]:
        a  b  c
0      1  2.0 3
1      1  NaN 4
2      2  1.0 3
3      1  2.0 2
[4 rows x 3 columns]
```

# Default `dropna` is set to True, which will exclude NaNs in keys
```python
In [23]: df_dropna.groupby(by=['b'], dropna=True).sum()
Out[23]:
        a  c
   b   
1.0  2  3
2.0  2  5
```

# In order to allow NaN in keys, set `dropna` to False
```python
In [24]: df_dropna.groupby(by=['b'], dropna=False).sum()
Out[24]:
        a  c
   b   
1.0  2  3
2.0  2  5
NaN  1  4
```

The default setting of `dropna` argument is `True` which means NA are not included in group keys.

Sorting with keys

We’ve added a `key` argument to the `DataFrame` and `Series` sorting methods, including `DataFrame.sort_values()`, `DataFrame.sort_index()`, `Series.sort_values()`, and `Series.sort_index()`. The key can be any callable function which is applied column-by-column to each column used for sorting, before sorting is performed (GH27237). See `sort_values with keys` and `sort_index with keys` for more information.

```python
In [25]: s = pd.Series(['C', 'a', 'B'])
In [26]: s
Out[26]:
```

(continues on next page)
Note how this is sorted with capital letters first. If we apply the `Series.str.lower()` method, we get

```python
In [28]: s.sort_values(key=lambda x: x.str.lower())
Out[28]:
  0 C
  1 a
  2 B
Length: 3, dtype: object
```

When applied to a `DataFrame`, they key is applied per-column to all columns or a subset if `by` is specified, e.g.

```python
In [29]: df = pd.DataFrame({'a': ['C', 'C', 'a', 'a', 'B', 'B'],
                       'b': [1, 2, 3, 4, 5, 6]})
In [30]: df.sort_values(by=['a'], key=lambda col: col.str.lower())
Out[30]:
     a  b
  2  a  3
  3  a  4
  4  B  5
  5  B  6
  0  C  1
  1  C  2
[6 rows x 2 columns]
```

For more details, see examples and documentation in `DataFrame.sort_values()`, `Series.sort_values()`, and `sort_index()`. 
Fold argument support in Timestamp constructor

Timestamp: now supports the keyword-only fold argument according to PEP 495 similar to parent `datetime.datetime` class. It supports both accepting fold as an initialization argument and inferring fold from other constructor arguments (GH25057, GH31338). Support is limited to `dateutil` timezones as `pytz` doesn’t support fold.

For example:

```
In [32]: ts = pd.Timestamp("2019-10-27 01:30:00+00:00")
In [33]: ts.fold
Out[33]: 0
```

```
In [34]: ts = pd.Timestamp(year=2019, month=10, day=27, hour=1, minute=30, ...
   ....:   tz="dateutil/Europe/London", fold=1)
   ....:
In [35]: ts
Out[35]: Timestamp('2019-10-27 01:30:00+0000', tz='dateutil//usr/share/zoneinfo/
   →Europe/London')
```

For more on working with fold, see Fold subsection in the user guide.

Parsing timezone-aware format with different timezones in to_datetime

`to_datetime()` now supports parsing formats containing timezone names (%Z) and UTC offsets (%z) from different timezones then converting them to UTC by setting `utc=True`. This would return a `DatetimeIndex` with timezone at UTC as opposed to an `Index` with object dtype if `utc=True` is not set (GH32792).

For example:

```
In [36]: tz_strs = ["2010-01-01 12:00:00 +0100", "2010-01-01 12:00:00 -0100",
   ....:   "2010-01-01 12:00:00 +0300", "2010-01-01 12:00:00 +0400"]
   ....:
In [37]: pd.to_datetime(tz_strs, format='%Y-%m-%d %H:%M:%S %z', utc=True)
Out[37]:
DatetimeIndex(['2010-01-01 11:00:00+00:00', '2010-01-01 13:00:00+00:00',
   '2010-01-01 09:00:00+00:00', '2010-01-01 08:00:00+00:00'],
   dtype='datetime64[ns, UTC]', freq=None)
```

```
In [38]: pd.to_datetime(tz_strs, format='%Y-%m-%d %H:%M:%S %z')
Out[38]:
Index(['2010-01-01 12:00:00+01:00', '2010-01-01 12:00:00+01:00',
   '2010-01-01 12:00:00+03:00', '2010-01-01 12:00:00+04:00'],
   dtype='object')
```
Grouper and resample now supports the arguments origin and offset

Grouper and DataFrame.resample() now supports the arguments origin and offset. It let the user control the timestamp on which to adjust the grouping. (GH31809)

The bins of the grouping are adjusted based on the beginning of the day of the time series starting point. This works well with frequencies that are multiples of a day (like 30D) or that divides a day (like 90s or 1min). But it can create inconsistencies with some frequencies that do not meet this criteria. To change this behavior you can now specify a fixed timestamp with the argument origin.

Two arguments are now deprecated (more information in the documentation of DataFrame.resample()):

- base should be replaced by offset.
- loffset should be replaced by directly adding an offset to the index DataFrame after being resampled.

Small example of the use of origin:

In [39]: start, end = '2000-10-01 23:30:00', '2000-10-02 00:30:00'
In [40]: middle = '2000-10-02 00:00:00'
In [41]: rng = pd.date_range(start, end, freq='7min')
In [42]: ts = pd.Series(np.arange(len(rng)) * 3, index=rng)
In [43]: ts
Out[43]:
2000-10-01 23:30:00    0
2000-10-01 23:37:00    3
2000-10-01 23:44:00    6
2000-10-01 23:51:00    9
2000-10-01 23:58:00   12
2000-10-02 00:05:00   15
2000-10-02 00:12:00   18
2000-10-02 00:19:00   21
2000-10-02 00:26:00   24
Freq: 7T, Length: 9, dtype: int64

Resample with the default behavior 'start_day' (origin is 2000-10-01 00:00:00):

In [44]: ts.resample('17min').sum()
Out[44]:
2000-10-01 23:14:00    0
2000-10-01 23:31:00    9
2000-10-01 23:48:00   21
2000-10-02 00:05:00   54
2000-10-02 00:22:00   24
Freq: 17T, Length: 5, dtype: int64

In [45]: ts.resample('17min', origin='start_day').sum()
Out[45]:
2000-10-01 23:14:00    0
2000-10-01 23:31:00    9
2000-10-01 23:48:00   21
2000-10-02 00:05:00   54
2000-10-02 00:22:00   24
Freq: 17T, Length: 5, dtype: int64

Resample using a fixed origin:
In [46]: ts.resample('17min', origin='epoch').sum()
Out[46]:
2000-10-01 23:18:00 0
2000-10-01 23:35:00 18
2000-10-01 23:52:00 27
2000-10-02 00:09:00 39
2000-10-02 00:26:00 24
Freq: 17T, Length: 5, dtype: int64

In [47]: ts.resample('17min', origin='2000-01-01').sum()
Out[47]:
2000-10-01 23:24:00 3
2000-10-01 23:41:00 15
2000-10-01 23:58:00 45
2000-10-02 00:15:00 45
Freq: 17T, Length: 4, dtype: int64

If needed you can adjust the bins with the argument offset (a `Timedelta`) that would be added to the default origin.

For a full example, see: Use origin or offset to adjust the start of the bins.

**fsspec now used for filesystem handling**

For reading and writing to filesystems other than local and reading from HTTP(S), the optional dependency `fsspec` will be used to dispatch operations (GH33452). This will give unchanged functionality for S3 and GCS storage, which were already supported, but also add support for several other storage implementations such as Azure Datalake and Blob, SSH, FTP, dropbox and github. For docs and capabilities, see the `fsspec` docs.

The existing capability to interface with S3 and GCS will be unaffected by this change, as `fsspec` will still bring in the same packages as before.

**Other enhancements**

- Compatibility with matplotlib 3.3.0 (GH34850)
- `IntegerArray.astype()` now supports `datetime64` dtype (GH32538)
- `IntegerArray` now implements the `sum` operation (GH33172)
- Added `pandas.errors.InvalidIndexError` (GH34570).
- Added `DataFrame.value_counts()` (GH5377)
- Added a `pandas.api.indexers.FixedForwardWindowIndexer()` class to support forward-looking windows during rolling operations.
- Added a `pandas.api.indexers.VariableOffsetWindowIndexer()` class to support rolling operations with non-fixed offsets (GH34994)
- `describe()` now includes a `datetime_is_numeric` keyword to control how datetime columns are summarized (GH30164, GH34798)
- `Styler` may now render CSS more efficiently where multiple cells have the same styling (GH30876)
- `highlight_null()` now accepts `subset` argument (GH31345)
- When writing directly to a sqlite connection `DataFrame.to_sql()` now supports the `multi` method (GH29921)
- pandas.errors.OptionError is now exposed in pandas.errors (GH27553)
- Added api.extensions.ExtensionArray.argmax() and api.extensions.ExtensionArray.argmin() (GH24382)
- timedelta_range() will now infer a frequency when passed start,stop, and periods (GH32377)
- Positional slicing on a IntervalIndex now supports slices with step > 1 (GH31658)
- Series.str now has a fullmatch method that matches a regular expression against the entire string in each row of the Series, similar to re.fullmatch (GH32806).
- DataFrame.sample() will now also allow array-like and BitGenerator objects to be passed to random_state as seeds (GH32503)
- Index.union() will now raise RunTimeWarning for MultiIndex objects if the object inside are un-sortable. Pass sort=False to suppress this warning (GH33015)
- Added Series.dt.isocalendar() and DatetimeIndex.isocalendar() that returns a DataFrame with year, week, and day calculated according to the ISO 8601 calendar (GH33206, GH34392).
- The DataFrame.to_feather() method now supports additional keyword arguments (e.g. to set the compression) that are added in pyarrow 0.17 (GH33422).
- The cut() will now accept parameter ordered with default ordered=True. If ordered=False and no labels are provided, an error will be raised (GH33141)
- DataFrame.to_csv(), DataFrame.to_pickle(), and DataFrame.to_json() now support passing a dict of compression arguments when using the gzip and bz2 protocols. This can be used to set a custom compression level, e.g., df.to_csv(path, compression={'method': 'gzip', 'compresslevel': 1}) (GH33196)
- melt() has gained an ignore_index (default True) argument that, if set to False, prevents the method from dropping the index (GH14440).
- Series.update() now accepts objects that can be coerced to a Series, such as dict and list, mirroring the behavior of DataFrame.update() (GH33215)
- transform() and aggregate() have gained engine and engine_kwags arguments that support executing functions with Numba (GH32854, GH33388)
- interpolate() now supports SciPy interpolation method scipy.interpolate.CubicSpline as method cubicspline (GH33670)
- DataFrameGroupBy and SeriesGroupBy now implement the sample method for doing random sampling within groups (GH31775)
- DataFrame.to_numpy() now supports the na_value keyword to control the NA sentinel in the output array (GH33820)
- Added api.extension.ExtensionArray.equals to the extension array interface, similar to Series.equals() (GH27081)
- The minimum supported dtypes version has increased to 105 in read_stata() and StataReader (GH26667).
- to_stata() supports compression using the compression keyword argument. Compression can either be inferred or explicitly set using a string or a dictionary containing both the method and any additional arguments that are passed to the compression library. Compression was also added to the low-level Stata-file writers StataWriter, StataWriter117, and StataWriterUTF8 (GH26599).
- HDFStore.put() now accepts a track_times parameter. This parameter is passed to the create_table method of PyTables (GH32682).
• Series.plot() and DataFrame.plot() now accepts xlabel and ylabel parameters to present labels on x and y axis (GH9093).
• Made pandas.core.window.rolling.Rolling and pandas.core.window.expanding. Expanding iterable(GH11704)
• Made option_context a contextlib.ContextDecorator, which allows it to be used as a decorator over an entire function (GH34253).
• DataFrame.to_csv() and Series.to_csv() now accept an errors argument (GH22610)
• transform() now allows func to be pad, backfill and cumcount (GH31260).
• read_json() now accepts an nrows parameter. (GH33916).
• DataFrame.hist(), Series.hist(), core.groupby.DataFrameGroupBy.hist(), and core.groupby.SeriesGroupBy.hist() have gained the legend argument. Set to True to show a legend in the histogram. (GH6279)
• concat() and append() now preserve extension dtypes, for example combining a nullable integer column with a numpy integer column will no longer result in object dtype but preserve the integer dtype (GH33607, GH34339, GH34095).
• read_gbq() now allows to disable progress bar (GH33360).
• read_gbq() now supports the max_results kwarg from pandas-gbq (GH34639).
• DataFrame.cov() and Series.cov() now support a new parameter ddof to support delta degrees of freedom as in the corresponding numpy methods (GH34611).
• DataFrame.to_html() and DataFrame.to_string()'s col_space parameter now accepts a list or dict to change only some specific columns’ width (GH28917).
• DataFrame.to_excel() can now also write OpenOffice spreadsheet (.ods) files (GH27222)
• explode() now accepts ignore_index to reset the index, similar to pd.concat() or DataFrame.sort_values() (GH34932).
• DataFrame.to_markdown() and Series.to_markdown() now accept index argument as an alias for tabulate’s showindex (GH32667)
• read_csv() now accepts string values like “0”, “0.0”, “1”, “1.0” as convertible to the nullable Boolean dtype (GH34859)
• pandas.core.window.ExponentialMovingWindow now supports a times argument that allows mean to be calculated with observations spaced by the timestamps in times (GH34839)
• DataFrame.agg() and Series.agg() now accept named aggregation for renaming the output columns/indexes. (GH26513)
• compute.use_numba now exists as a configuration option that utilizes the numba engine when available (GH33966, GH35374)
• Series.plot() now supports asymmetric error bars. Previously, if Series.plot() received a “2xN” array with error values for yerr and/or xerr, the left/lower values (first row) were mirrored, while the right/upper values (second row) were ignored. Now, the first row represents the left/lower error values and the second row the right/upper error values. (GH9536)
Notable bug fixes

These are bug fixes that might have notable behavior changes.

**MultiIndex.get_indexer interprets method argument correctly**

This restores the behavior of `MultiIndex.get_indexer()` with `method='backfill'` or `method='pad'` to the behavior before pandas 0.23.0. In particular, MultiIndexes are treated as a list of tuples and padding or backfilling is done with respect to the ordering of these lists of tuples (GH29896).

As an example of this, given:

```python
In [48]: df = pd.DataFrame({
    ....:     'a': [0, 0, 0, 0],
    ....:     'b': [0, 2, 3, 4],
    ....:     'c': ['A', 'B', 'C', 'D'],
    ....:}).set_index(['a', 'b'])
    ....:
In [49]: mi_2 = pd.MultiIndex.from_product([[0], [-1, 0, 1, 3, 4, 5]])
```

The differences in reindexing `df` with `mi_2` and using `method='backfill'` can be seen here:

- For pandas `>= 0.23, < 1.1.0`:
  ```python
  In [1]: df.reindex(mi_2, method='backfill')
  Out[1]:
  c
  0  -1  A
  0     A
  1     D
  3     A
  4     A
  5     C
  [6 rows x 1 columns]
  ```

- For pandas `<0.23, >= 1.1.0`:
  ```python
  In [50]: df.reindex(mi_2, method='backfill')
  Out[50]:
  c
  0  -1  A
  0     A
  1     B
  3     C
  4     D
  5     NaN
  [6 rows x 1 columns]
  ```

And the differences in reindexing `df` with `mi_2` and using `method='pad'` can be seen here:

- For pandas `>= 0.23, < 1.1.0`:
  ```python
  In [1]: df.reindex(mi_2, method='pad')
  Out[1]:
  c
  0  -1  NaN
  ```

(continues on next page)
pandas: powerful Python data analysis toolkit, Release 1.1.1

<table>
<thead>
<tr>
<th></th>
<th>NaN</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>NaN</td>
<td>1</td>
<td>D</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>NaN</td>
<td>4</td>
<td>A</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>C</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

pandas < 0.23, >= 1.1.0

```
In [51]: df.reindex(mi_2, method='pad')
Out[51]:
        c
0  -1  NaN
0   A
1   A
3   C
4   D
5   D
[6 rows x 1 columns]
```

Failed Label-Based Lookups Always Raise KeyError

Label lookups `series[key], series.loc[key]` and `frame.loc[key]` used to raise either `KeyError` or `TypeError` depending on the type of key and type of `Index`. These now consistently raise `KeyError (GH31867)`.

```
In [52]: ser1 = pd.Series(range(3), index=[0, 1, 2])
In [53]: ser2 = pd.Series(range(3), index=pd.date_range("2020-02-01", periods=3))

Previous behavior:
```
```
In [3]: ser1[1.5]
...  
TypeError: cannot do label indexing on Int64Index with these indexers [1.5] of type float

In [4] ser1["foo"]
...
KeyError: 'foo'

In [5]: ser1.loc[1.5]
...  
TypeError: cannot do label indexing on Int64Index with these indexers [1.5] of type float

In [6]: ser1.loc["foo"]
...  
KeyError: 'foo'

In [7]: ser2.loc[1]
...  
TypeError: cannot do label indexing on DatetimeIndex with these indexers [1] of type int

In [8]: ser2.loc[pd.Timestamp(0)]
```

(continues on next page)
...  
KeyError: Timestamp('1970-01-01 00:00:00')  

New behavior:

```
In [3]: ser1[1.5]  
...  
KeyError: 1.5  
In [4] ser1['foo']  
...  
KeyError: 'foo'  
In [5]: ser1.loc[1.5]  
...  
KeyError: 1.5  
In [6]: ser1.loc['foo']  
...  
KeyError: 'foo'  
In [7]: ser2.loc[1]  
...  
KeyError: 1  
In [8]: ser2.loc[pd.Timestamp(0)]  
...  
KeyError: Timestamp('1970-01-01 00:00:00')
```

Similarly, `DataFrame.at()` and `Series.at()` will raise a `TypeError` instead of a `ValueError` if an incompatible key is passed, and `KeyError` if a missing key is passed, matching the behavior of `.loc[]` (GH31722)

**Failed Integer Lookups on MultiIndex Raise KeyError**

Indexing with integers with a `MultiIndex` that has an integer-dtype first level incorrectly failed to raise `KeyError` when one or more of those integer keys is not present in the first level of the index (GH33539)

```
In [54]: idx = pd.Index(range(4))  
In [55]: dti = pd.date_range("2000-01-03", periods=3)  
In [56]: mi = pd.MultiIndex.from_product([idx, dti])  
In [57]: ser = pd.Series(range(len(mi)), index=mi)
```

Previous behavior:

```
In [5]: ser[[5]]  
Out[5]: Series([], dtype: int64)
```

New behavior:

```
In [5]: ser[[5]]  
...  
KeyError: '[5] not in index'
```
DataFrame.merge() preserves right frame’s row order

`DataFrame.merge()` now preserves the right frame’s row order when executing a right merge (GH27453)

In [58]: left_df = pd.DataFrame({'animal': ['dog', 'pig'],  
                         'max_speed': [40, 11]})

In [59]: right_df = pd.DataFrame({'animal': ['quetzal', 'pig'],  
                            'max_speed': [80, 11]})

In [60]: left_df
Out[60]:
         animal  max_speed
0       dog        40
1       pig        11

[2 rows x 2 columns]

In [61]: right_df
Out[61]:
         animal  max_speed
0     quetzal        80
1       pig        11

[2 rows x 2 columns]

Previous behavior:

`>> left_df.merge(right_df, on=['animal', 'max_speed'], how="right")`

<table>
<thead>
<tr>
<th>animal</th>
<th>max_speed</th>
</tr>
</thead>
<tbody>
<tr>
<td>pig</td>
<td>11</td>
</tr>
<tr>
<td>quetzal</td>
<td>80</td>
</tr>
</tbody>
</table>

New behavior:

In [62]: left_df.merge(right_df, on=['animal', 'max_speed'], how="right")
Out[62]:
         animal  max_speed
0     quetzal        80
1       pig        11

[2 rows x 2 columns]

Assignment to multiple columns of a DataFrame when some columns do not exist

Assignment to multiple columns of a `DataFrame` when some of the columns do not exist would previously assign the values to the last column. Now, new columns will be constructed with the right values. (GH13658)

In [63]: df = pd.DataFrame({'a': [0, 1, 2], 'b': [3, 4, 5]})

In [64]: df
Out[64]:
     a  b
0   0  3
1   1  4
2   2  5

(continues on next page)
Previous behavior:

```python
In [3]: df[['a', 'c']] = 1
In [4]: df
Out[4]:
   a  b
  0 1 1
  1 1 1
  2 1 1
[3 rows x 2 columns]
```

New behavior:

```python
In [65]: df[['a', 'c']] = 1
In [66]: df
Out[66]:
   a  b  c
  0 1 3 1
  1 1 4 1
  2 1 5 1
[3 rows x 3 columns]
```

Consistency across groupby reductions

Using `DataFrame.groupby()` with `as_index=True` and the aggregation `nunique` would include the grouping column(s) in the columns of the result. Now the grouping column(s) only appear in the index, consistent with other reductions. (GH32579)

```python
In [67]: df = pd.DataFrame({"a": ["x", "x", "y", "y"], "b": [1, 1, 2, 3]})
In [68]: df.groupby("a", as_index=True).nunique()
Out[68]:
   a  b
  0 1 1
  1 1 2
  2 1 3
[4 rows x 2 columns]
```

Previous behavior:

```python
In [3]: df.groupby("a", as_index=True).nunique()
Out[4]:
   a  b
  a
  x 1 1
  y 1 2
```
New behavior:

```python
In [69]: df.groupby("a", as_index=True).nunique()
Out[69]:
   b
  a
 x 1
 y 2
[2 rows x 1 columns]
```

Using `DataFrame.groupby()` with `as_index=False` and the function `idxmax, idxmin, mad, nunique, sem, skew, or std` would modify the grouping column. Now the grouping column remains unchanged, consistent with other reductions. (GH21090, GH10355)

Previous behavior:

```python
In [3]: df.groupby("a", as_index=False).nunique()
Out[4]:
   a  b
  0 1 1
 1 1 2
```

New behavior:

```python
In [70]: df.groupby("a", as_index=False).nunique()
Out[70]:
   a  b
  0 x 1
 1 y 2
[2 rows x 2 columns]
```

The method `size()` would previously ignore `as_index=False`. Now the grouping columns are returned as columns, making the result a `DataFrame` instead of a `Series`. (GH32599)

Previous behavior:

```python
In [3]: df.groupby("a", as_index=False).size()
Out[4]:
   a
  x  2
  y  2
dtype: int64
```

New behavior:

```python
In [71]: df.groupby("a", as_index=False).size()
Out[71]:
   a  size
  0 x  2
 1 y  2
[2 rows x 2 columns]
```
**agg() lost results with as_index=False when relabeling columns**

Previously `agg()` lost the result columns, when the `as_index` option was set to `False` and the result columns were relabeled. In this case the result values were replaced with the previous index (GH32240).

```python
In [72]: df = pd.DataFrame({
    "key": ["x", "y", "z", "x", "y", "z"],
    "val": [1.0, 0.8, 2.0, 3.0, 3.6, 0.75]})

In [73]: df
Out[73]:
   key  val
  0   x  1.00
  1   y  0.80
  2   z  2.00
  3   x  3.00
  4   y  3.60
  5   z  0.75

Previous behavior:

```python
In [2]: grouped = df.groupby("key", as_index=False)
In [3]: result = grouped.agg(min_val=pd.NamedAgg(column="val", aggfunc="min"))
In [4]: result
Out[4]:
   min_val
  0   x
  1   y
  2   z
```

New behavior:

```python
In [74]: grouped = df.groupby("key", as_index=False)
In [75]: result = grouped.agg(min_val=pd.NamedAgg(column="val", aggfunc="min"))
In [76]: result
Out[76]:
   key  min_val
  0   x    1.00
  1   y    0.80
  2   z    0.75
```

[3 rows x 2 columns]
apply and applymap on DataFrame evaluates first row/column only once

```
In [77]: df = pd.DataFrame({'a': [1, 2], 'b': [3, 6]})

In [78]: def func(row):
    ....:     print(row)
    ....:     return row
    ....:

Previous behavior:

```
In [4]: df.apply(func, axis=1)
   a    1
   b    3
Name: 0, dtype: int64
   a    1
   b    3
Name: 0, dtype: int64
   a    2
   b    6
Name: 1, dtype: int64
Out[4]:
   a  b
  0 1 3
  1 2 6

New behavior:

```
In [79]: df.apply(func, axis=1)
   a    1
   b    3
Name: 0, Length: 2, dtype: int64
   a    2
   b    6
Name: 1, Length: 2, dtype: int64
Out[79]:
   a  b
  0 1 3
  1 2 6
[2 rows x 2 columns]

Increased minimum versions for dependencies

Some minimum supported versions of dependencies were updated (GH33718, GH29766, GH29723, pytables >= 3.4.3). If installed, we now require:

<table>
<thead>
<tr>
<th>Package</th>
<th>Minimum Version</th>
<th>Required</th>
<th>Changed</th>
</tr>
</thead>
<tbody>
<tr>
<td>numpy</td>
<td>1.15.4</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>pytz</td>
<td>2015.4</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>python-dateutil</td>
<td>2.7.3</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>bottleneck</td>
<td>1.2.1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>numexpr</td>
<td>2.6.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>pytest (dev)</td>
<td>4.0.2</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
For **optional libraries** the general recommendation is to use the latest version. The following table lists the lowest version per library that is currently being tested throughout the development of pandas. Optional libraries below the lowest tested version may still work, but are not considered supported.

<table>
<thead>
<tr>
<th>Package</th>
<th>Minimum Version</th>
<th>Changed</th>
</tr>
</thead>
<tbody>
<tr>
<td>beautifulsoup4</td>
<td>4.6.0</td>
<td></td>
</tr>
<tr>
<td>fastparquet</td>
<td>0.3.2</td>
<td></td>
</tr>
<tr>
<td>fsspec</td>
<td>0.7.4</td>
<td></td>
</tr>
<tr>
<td>gcsfs</td>
<td>0.6.0</td>
<td>X</td>
</tr>
<tr>
<td>lxml</td>
<td>3.8.0</td>
<td></td>
</tr>
<tr>
<td>matplotlib</td>
<td>2.2.2</td>
<td></td>
</tr>
<tr>
<td>numba</td>
<td>0.46.0</td>
<td></td>
</tr>
<tr>
<td>openpyxl</td>
<td>2.5.7</td>
<td></td>
</tr>
<tr>
<td>pymysql</td>
<td>0.13.0</td>
<td></td>
</tr>
<tr>
<td>pyarrow</td>
<td>0.7.1</td>
<td></td>
</tr>
<tr>
<td>pytables</td>
<td>3.4.3</td>
<td>X</td>
</tr>
<tr>
<td>pymysql</td>
<td>0.4.0</td>
<td>X</td>
</tr>
<tr>
<td>scipy</td>
<td>1.2.0</td>
<td>X</td>
</tr>
<tr>
<td>sqlalchemy</td>
<td>1.1.4</td>
<td></td>
</tr>
<tr>
<td>xarray</td>
<td>0.8.2</td>
<td></td>
</tr>
<tr>
<td>xlrd</td>
<td>1.1.0</td>
<td></td>
</tr>
<tr>
<td>xlsxwriter</td>
<td>0.9.8</td>
<td></td>
</tr>
<tr>
<td>xlwt</td>
<td>1.2.0</td>
<td></td>
</tr>
<tr>
<td>pandas-gbq</td>
<td>1.2.0</td>
<td>X</td>
</tr>
</tbody>
</table>

See *Dependencies* and *Optional dependencies* for more.

**Development Changes**

- The minimum version of Cython is now the most recent bug-fix version (0.29.16) (GH33334).

**Deprecations**

- Lookups on a *Series* with a single-item list containing a slice (e.g. `ser[[slice(0, 4)]]`) are deprecated and will raise in a future version. Either convert the list to a tuple, or pass the slice directly instead (GH31333).

- `DataFrame.mean()` and `DataFrame.median()` with `numeric_only=None` will include `datetime64` and `datetime64[ tz]` columns in a future version (GH29941).

- Setting values with `.loc` using a positional slice is deprecated and will raise in a future version. Use `.loc` with labels or `.iloc` with positions instead (GH31840).

- `DataFrame.to_dict()` has deprecated accepting short names for `orient` and will raise in a future version (GH32515).

- `Categorical.to_dense()` is deprecated and will be removed in a future version, use `np.asarray(cat)` instead (GH32639).

- The fastpath keyword in the `SingleBlockManager` constructor is deprecated and will be removed in a future version (GH33092).

- Providing suffixes as a set in `pandas.merge()` is deprecated. Provide a tuple instead (GH33740, GH34741).
• Indexing a `Series` with a multi-dimensional indexer like `[:, None]` to return an ndarray now raises a `FutureWarning`. Convert to a NumPy array before indexing instead (GH27837)

• `Index.is_mixed()` is deprecated and will be removed in a future version, check `index.inferred_type` directly instead (GH32922)

• Passing any arguments but the first one to `read_html()` as positional arguments is deprecated. All other arguments should be given as keyword arguments (GH27573).

• Passing any arguments but `path_or_buf` (the first one) to `read_json()` as positional arguments is deprecated. All other arguments should be given as keyword arguments (GH27573).

• Passing any arguments but the first two to `read_excel()` as positional arguments is deprecated. All other arguments should be given as keyword arguments (GH27573).

• `pandas.api.types.is_categorical()` is deprecated and will be removed in a future version; use `pandas.api.types.is_categorical_dtype()` instead (GH33385)

• `Index.get_value()` is deprecated and will be removed in a future version (GH19728)

• `Series.dt.week()` and `Series.dt.weekofyear()` are deprecated and will be removed in a future version, use `Series.dt.isocalendar().week()` instead (GH33595)

• `DatetimeIndex.week()` and `DatetimeIndex.weekofyear` are deprecated and will be removed in a future version, use `DatetimeIndex.isocalendar().week` instead (GH33595)

• `DateOffset.__call__()` is deprecated and will be removed in a future version, use `offset + other` instead (GH34171)

• `apply_index()` is deprecated and will be removed in a future version. Use `offset + other` instead (GH34580)

• `DataFrame.tshift()` and `Series.tshift()` are deprecated and will be removed in a future version, use `DataFrame.shift()` and `Series.shift()` instead (GH11631)

• Indexing an `Index` object with a float key is deprecated, and will raise an `IndexError` in the future. You can manually convert to an integer key instead (GH34191).

• The `squeeze` keyword in `groupby()` is deprecated and will be removed in a future version (GH32380)

• The `tz` keyword in `Period.to_timestamp()` is deprecated and will be removed in a future version; use `per.to_timestamp(...).tz_localize(tz)` instead (GH34522)

• `DatetimeIndex.to_perioddelta()` is deprecated and will be removed in a future version. Use `index - index.to_period(freq).to_timestamp()` instead (GH34853)

• `DataFrame.melt()` accepting a `value_name` that already exists is deprecated, and will be removed in a future version (GH34731)

• The `center` keyword in the `DataFrame.expanding()` function is deprecated and will be removed in a future version (GH20647)
Performance improvements

- Performance improvement in `Timedelta` constructor (GH30543)
- Performance improvement in `Timestamp` constructor (GH30543)
- Performance improvement in flex arithmetic ops between `DataFrame` and `Series` with `axis=0` (GH31296)
- Performance improvement in arithmetic ops between `DataFrame` and `Series` with `axis=1` (GH33600)
- The internal index method `_shallow_copy()` now copies cached attributes over to the new index, avoiding creating these again on the new index. This can speed up many operations that depend on creating copies of existing indexes (GH28584, GH32640, GH32669)
- Significant performance improvement when creating a `DataFrame` with sparse values from `scipy.sparse` matrices using the `DataFrame.sparse.from_spmatrix()` constructor (GH32821, GH32825, GH32826, GH32856, GH32858).
- Performance improvement for groupby methods `first()` and `last()` (GH34178)
- Performance improvement in `factorize()` for nullable (integer and Boolean) dtypes (GH33064).
- Performance improvement when constructing `Categorical` objects (GH33921)
- Fixed performance regression in `pandas.qcut()` and `pandas.cut()` (GH33921)
- Performance improvement in reductions (sum, prod, min, max) for nullable (integer and Boolean) dtypes (GH30982, GH33261, GH33442).
- Performance improvement in arithmetic operations between two `DataFrame` objects (GH32779)
- Performance improvement in `pandas.core.groupby.RollingGroupby` (GH34052)
- Performance improvement in arithmetic operations (sub, add, mul, div) for `MultiIndex` (GH34297)
- Performance improvement in `DataFrame[bool_indexer]` when `bool_indexer` is a list (GH33924)
- Significant performance improvement of `io.formats.style.Styler.render()` with styles added with various ways such as `io.formats.style.Styler.apply()`, `io.formats.style.Styler.applymap()` or `io.formats.style.Styler.bar()` (GH19917)

Bug fixes

Categorical

- Passing an invalid `fill_value` to `Categorical.take()` raises a `ValueError` instead of `TypeError` (GH33660)
- Combining a `Categorical` with integer categories and which contains missing values with a float dtype column in operations such as `concat()` or `append()` will now result in a float column instead of an object dtype column (GH33607)
- Bug where `merge()` was unable to join on non-unique categorical indices (GH28189)
- Bug when passing categorical data to `Index` constructor along with `dtype=object` incorrectly returning a `CategoricalIndex` instead of object-dtype `Index` (GH32167)
- Bug where `Categorical` comparison operator `__ne__` would incorrectly evaluate to `False` when either element was missing (GH32276)
- `Categorical.fillna()` now accepts `Categorical` other argument (GH32420)
- Repr of `Categorical` was not distinguishing between `int` and `str` (GH33676)
Datetimelike

- Passing an integer dtype other than `int64` to `np.array(period_index, dtype=...)` will now raise `TypeError` instead of incorrectly using `int64` (GH32255)
- `Series.to_timestamp()` now raises a `TypeError` if the axis is not a `PeriodIndex`. Previously an `AttributeError` was raised (GH33327)
- `Series.to_period()` now raises a `TypeError` if the axis is not a `DatetimeIndex`. Previously an `AttributeError` was raised (GH33327)
- `Period` no longer accepts tuples for the `freq` argument (GH34658)
- Bug in `Timestamp` where constructing a `Timestamp` from ambiguous epoch time and calling constructor again changed the `Timestamp.value()` property (GH24329)
- `DateTimeArray.searchsorted()`, `TimedeltaArray.searchsorted()`, `PeriodArray.searchsorted()` not recognizing non-pandas scalars and incorrectly raising `ValueError` instead of `TypeError` (GH30950)
- Bug in `Timestamp` where constructing `Timestamp` with dateutil timezone less than 128 nanoseconds before daylight saving time switch from winter to summer would result in nonexistent time (GH31043)
- Bug in `Period.to_timestamp()`, `Period.start_time()` with microsecond frequency returning a timestamp one nanosecond earlier than the correct time (GH31475)
- `Timestamp` raised a confusing error message when year, month or day is missing (GH31200)
- Bug in `DatetimeIndex` constructor incorrectly accepting `bool`-dtype inputs (GH32668)
- Bug in `DatetimeIndex.searchsorted()` not accepting a list or `Series` as its argument (GH32762)
- Bug where `PeriodIndex()` raised when passed a `Series` of strings (GH26109)
- Bug in `Timestamp` arithmetic when adding or subtracting an `np.ndarray` with `timedelta64` dtype (GH33296)
- Bug in `DatetimeIndex.to_period()` not inferring the frequency when called with no arguments (GH33358)
- Bug in `DatetimeIndex.tz_localize()` incorrectly retaining `freq` in some cases where the original `freq` is no longer valid (GH30511)
- Bug in `DatetimeIndex.intersection()` losing `freq` and timezone in some cases (GH33604)
- Bug in `DatetimeIndex.get_indexer()` where incorrect output would be returned for mixed datetime-like targets (GH33741)
- Bug in `DatetimeIndex` addition and subtraction with some types of `DateOffset` objects incorrectly retaining an invalid `freq` attribute (GH33779)
- Bug in `DatetimeIndex` where setting the `freq` attribute on an index could silently change the `freq` attribute on another index viewing the same data (GH33552)
- `DataFrame.min()` and `DataFrame.max()` were not returning consistent results with `Series.min()` and `Series.max()` when called on objects initialized with empty `pd.to_datetime()`
- Bug in `DatetimeIndex.intersection()` and `TimedeltaIndex.intersection()` with results not having the correct name attribute (GH33904)
- Bug in `DatetimeArray.__setitem__()`, `TimedeltaArray.__setitem__()`, `PeriodArray.__setitem__()` incorrectly allowing values with `int64` dtype to be silently cast (GH33717)
- Bug in subtracting `TimedeltaIndex` from `Period` incorrectly raising `TypeError` in some cases where it should succeed and `IncompatibleFrequency` in some cases where it should raise `TypeError` (GH33883)

- Bug in constructing a `Series` or `Index` from a read-only NumPy array with non-ns resolution which converted to object dtype instead of coercing to `datetime64[ns]` dtype when within the timestamp bounds (GH34843).

- The `freq` keyword in `Period, date_range(), period_range(), pd.tseries.frequencies.to_offset()` no longer allows tuples, pass as string instead (GH34703)

- Bug in `DataFrame.append()` when appending a `Series` containing a scalar tz-aware `Timestamp` to an empty `DataFrame` resulted in an object column instead of `datetime64[ns, tz]` dtype (GH35038)

- OutOfBoundsDatetime issues an improved error message when timestamp is out of implementation bounds. (GH32967)

- Bug in `AbstractHolidayCalendar.holidays()` when no rules were defined (GH31415)

- Bug in `Tick` comparisons raising `TypeError` when comparing against timedelta-like objects (GH34088)

- Bug in `Tick` multiplication raising `TypeError` when multiplying by a float (GH34486)

**Timedelta**

- Bug in constructing a `Timedelta` with a high precision integer that would round the `Timedelta` components (GH31354)

- Bug in dividing `np.nan` or `None` by `Timedelta` incorrectly returning `NaT` (GH31869)

- `Timedelta` now understands `µs` as an identifier for microsecond (GH32899)

- `Timedelta` string representation now includes nanoseconds, when nanoseconds are non-zero (GH32899)

- Bug in comparing a `Timedelta` object against an `np.ndarray` with `timedelta64` dtype incorrectly viewing all entries as unequal (GH33441)

- Bug in `timedelta_range()` that produced an extra point on a edge case (GH30353, GH33498)

- Bug in `DataFrame.resample()` that produced an extra point on a edge case (GH30353, GH13022, GH33498)

- Bug in `DataFrame.resample()` that ignored the `loffset` argument when dealing with `timedelta` (GH7687, GH33498)

- Bug in `Timedelta` and `pandas.to_timedelta()` that ignored the `unit` argument for string input (GH12136)

**Timezones**

- Bug in `to_datetime()` with `infer_datetime_format=True` where timezone names (e.g. UTC) would not be parsed correctly (GH33133)
Numeric

- Bug in `DataFrame.floordiv()` with axis=0 not treating division-by-zero like `Series.floordiv()` (GH31271)
- Bug in `to_numeric()` with string argument "uint64" and errors="coerce" silently fails (GH32394)
- Bug in `to_numeric()` with downcast="unsigned" fails for empty data (GH32493)
- Bug in `DataFrame.mean()` with numeric_only=False and either datetime64 dtype or PeriodDtype column incorrectly raising TypeError (GH32426)
- Bug in `DataFrame.count()` with level="foo" and index level "foo" containing NaNs causes segmentation fault (GH21824)
- Bug in `DataFrame.diff()` with axis=1 returning incorrect results with mixed dtypes (GH32995)
- Bug in `DataFrame.corr()` and `DataFrame.cov()` raising when handling nullable integer columns with pandas.NA (GH33803)
- Bug in arithmetic operations between `DataFrame` objects with non-overlapping columns with duplicate labels causing an infinite loop (GH35194)
- Bug in `DataFrame` and `Series` addition and subtraction between object-dtype objects and datetime64 dtype objects (GH33824)
- Bug in `Index.difference()` giving incorrect results when comparing a `Float64Index` and object `Index` (GH35217)
- Bug in `DataFrame` reductions (e.g. `df.min()`, `df.max()`) with ExtensionArray dtypes (GH34520, GH32651)
- `Series.interpolate()` and `DataFrame.interpolate()` now raise a ValueError if limit_direction is 'forward' or 'both' and method is 'backfill' or 'bfill' or limit_direction is 'backward' or 'both' and method is 'pad' or 'ffill' (GH34746)

Conversion

- Bug in `Series` construction from NumPy array with big-endian datetime64 dtype (GH29684)
- Bug in `Timedelta` construction with large nanoseconds keyword value (GH32402)
- Bug in `DataFrame` construction where sets would be duplicated rather than raising (GH32582)
- The `DataFrame` constructor no longer accepts a list of `DataFrame` objects. Because of changes to NumPy, `DataFrame` objects are now consistently treated as 2D objects, so a list of `DataFrame` objects is considered 3D, and no longer acceptable for the `DataFrame` constructor (GH32289).
- Bug in `DataFrame` when initiating a frame with lists and assign columns with nested list for MultiIndex (GH32173)
- Improved error message for invalid construction of list when creating a new index (GH35190)
Strings

- Bug in the `astype()` method when converting “string” dtype data to nullable integer dtype (GH32450).
- Fixed issue where taking `min` or `max` of a `StringArray` or `Series` with `StringDtype` type would raise. (GH31746)
- Bug in `Series.str.cat()` returning NaN output when other had `Index` type (GH33425)
- `pandas.api.dtypes.is_string_dtype()` no longer incorrectly identifies categorical series as string.

Interval

- Bug in `IntervalArray` incorrectly allowing the underlying data to be changed when setting values (GH32782)

Indexing

- `DataFrame.xs()` now raises a TypeError if a level keyword is supplied and the axis is not a `MultiIndex`. Previously an AttributeError was raised (GH33610)
- Bug in slicing on a `DatetimeIndex` with a partial-timestamp dropping high-resolution indices near the end of a year, quarter, or month (GH31064)
- Bug in `PeriodIndex.get_loc()` treating higher-resolution strings differently from `PeriodIndex.get_value()` (GH31172)
- Bug in `Series.at()` and `DataFrame.at()` not matching `.loc` behavior when looking up an integer in a `Float64Index` (GH31329)
- Bug in `PeriodIndex.is_monotonic()` incorrectly returning True when containing leading NaT entries (GH31437)
- Bug in `DatetimeIndex.get_loc()` raising KeyError with converted-integer key instead of the user-passed key (GH31425)
- Bug in `Series.xs()` incorrectly returning `Timestamp` instead of `datetime64` in some object-dtype cases (GH31630)
- Bug in `DataFrame.iat()` incorrectly returning `Timestamp` instead of `datetime` in some object-dtype cases (GH32809)
- Bug in `DataFrame.at()` when either columns or index is non-unique (GH33041)
- Bug in `Series.loc()` and `DataFrame.loc()` when indexing with an integer key on a object-dtype `Index` that is not all-integers (GH31905)
- Bug in `DataFrame.iat.__setitem__()` on a `DataFrame` with duplicate columns incorrectly setting values for all matching columns (GH15686, GH22036)
- Bug in `DataFrame.loc()` and `Series.loc()` with a `DatetimeIndex`, `TimedeltaIndex`, or `PeriodIndex` incorrectly allowing lookups of non-matching datetime-like dtypes (GH32650)
- Bug in `Series.__getitem__()` indexing with non-standard scalars, e.g. np.dtype (GH32684)
- Bug in `Index` constructor where an unhelpful error message was raised for NumPy scalars (GH33017)
- Bug in `DataFrame.lookup()` incorrectly raising an AttributeError when frame.index or frame.columns is not unique; this will now raise a `ValueError` with a helpful error message (GH33041)
• Bug in `Interval` where a `Timedelta` could not be added or subtracted from a `Timestamp` interval (GH32023)

• Bug in `DataFrame.copy()` not invalidating _item_cache after copy caused post-copy value updates to not be reflected (GH31784)

• Fixed regression in `DataFrame.loc()` and `Series.loc()` throwing an error when a `datetime64[ns, tz]` value is provided (GH32395)

• Bug in `Series.__getitem__()` with an integer key and a `MultiIndex` with leading integer level failing to raise `KeyError` if the key is not present in the first level (GH33355)

• Bug in `DataFrame.iloc()` when slicing a single column `DataFrame` with `ExtensionDtype` (e.g. `df.iloc[:, :1]`) returning an invalid result (GH32957)

• Bug in `DatetimeIndex.insert()` and `TimedeltaIndex.insert()` causing `index freq` to be lost when setting an element into an empty `Series` (GH33573)

• Bug in `Series.__setitem__()` with an `IntervalIndex` and a list-like key of integers (GH33473)

• Bug in `Series.__getitem__()` allowing missing labels with `np.ndarray`, `Index`, `Series` indexers but not list, these now all raise `KeyError` (GH33646)

• Bug in `DataFrame.truncate()` and `Series.truncate()` where index was assumed to be monotone increasing (GH33756)

• Indexing with a list of strings representing datetimes failed on `DatetimeIndex` or `PeriodIndex` (GH11278)

• Bug in `Series.at()` when used with a `MultiIndex` would raise an exception on valid inputs (GH26989)

• Bug in `DataFrame.loc()` with dictionary of values changes columns with `dtype` of `int` to `float` (GH34573)

• Bug in `Series.loc()` when used with a `MultiIndex` would raise an `IndexingError` when accessing a `None` value (GH34318)

• Bug in `DataFrame.reset_index()` and `Series.reset_index()` would not preserve data types on an empty `DataFrame` or `Series` with a `MultiIndex` (GH19602)

• Bug in `Series` and `DataFrame` indexing with a time key on a `DatetimeIndex` with `NaT` entries (GH35114)

**Missing**

• Calling `fillna()` on an empty `Series` now correctly returns a shallow copied object. The behaviour is now consistent with `index`, `DataFrame` and a non-empty `Series` (GH32543).

• Bug in `Series.replace()` when argument `to_replace` is of type dict/list and is used on a `Series` containing `<NA>` was raising a `TypeError`. The method now handles this by ignoring `<NA>` values when doing the comparison for the replacement (GH32621)

• Bug in `any()` and `all()` incorrectly returning `<NA>` for all `False` or all `True` values using the nullable Boolean `dtype` and with `skipna=False` (GH33253)

• Clarified documentation on `interpolate` with `method=akima`. The `der` parameter must be scalar or `None` (GH33426)

• `DataFrame.interpolate()` uses the correct axis convention now. Previously interpolating along columns lead to interpolation along indices and vice versa. Furthermore interpolating with methods `pad`, `ffill`, `bfill` and `backfill` are identical to using these methods with `DataFrame.fillna()` (GH12918, GH29146)
• Bug in `DataFrame.interpolate()` when called on a `DataFrame` with column names of string type was throwing a ValueError. The method is now independent of the type of the column names (GH33956)

• Passing NA into a format string using format specs will now work. For example `"{:1f}".format(pd.NA)` would previously raise a ValueError, but will now return the string "<NA>" (GH34740)

• Bug in `Series.map()` not raising on invalid na_action (GH32815)

**MultiIndex**

• `DataFrame.swaplevels()` now raises a TypeError if the axis is not a `MultiIndex`. Previously an AttributeError was raised (GH31126)

• Bug in `DataFrame.loc()` when used with a `MultiIndex`. The returned values were not in the same order as the given inputs (GH22797)

```python
In [80]: df = pd.DataFrame(np.arange(4),
    ....:     index=["a", "a", "b", "b"], [1, 2, 1, 2])

# Rows are now ordered as the requested keys
In [81]: df.loc[['b', 'a'], [2, 1], :]
Out[81]:
     b  c
0  2  3
1  1  2

[4 rows x 1 columns]
```

• Bug in `MultiIndex.intersection()` was not guaranteed to preserve order when sort=False. (GH31325)

• Bug in `DataFrame.truncate()` was dropping `MultiIndex` names. (GH34564)

```python
In [82]: left = pd.MultiIndex.from_arrays(["b", "a"], [2, 1])
In [83]: right = pd.MultiIndex.from_arrays(["a", "b", "c"], [1, 2, 3])

# Common elements are now guaranteed to be ordered by the left side
In [84]: left.intersection(right, sort=False)
Out[84]:
MultiIndex([('b', 2),
            ('a', 1),
            ])
```

• Bug when joining two `MultiIndex` without specifying level with different columns. Return-indexers parameter was ignored. (GH34074)
I/O

- Passing a set as names argument to `pandas.read_csv()`, `pandas.read_table()`, or `pandas.read_fwf()` will raise `ValueError`: Names should be an ordered collection. (GH34946)
- Bug in print-out when `display.precision` is zero. (GH20359)
- Bug in `read_json()` where integer overflow was occurring when json contains big number strings. (GH30320)
- `read_csv()` will now raise a `ValueError` when the arguments `header` and `prefix` both are not `None`. (GH27394)
- Bug in `DataFrame.to_json()` was raising `NotFoundError` when `path_or_buf` was an S3 URI (GH28375)
- Bug in `DataFrame.to_parquet()` overwriting pyarrow’s default for `coerce_timestamps`; following pyarrow’s default allows writing nanosecond timestamps with `version="2.0"` (GH31652).
- Bug in `read_csv()` was raising `TypeError` when `sep=None` was used in combination with `comment` keyword (GH31396)
- Bug in HDFStore that caused it to set to `int64` the dtype of a `datetime64` column when reading a `DataFrame` in Python 3 from fixed format written in Python 2 (GH31750)
- `read_sas()` now handles dates and datetimes larger than `Timestamp.max` returning them as `datetime` objects (GH20927)
- Bug in `DataFrame.to_json()` where `Timedelta` objects would not be serialized correctly with `date_format="iso"` (GH28256)
- `read_csv()` will raise a `ValueError` when the column names passed in `parse_dates` are missing in the DataFrame (GH31251)
- Bug in `read_excel()` where a UTF-8 string with a high surrogate would cause a segmentation violation (GH23809)
- Bug in `read_csv()` was causing a file descriptor leak on an empty file (GH31488)
- Bug in `read_csv()` was causing a segfault when there were blank lines between the header and data rows (GH28071)
- Bug in `read_csv()` was raising a misleading exception on a permissions issue (GH23784)
- Bug in `read_csv()` was raising an `IndexError` when `header=None` and two extra data columns
- Bug in `read_sas()` was raising an `AttributeError` when reading files from Google Cloud Storage (GH33069)
- Bug in `DataFrame.to_sql()` where an `AttributeError` was raised when saving an out of bounds date (GH26761)
- Bug in `read_excel()` did not correctly handle multiple embedded spaces in OpenDocument text cells. (GH32207)
- Bug in `read_json()` was raising `TypeError` when reading a list of Booleans into a `Series`. (GH31464)
- Bug in `pandas.io.json.json_normalize()` where location specified by `record_path` doesn’t point to an array. (GH26284)
- `pandas.read_hdf()` has a more explicit error message when loading an unsupported HDF file (GH9539)
- Bug in `read_feather()` was raising an `ArrowIOError` when reading an s3 or http file path (GH29055)
• Bug in `to_excel()` could not handle the column name `render` and was raising an `KeyError` (GH34331)
• Bug in `execute()` was raising a `ProgrammingError` for some DB-API drivers when the SQL statement contained the % character and no parameters were present (GH34211)
• Bug in `StataReader()` which resulted in categorical variables with different dtypes when reading data using an iterator. (GH31544)
• `HDFStore.keys()` has now an optional `include` parameter that allows the retrieval of all native HDF5 table names (GH29916)
• TypeError exceptions raised by `read_csv()` and `read_table()` were showing as `parser_f` when an unexpected keyword argument was passed (GH25648)
• Bug in `read_excel()` for ODS files removes 0.0 values (GH27222)
• Bug in `ujson.encode()` was raising an `OverflowError` with numbers larger than `sys.maxsize` (GH34395)
• Bug in `HDFStore.append_to_multiple()` was raising a `ValueError` when the `min_itemsize` parameter is set (GH11238)
• Bug in `create_table()` now raises an error when column argument was not specified in `data_columns` on input (GH28156)
• `read_json()` now could read line-delimited json file from a file url while `lines` and `chunksize` are set.
• Bug in `DataFrame.to_sql()` when reading DataFrames with `np.inf` entries with MySQL now has a more explicit `ValueError` (GH34431)
• Bug where capitalised files extensions were not decompressed by read_* functions (GH35164)
• Bug in `read_excel()` that was raising a `TypeError` when `header=None` and `index_col` is given as a list (GH31783)
• Bug in `read_excel()` where datetime values are used in the header in a `MultiIndex` (GH34748)
• `read_excel()` no longer takes `**kwds` arguments. This means that passing in the keyword argument `chunksize` now raises a `TypeError` (previously raised a `NotImplementedError`), while passing in the keyword argument `encoding` now raises a `TypeError` (GH34464)
• Bug in `DataFrame.to_records()` was incorrectly losing timezone information in timezone-aware datetime64 columns (GH32535)

**Plotting**

• `DataFrame.plot()` for line/bar now accepts color by dictionary (GH8193).
• Bug in `DataFrame.plot.hist()` where weights are not working for multiple columns (GH33173)
• Bug in `DataFrame.boxplot()` and `DataFrame.plot.boxplot()` lost color attributes of `medianprops`, `whiskerprops`, `capprops` and `boxprops` (GH30346)
• Bug in `DataFrame.hist()` where the order of column argument was ignored (GH29235)
• Bug in `DataFrame.plot.scatter()` that when adding multiple plots with different `cmap`, `colorbars` always use the first `cmap` (GH33389)
• Bug in `DataFrame.plot.scatter()` was adding a colorbar to the plot even if the argument `c` was assigned to a column containing color names (GH34316)
• Bug in `pandas.plotting.bootstrap_plot()` was causing cluttered axes and overlapping labels (GH34905)
• Bug in `DataFrame.plot.scatter()` caused an error when plotting variable marker sizes (GH32904)

**Groupby/resample/rolling**

• Using a `pandas.api.indexers.BaseIndexer` with count, min, max, median, skew, cov, corr will now return correct results for any monotonic `pandas.api.indexers.BaseIndexer` descendant (GH32865)

• `DataFrameGroupBy.mean()` and `SeriesGroupby.mean()` (and similarly for `median()`, `std()` and `var()`) now raise a `TypeError` if a non-accepted keyword argument is passed into it. Previously an `UnsupportedFunctionCall` was raised (AssertionError if `min_count` passed into `median()`) (GH31485)

• Bug in `GroupBy.apply()` raises `ValueError` when the `by` axis is not sorted, has duplicates, and the applied `func` does not mutate passed in objects (GH30667)

• Bug in `DataFrameGroupBy.transform()` produces an incorrect result with transformation functions (GH30918)

• `DataFrame.resample()` produces inconsistent type when aggregating `Boolean Series` (GH32894)

• `DataFrame.groupby()` and `Series.groupby()` produces inconsistent type when aggregating `Boolean Series` (GH32894)

• Bug in `DataFrameGroupBy.transform()` where a large negative number would be returned when the number of non-null values was below `min_count` for nullable integer dtypes (GH32861)

• Bug in `SeriesGroupBy.agg()` where any column name was accepted in the named aggregation of `SeriesGroupBy` previously. The behaviour now allows only `str` and callables else would raise `TypeError`. (GH34422)

• Bug in `DataFrame.groupby()` lost the name of the `Index` when one of the `agg` keys referenced an empty list (GH32580)

• Bug in `DataFrame.groupby()` raising an `AttributeError` when selecting a column and aggregating with `as_index=False` (GH35246).
• Bug in DataFrameGroupBy.first() and DataFrameGroupBy.last() that would raise an unnecessary ValueError when grouping on multiple Categoricals (GH34951)

Reshaping

• Bug effecting all numeric and Boolean reduction methods not returning subclassed data type. (GH25596)
• Bug in DataFrame.pivot_table() when only MultiIndexed columns is set (GH17038)
• Bug in DataFrame.unstack() and Series.unstack() can take tuple names in MultiIndexed data (GH19966)
• Bug in DataFrame.pivot_table() when margin is True and only column is defined (GH31016)
• Fixed incorrect error message in DataFrame.pivot() when columns is set to None. (GH30924)
• Bug in crosstab() when inputs are two Series and have tuple names, the output will keep a dummy MultiIndex as columns. (GH18321)
• DataFrame.pivot() can now take lists for index and columns arguments (GH21425)
• Bug in concat() where the resulting indices are not copied when copy=True (GH29879)
• Bug in SeriesGroupBy.aggregate() was resulting in aggregations being overwritten when they shared the same name (GH30880)
• Bug where Index.astype() would lose the name attribute when converting from Float64Index to Int64Index, or when casting to an ExtensionArray dtype (GH32013)
• Series.append() will now raise a TypeError when passed a DataFrame or a sequence containing DataFrame (GH31413)
• DataFrame.replace() and Series.replace() will raise a TypeError if to_replace is not an expected type. Previously the replace would fail silently (GH18634)
• Bug on inplace operation of a Series that was adding a column to the DataFrame from where it was originally dropped from (using inplace=True) (GH30484)
• Bug in DataFrame.apply() where callback was called with Series parameter even though raw=True requested. (GH32423)
• Bug in DataFrame.pivot_table() losing timezone information when creating a MultiIndex level from a column with timezone-aware dtype (GH32558)
• Bug in concat() where when passing a non-dict mapping as objs would raise a TypeError (GH32863)
• DataFrame.agg() now provides more descriptive SpecificationError message when attempting to aggregate a non-existent column (GH32755)
• Bug in DataFrame.unstack() when MultiIndex columns and MultiIndex rows were used (GH32624, GH24729 and GH28306)
• Appending a dictionary to a DataFrame without passing ignore_index=True will raise TypeError: Can only append a dict if ignore_index=True instead of TypeError: Can only append a :class:`Series` if ignore_index=True or if the :class:`Series` has a name (GH30871)
• Bug in DataFrame.corrwith(), DataFrame.memory_usage(), DataFrame.dot(), DataFrame.idxmin(), DataFrame.idxmax(), DataFrame.duplicated(), DataFrame.isin(), DataFrame.count(), Series.explode(), Series.asof() and DataFrame.asof() not returning subclassed types. (GH31331)
• Bug in `concat()` was not allowing for concatenation of `DataFrame` and `Series` with duplicate keys (GH33654)
• Bug in `cut()` raised an error when the argument `labels` contains duplicates (GH33141)
• Ensure only named functions can be used in `eval()` (GH32460)
• Bug in `DataFrame.aggregate()` and `Series.aggregate()` was causing a recursive loop in some cases (GH34224)
• Fixed bug in `melt()` where melting `MultiIndex` columns with `col_level > 0` would raise a `KeyError` on `id_vars` (GH34129)
• Bug in `Series.where()` with an empty `Series` and empty `cond` having non-bool dtype (GH34592)
• Fixed regression where `DataFrame.apply()` would raise `ValueError` for elements with S dtype (GH34529)

Sparse

• Creating a `SparseArray` from timezone-aware dtype will issue a warning before dropping timezone information, instead of doing so silently (GH32501)
• Bug in `arrays.SparseArray.from_spmatrix()` wrongly read scipy sparse matrix (GH31991)
• Bug in `Series.sum()` with `SparseArray` raised a `TypeError` (GH34526, GH34540)
• Bug where empty `DataFrame` could not be cast to `SparseDtype` (GH33113)
• Bug in `arrays.SparseArray()` was returning the incorrect type when indexing a sparse dataframe with an iterable (GH34526, GH34540)

ExtensionArray

• Fixed bug where `Series.value_counts()` would raise on empty input of Int64 dtype (GH33317)
• Fixed bug in `concat()` when concatenating `DataFrame` objects with non-overlapping columns resulting in object-dtype columns rather than preserving the extension dtype (GH27692, GH33027)
• Fixed bug where `StringArray.isna()` would return `False` for NA values when `pandas.options.mode.use_inf_as_na` was set to `True` (GH33655)
• Fixed bug in `Series` construction with EA dtype and index but no data or scalar data fails (GH26469)
• Fixed bug that caused `Series.__repr__()` to crash for extension types whose elements are multidimensional arrays (GH33770).
• Fixed bug where `Series.update()` would raise a `ValueError` for `ExtensionArray` dtypes with missing values (GH33980)
• Fixed bug where `StringArray.memory_usage()` was not implemented (GH33963)
• Fixed bug where `DataFrameGroupBy()` would ignore the `min_count` argument for aggregations on nullable Boolean dtypes (GH34051)
• Fixed bug where the constructor of `DataFrame` with `dtype='string'` would fail (GH27953, GH33623)
• Bug where DataFrame column set to scalar extension type was considered an object type rather than the extension type (GH34832)
• Fixed bug in IntegerArray.astype() to correctly copy the mask as well (GH34931).

Other

• Set operations on an object-dtype Index now always return object-dtype results (GH31401)
• Fixed pandas.testing.assert_series_equal() to correctly raise if the left argument is a different subclass with check_series_type=True (GH32670).
• Getting a missing attribute in a DataFrame.query() or DataFrame.eval() string raises the correct AttributeError (GH32408)
• Fixed bug in pandas.testing.assert_series_equal() where dtypes were checked for Interval and ExtensionArray operands when check_dtypes was False (GH32747)
• Bug in DataFrame.__dir__() caused a segfault when using unicode surrogates in a column name (GH25509)
• Bug in DataFrame.equals() and Series.equals() in allowing subclasses to be equal (GH34402).

Contributors

A total of 368 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

• 3vts +
• A Brooks +
• Abbie Popa +
• Achmad Syarif Hidayatullah +
• Adam W Bagaskarta +
• Adrian Mastronardi +
• Aidan Montare +
• Akbar Septiyan +
• Akos Furton +
• Alejandro Hall +
• Alex Hall +
• Alex Itkes +
• Alex Kirko +
• Ali McMaster +
• Alvaro Aleman +
• Amy Graham +
• Andrew Schonfeld +
• Andrew Shumanskiy +
• Andrew Wieteska +
• Angela Ambroz
• Anjali Singh +
• Anna Daglis
• Anthony Milbourne +
• Antony Lee +
• Ari Sosnovsky +
• Arkadeep Adhikari +
• Arunim Samudra +
• Ashkan +
• Ashwin Prakash Nalwade +
• Ashwin Srinath +
• Atsushi Nukariya +
• Ayappan +
• Ayla Khan +
• Bart +
• Bart Broere +
• Benjamin Beier Liu +
• Benjamin Fischer +
• Bharat Raghunathan
• Bradley Dice +
• Brendan Sullivan +
• Brian Strand +
• Carsten van Weelden +
• Chamoun Saoma +
• ChrisRobo +
• Christian Chwala
• Christopher Whelan
• Christos Petropoulos +
• Chuanzhu Xu
• CloseChoice +
• Clément Robert +
• CuylenE +
• DanBasson +
• Daniel Saxton
• Danilo Horta +
• DavallhamHaeruzaman +
• Dave Hirschfeld
• Dave Hughes
• David Rouquet +
• David S +
• Deepyaman Datta
• Dennis Bakhuys +
• Derek McCammond +
• Devjeet Roy +
• Diane Trout
• Dina +
• Dom +
• Drew Seibert +
• EdAbati
• Emiliano Jordan +
• Erfan Nariman +
• Eric Groszman +
• Erik Hasse +
• Erkam Uyanik +
• Evan D +
• Evan Kanter +
• Fangchen Li +
• Farhan Reynaldo +
• Farhan Reynaldo Hutabarat +
• Florian Jetter +
• Fred Reiss +
• GYHHAHA +
• Gabriel Moreira +
• Gabriel Tutui +
• Galuh Sahid
• Gaurav Chauhan +
• George Hartzell +
• Gim Seng +
• Giovanni Lanzani +
• Gordon Chen +
• Graham Wetzler +
• Guillaume Lemaitre
• Guillem Sánchez +
• HH-MWB +
• Harshavardhan Bachina
• How Si Wei
• Ian Eaves
• Iqrar Agalosi Nureyza +
• Irv Lustig
• Iva Lajinja +
• JDkuba
• Jack Greisman +
• Jacob Austin +
• Jacob Deppen +
• Jacob Peacock +
• Jake Tae +
• Jake Vanderplas +
• James Cobon-Kerr
• Jan Červenka +
• Jan Škoda
• Jane Chen +
• Jean-François Zinque +
• Jeanderson Barros Candido +
• Jeff Reback
• Jered Dominguez-Trujillo +
• Jeremy Schendel
• Jesse Farnham
• Jiaxiang
• Jihwan Song +
• Joaquim L. Viegas +
• Joel Nothman
• John Bodley +
• John Paton +
• Jon Thielen +
• Joris Van den Bossche
• Jose Manuel Martí +
• Joseph Gulian +
• Josh Dimarsky
• Joy Bhalla +
• João Veiga +
• Julian de Ruiter +
• Justin Essert +
• Justin Zheng
• KD-dev-lab +
• Kaiqi Dong
• Karthik Mathur +
• Kaushal Rohit +
• Kee Chong Tan
• Ken Mankoff +
• Kendall Masse
• Kenny Huynh +
• Ketan +
• Kevin Anderson +
• Kevin Bowey +
• Kevin Sheppard
• Kilian Lieret +
• Koki Nishihara +
• Krishna Chivukula +
• KrishnaSai2020 +
• Lesley +
• Lewis Cowles +
• Linda Chen +
• Linxiao Wu +
• Lucca Delchiaro Costabile +
• MBrouns +
• Mabel Villalba
• Mabroor Ahmed +
• Madhuri Palanivelu +
• Mak Sze Chun
• Malcolm +
• Marc Garcia
• Marco Gorelli
• Marian Denes +
• Martin Bjeldbak Madsen +
pandas: powerful Python data analysis toolkit, Release 1.1.1

- Martin Durant +
- Martin Fleischmann +
- Martin Jones +
- Martin Winkel
- Martina Oefelein +
- Marvzinc +
- María Marino +
- Matheus Cardoso +
- Mathis Felardos +
- Matt Roeschke
- Matteo Felici +
- Matteo Santamaria +
- Matthew Roeschke
- Matthias Bussonnier
- Max Chen
- Max Halford +
- Mayank Bisht +
- Megan Thong +
- Michael Marino +
- Miguel Marques +
- Mike Kutzma
- Mohammad Hasnain Mohsin Rajan +
- Mohammad Jafar Mashhadi +
- MomIsBestFriend
- Monica +
- Natalie Jann
- Nate Armstrong +
- Nathanael +
- Nick Newman +
- Nico Schlömer +
- Niklas Weber +
- ObliviousParadigm +
- Olga Lyshevskaja +
- OlivierLuG +
- Pandas Development Team
- Parallels +
• Patrick +
• Patrick Cando +
• Paul Lilley +
• Paul Sanders +
• Pearcekieser +
• Pedro Larroy +
• Pedro Reys +
• Peter Bull +
• Peter Steinbach +
• Phan Duc Nhat Minh +
• Phil Kirlin +
• Pierre-Yves Bourguignon +
• Piotr Kasprzyk +
• Piotr Niłacny +
• Prakhar Pandey +
• Prashant Anand +
• Puneetha Pai +
• Quang Nguyen +
• Rafael Jaímes III +
• Rafif +
• RaisaDZ +
• Rakshit Naidu +
• Ram Rachum +
• Red +
• Ricardo Alanis +
• Richard Shadrach +
• Rik-de-Kort
• Robert de Vries
• Robin to Roxel +
• Roger Erens +
• Rohith295 +
• Roman Yurchak +
• Ror +
• Rushabh Vasani +
• Ryan +
• Ryan Nazareth +
pandas: powerful Python data analysis toolkit, Release 1.1.1

- SAI SRAVAN MEDICHERLA +
- SHUBH CHATTERJEE +
- Sam Cohan
- Samira-g-js +
- Sandu Ursu +
- Sang Agung +
- SanthoshBala18 +
- Sasidhar Kasturi +
- SatheeshKumar Mohan +
- Saul Shanabrook
- Scott Gigante +
- Sebastian Berg +
- Sebastián Vanrell
- Sergei Chipiga +
- Sergey +
- ShilpaSugan +
- Simon Gibbons
- Simon Hawkins
- Simon Legner +
- Soham Tiwari +
- Song Wenhao +
- Souvik Mandal
- Spencer Clark
- Steffen Rehberg +
- Steffen Schmitz +
- Stijn Van Hoey
- Stéphan Taljaard
- SultanOrazbayev +
- Sumanau Sareen
- SurajH1 +
- Suvayu Ali +
- Terji Petersen
- Thomas J Fan +
- Thomas Li
- Thomas Smith +
- Tim Swast
• dhuettenmoser +
• dilex42 +
• elmonsomiat +
• epizzigoni +
• fjetter
• gabrielvf1 +
• gdex1 +
• gfyoung
• guru kiran +
• h-vishal
• iamshwin
• jamin-aws-ospo +
• jbrockmendel
• jfcorbett +
• jnecus +
• kernc
• kota matsuoka +
• kylekeppler +
• leandardaben +
• link2xt +
• manoj_koneni +
• marydmit +
• masterpiga +
• maxime.song +
• mglasder +
• moaraccounts +
• mproszewska
• neilkg
• narebena
• ossdev07 +
• paihu
• pan Jacek +
• partev +
• patrick +
• pedrooa +
• pizzathief +
5.2 Version 1.0

5.2.1 What’s new in 1.0.5 (June 17, 2020)

These are the changes in pandas 1.0.5. See Release notes for a full changelog including other versions of pandas.
**Fixed regressions**

- Fix regression in `read_parquet()` when reading from file-like objects (GH34467).
- Fix regression in reading from public S3 buckets (GH34626).

Note this disables the ability to read Parquet files from directories on S3 again (GH26388, GH34632), which was added in the 1.0.4 release, but is now targeted for pandas 1.1.0.

- Fixed regression in `replace()` raising an `AssertionError` when replacing values in an extension dtype with values of a different dtype (GH34530)

**Bug fixes**

- Fixed building from source with Python 3.8 fetching the wrong version of NumPy (GH34666)

**Contributors**

A total of 8 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Joris Van den Bossche
- MeeseeksMachine
- Natalie Jann +
- Pandas Development Team
- Simon Hawkins
- Tom Augspurger
- William Ayd
- alimcmaster1

**5.2.2 What’s new in 1.0.4 (May 28, 2020)**

These are the changes in pandas 1.0.4. See Release notes for a full changelog including other versions of pandas.

**Fixed regressions**

- Fix regression where `Series.isna()` and `DataFrame.isna()` would raise for categorical dtype when `pandas.options.mode.use_inf_as_na` was set to True (GH33594)
- Fix regression in `GroupBy.first()` and `GroupBy.last()` where None is not preserved in object dtype (GH32800)
- Fix regression in `DataFrame` reductions using `numeric_only=True` and `ExtensionArrays` (GH33256).
- Fix performance regression in `memory_usage(deep=True)` for object dtype (GH33012)
- Fix regression where `Categorical.replace()` would replace with NaN whenever the new value and replacement value were equal (GH33288)
- Fix regression where an ordered `Categorical` containing only NaN values would raise rather than returning NaN when taking the minimum or maximum (GH33450)
Fix regression in `DataFrameGroupBy.agg()` with dictionary input losing `ExtensionArray` dtypes (GH32194)

Fix to preserve the ability to index with the “nearest” method with xarray’s CFTimeIndex, an `Index` subclass (pydata/xarray#3751, GH32905).

Fix regression in `DataFrame.describe()` raising `TypeError: unhashable type: 'dict'` (GH32409)

Fix regression in `DataFrame.replace()` casts columns to `object` dtype if items in to_replace not in values (GH32988)

Fix regression in `Series.groupby()` would raise `ValueError` when grouping by `PeriodIndex` level (GH34010)

Fix regression in `GroupBy.rolling.apply()` ignores args and kwargs parameters (GH33433)

Fix regression in error message with `np.min` or `np.max` on unordered `Categorical` (GH33115)

Fix regression in `DataFrame.loc()` and `Series.loc()` throwing an error when a datetime64[ns, tz] value is provided (GH32395)

### Bug fixes

- Bug in `SeriesGroupBy.first()`, `SeriesGroupBy.last()`, `SeriesGroupBy.min()`, and `SeriesGroupBy.max()` returning floats when applied to nullable Booleans (GH33071)
- Bug in `Rolling.min()` and `Rolling.max()`: Growing memory usage after multiple calls when using a fixed window (GH30726)
- Bug in `to_parquet()` was not raising `PermissionError` when writing to a private s3 bucket with invalid creds. (GH27679)
- Bug in `to_csv()` was silently failing when writing to an invalid s3 bucket. (GH32486)
- Bug in `read_parquet()` was raising a `FileNotFoundError` when passed an s3 directory path. (GH26388)
- Bug in `to_parquet()` was throwing an `AttributeError` when writing a partitioned parquet file to s3 (GH27596)
- Bug in `GroupBy.quantile()` causes the quantiles to be shifted when the `by` axis contains NaN (GH33200, GH33569)

### Contributors

A total of 18 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Daniel Saxton
- JDbuka +
- Joris Van den Bossche
- Kaiqi Dong
- Mabel Villalba
- MeeseeksMachine
- MomIsBestFriend
5.2.3 What’s new in 1.0.3 (March 17, 2020)

These are the changes in pandas 1.0.3. See Release notes for a full changelog including other versions of pandas.

Fixed regressions

- Fixed regression in `resample.agg` when the underlying data is non-writeable (GH31710)
- Fixed regression in `DataFrame` exponentiation with reindexing (GH32685)

Bug fixes

Contributors

A total of 5 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- MeeseeksMachine
- Pandas Development Team
- Tom Augspurger
- William Ayd
- jbrockmendel

5.2.4 What’s new in 1.0.2 (March 12, 2020)

These are the changes in pandas 1.0.2. See Release notes for a full changelog including other versions of pandas.
Fixed regressions

Groupby

- Fixed regression in `groupby(..).agg()` which was failing on frames with `MultiIndex` columns and a custom function (GH31777)
- Fixed regression in `groupby(..).rolling(..).apply()` (RollingGroupby) where the `raw` parameter was ignored (GH31754)
- Fixed regression in `rolling(..).corr()` when using a time offset (GH31789)
- Fixed regression in `groupby(..).nunique()` which was modifying the original values if NaN values were present (GH31950)
- Fixed regression in `DataFrame.groupby` raising a `ValueError` from an internal operation (GH31802)
- Fixed regression in `groupby(..).agg()` calling a user-provided function an extra time on an empty input (GH31760)

I/O

- Fixed regression in `read_csv()` in which the `encoding` option was not recognized with certain file-like objects (GH31819)
- Fixed regression in `DataFrame.to_excel()` when the `columns` keyword argument is passed (GH31677)
- Fixed regression in `ExcelFile` where the stream passed into the function was closed by the destructor. (GH31467)
- Fixed regression where `read_pickle()` raised a `UnicodeDecodeError` when reading a py27 pickle with `MultiIndex` column (GH31988).

Reindexing/alignment

- Fixed regression in `Series.align()` when `other` is a `DataFrame` and `method` is not `None` (GH31785)
- Fixed regression in `DataFrame.reindex()` and `Series.reindex()` when reindexing with (tz-aware) index and `method=nearest` (GH26683)
- Fixed regression in `DataFrame.reindex_like()` on a `DataFrame` subclass raised an `AssertionError` (GH31925)
- Fixed regression in `DataFrame` arithmetic operations with mis-matched columns (GH31623)

Other

- Fixed regression in joining on `DatetimeIndex` or `TimedeltaIndex` to preserve `freq` in simple cases (GH32166)
- Fixed regression in `Series.shift()` with `datetime64` dtype when passing an integer `fill_value` (GH32591)
- Fixed regression in the repr of an object-dtype `Index` with bools and missing values (GH32146)
Indexing with Nullable Boolean Arrays

Previously indexing with a nullable Boolean array containing NA would raise a ValueError, however this is now permitted with NA being treated as False. (GH31503)

```
In [1]: s = pd.Series([1, 2, 3, 4])
In [2]: mask = pd.array([True, True, False, None], dtype="boolean")
In [3]: s
Out[3]:
0    1
1    2
2    3
3    4
Length: 4, dtype: int64
In [4]: mask
Out[4]:
<BooleanArray>
[True, True, False, <NA>]
Length: 4, dtype: boolean
```

```
pandas 1.0.0-1.0.1
```

```
>>> s[mask]
Traceback (most recent call last):
  ...
ValueError: cannot mask with array containing NA / NaN values
```

```
pandas 1.0.2
```

```
In [5]: s[mask]
Out[5]:
0    1
1    2
Length: 2, dtype: int64
```

Bug fixes

### Datetimelike

- Bug in `Series.astype()` not copying for tz-naive and tz-aware `datetime64` dtype (GH32490)
- Bug where `to_datetime()` would raise when passed `pd.NA` (GH32213)
- Improved error message when subtracting two `Timestamp` that result in an out-of-bounds `Timedelta` (GH31774)

### Categorical

- Fixed bug where `Categorical.from_codes()` improperly raised a `ValueError` when passed nullable integer codes. (GH31779)
- Fixed bug where `Categorical()` constructor would raise a `TypeError` when given a numpy array containing `pd.NA`. (GH31927)
- Bug in `Categorical` that would ignore or crash when calling `Series.replace()` with a list-like `to_replace` (GH31720)
I/O

- Using `pd.NA` with `DataFrame.to_json()` now correctly outputs a null value instead of an empty object (GH31615)
- Bug in `pandas.json_normalize()` when value in meta path is not iterable (GH31507)
- Fixed picking of `pandas.NA`. Previously a new object was returned, which broke computations relying on NA being a singleton (GH31847)
- Fixed bug in parquet roundtrip with nullable unsigned integer dtypes (GH31896).

Experimental dtypes

- Fixed bug in `DataFrame.convert_dtypes()` for columns that were already using the "string" dtype (GH31731).
- Fixed bug in `DataFrame.convert_dtypes()` for series with mix of integers and strings (GH32117)
- Fixed bug in `DataFrame.convert_dtypes()` where BooleanDtype columns were converted to `Int64` (GH32287)
- Fixed bug in setting values using a slice indexer with string dtype (GH31772)
- Fixed bug where `pandas.core.groupby.GroupBy.first()` and `pandas.core.groupby.GroupBy.last()` would raise a TypeError when groups contained pd.NA in a column of object dtype (GH32123)
- Fixed bug where `DataFrameGroupBy.mean()`, `DataFrameGroupBy.median()`, `DataFrameGroupBy.var()`, and `DataFrameGroupBy.std()` would raise a TypeError on `Int64` dtype columns (GH32219)

Strings

- Using `pd.NA` with `Series.str.repeat()` now correctly outputs a null value instead of raising error for vector inputs (GH31632)

Rolling

- Fixed rolling operations with variable window (defined by time duration) on decreasing time index (GH32385).

Contributors

A total of 25 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Anna Daglis +
- Daniel Saxton
- Irv Lustig
- Jan Škoda
- Joris Van den Bossche
- Justin Zheng
- Kaiqi Dong
- Kendall Masse
- Marco Gorelli
- Matthew Roeschke
5.2.5 What's new in 1.0.1 (February 5, 2020)

These are the changes in pandas 1.0.1. See Release notes for a full changelog including other versions of pandas.

Fixed regressions

- Fixed regression in DataFrame setting values with a slice (e.g. df[-4:] = 1) indexing by label instead of position (GH31469)
- Fixed regression when indexing a Series or DataFrame indexed by DatetimeIndex with a slice containing a datetime.date (GH31501)
- Fixed regression in DataFrame.__setitem__ raising an AttributeError with a MultiIndex and a non-monotonic indexer (GH31449)
- Fixed regression in Series multiplication when multiplying a numeric Series with >10000 elements with a timedelta-like scalar (GH31457)
- Fixed regression in .groupby().agg() raising an AssertionError for some reductions like min on object-dtype columns (GH31522)
- Fixed regression in .groupby() aggregations with categorical dtype using Cythonized reduction functions (e.g. first) (GH31450)
- Fixed regression in GroupBy.apply() if called with a function which returned a non-pandas non-scalar object (e.g. a list or numpy array) (GH31441)
- Fixed regression in DataFrame.groupby() whereby taking the minimum or maximum of a column with period dtype would raise a TypeError. (GH31471)
- Fixed regression in DataFrame.groupby() with an empty DataFrame grouping by a level of a MultiIndex (GH31670).
- Fixed regression in DataFrame.apply() with object dtype and non-reducing function (GH31505)
- Fixed regression in `to_datetime()` when parsing non-nanosecond resolution datetimes (GH31491)
- Fixed regression in `to_csv()` where specifying an `na_rep` might truncate the values written (GH31447)
- Fixed regression in `Categorical` construction with `numpy.str_.categories` (GH31499)
- Fixed regression in `DataFrame.loc()` and `DataFrame.iloc()` when selecting a row containing a single datetime64 or timedelta64 column (GH31649)
- Fixed regression where setting `pd.options.display.max_colwidth` was not accepting negative integer. In addition, this behavior has been deprecated in favor of using None (GH31532)
- Fixed regression in `objTOJSON.c` fix return-type warning (GH31463)
- Fixed regression in `qcut()` when passed a nullable integer. (GH31389)
- Fixed regression in assigning to a `Series` using a nullable integer dtype (GH31446)
- Fixed performance regression when indexing a `DataFrame` or `Series` with a `MultiIndex` for the index using a list of labels (GH31648)
- Fixed regression in `read_csv()` used in file like object `RawIOBase` is not recognize encoding option (GH31575)

**Deprecations**

- Support for negative integer for `pd.options.display.max_colwidth` is deprecated in favor of using None (GH31532)

**Bug fixes**

**Datetimelike**

- Fixed bug in `to_datetime()` raising when `cache=True` and out-of-bound values are present (GH31491)

**Numeric**

- Bug in dtypes being lost in `DataFrame.__invert__ (~ operator)` with mixed dtypes (GH31183) and for extension-array backed `Series` and `DataFrame` (GH23087)

**Plotting**

- Plotting tz-aware timeseries no longer gives UserWarning (GH31205)

**Interval**

- Bug in `Series.shift()` with `interval` dtype raising a `TypeError` when shifting an interval array of integers or datetimes (GH34195)

**Contributors**

A total of 15 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Daniel Saxton
- Guillaume Lemaitre
- Jeff Reback
- Joris Van den Bossche
5.2.6 What's new in 1.0.0 (January 29, 2020)

These are the changes in pandas 1.0.0. See Release notes for a full changelog including other versions of pandas.

Note: The pandas 1.0 release removed a lot of functionality that was deprecated in previous releases (see below for an overview). It is recommended to first upgrade to pandas 0.25 and to ensure your code is working without warnings, before upgrading to pandas 1.0.

New deprecation policy

Starting with Pandas 1.0.0, pandas will adopt a variant of SemVer to version releases. Briefly,

- Deprecations will be introduced in minor releases (e.g. 1.1.0, 1.2.0, 2.1.0, …)
- Deprecations will be enforced in major releases (e.g. 1.0.0, 2.0.0, 3.0.0, …)
- API-breaking changes will be made only in major releases (except for experimental features)

See Version policy for more.

Enhancements

Using Numba in rolling.apply and expanding.apply

We’ve added an engine keyword to apply() and apply() that allows the user to execute the routine using Numba instead of Cython. Using the Numba engine can yield significant performance gains if the apply function can operate on numpy arrays and the data set is larger (1 million rows or greater). For more details, see rolling apply documentation (GH28987, GH30936)
Defining custom windows for rolling operations

We’ve added a `pandas.api.indexers.BaseIndexer()` class that allows users to define how window bounds are created during rolling operations. Users can define their own `get_window_bounds` method on a `pandas.api.indexers.BaseIndexer()` subclass that will generate the start and end indices used for each window during the rolling aggregation. For more details and example usage, see the [custom window rolling documentation](#).

Converting to markdown

We’ve added `to_markdown()` for creating a markdown table (GH11052)

```python
In [1]: df = pd.DataFrame({"A": [1, 2, 3], "B": [1, 2, 3]}, index=['a', 'a', 'b'])

In [2]: print(df.to_markdown())
<table>
<thead>
<tr>
<th></th>
<th align="right">A</th>
<th align="right">B</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td align="right">1</td>
<td align="right">1</td>
</tr>
<tr>
<td>a</td>
<td align="right">2</td>
<td align="right">2</td>
</tr>
<tr>
<td>b</td>
<td align="right">3</td>
<td align="right">3</td>
</tr>
</tbody>
</table>
```

Experimental new features

Experimental NA scalar to denote missing values

A new `pd.NA` value (singleton) is introduced to represent scalar missing values. Up to now, pandas used several values to represent missing data: `np.nan` is used for this for float data, `np.nan` or `None` for object-dtype data and `pd.NaT` for datetime-like data. The goal of `pd.NA` is to provide a “missing” indicator that can be used consistently across data types. `pd.NA` is currently used by the nullable integer and boolean data types and the new string data type (GH28095).

**Warning**: Experimental: the behaviour of `pd.NA` can still change without warning.

For example, creating a Series using the nullable integer dtype:

```python
In [3]: s = pd.Series([1, 2, None], dtype="Int64")

In [4]: s
Out[4]:
0   1
1   2
2  <NA>
Length: 3, dtype: Int64

In [5]: s[2]
Out[5]: <NA>
```

Compared to `np.nan`, `pd.NA` behaves differently in certain operations. In addition to arithmetic operations, `pd.NA` also propagates as “missing” or “unknown” in comparison operations:

```python
In [6]: np.nan > 1
Out[6]: False
```

(continues on next page)
In [7]: pd.NA > 1  
Out[7]: <NA>

For logical operations, pd.NA follows the rules of the three-valued logic (or Kleene logic). For example:

In [8]: pd.NA | True  
Out[8]: True

For more, see NA section in the user guide on missing data.

**Dedicated string data type**

We’ve added StringDtype, an extension type dedicated to string data. Previously, strings were typically stored in object-dtype NumPy arrays. (GH29975)

**Warning:** StringDtype is currently considered experimental. The implementation and parts of the API may change without warning.

The 'string' extension type solves several issues with object-dtype NumPy arrays:

1. You can accidentally store a mixture of strings and non-strings in an object dtype array. A StringArray can only store strings.
2. object dtype breaks dtype-specific operations like DataFrame.select_dtypes(). There isn’t a clear way to select just text while excluding non-text, but still object-dtype columns.
3. When reading code, the contents of an object dtype array is less clear than string.

In [9]: pd.Series(['abc', None, 'def'], dtype=pd.StringDtype())  
Out[9]:  
0  abc
1  <NA>
2  def
Length: 3, dtype: string

You can use the alias "string" as well.

In [10]: s = pd.Series(['abc', None, 'def'], dtype="string")
In [11]: s  
Out[11]:  
0  abc
1  <NA>
2  def
Length: 3, dtype: string

The usual string accessor methods work. Where appropriate, the return type of the Series or columns of a DataFrame will also have string dtype.

In [12]: s.str.upper()  
Out[12]:  
0  ABC
1  <NA>
DEF Length: 3, dtype: string

In [13]: s.str.split('b', expand=True).dtypes
Out[13]:
0  string
1  string
Length: 2, dtype: object

String accessor methods returning integers will return a value with Int64Dtype

In [14]: s.str.count("a")
Out[14]:
0   1
1  <NA>
2   0
Length: 3, dtype: Int64

We recommend explicitly using the string data type when working with strings. See Text data types for more.

Boolean data type with missing values support

We’ve added BooleanDtype/BooleanArray, an extension type dedicated to boolean data that can hold missing values. The default bool data type based on a bool-dtype NumPy array, the column can only hold True or False, and not missing values. This new BooleanArray can store missing values as well by keeping track of this in a separate mask. (GH29555, GH30095, GH31131)

In [15]: pd.Series([True, False, None], dtype=pd.BooleanDtype())
Out[15]:
0   True
1  False
2  <NA>
Length: 3, dtype: boolean

You can use the alias "boolean" as well.

In [16]: s = pd.Series([True, False, None], dtype="boolean")

In [17]: s
Out[17]:
0   True
1  False
2  <NA>
Length: 3, dtype: boolean
convert_dtypes method to ease use of supported extension dtypes

In order to encourage use of the extension dtypes `StringDtype`, `BooleanDtype`, `Int64Dtype`, `Int32Dtype`, etc., that support `pd.NA`, the methods `DataFrame.convert_dtypes()` and `Series.convert_dtypes()` have been introduced. (GH29752) (GH30929)

Example:

```python
In [18]: df = pd.DataFrame({'x': ['abc', None, 'def'],
                       ....:             'y': [1, 2, np.nan],
                       ....:             'z': [True, False, True]})

In [19]: df
Out[19]:
   x    y    z
0  abc  1.0  True
1  NaN  2.0  False
2  def  NaN  True
[3 rows x 3 columns]

In [20]: df.dtypes
Out[20]:
   x    y    z
dtype: object  float64  bool

In [21]: converted = df.convert_dtypes()

In [22]: converted
Out[22]:
   x    y    z
0  abc  1.0  True
1  NaN  2.0  False
2  def  NaN  True
[3 rows x 3 columns]

In [23]: converted.dtypes
Out[23]:
   x    y    z
dtype: object  Int64  bool

This is especially useful after reading in data using readers such as `read_csv()` and `read_excel()`. See here for a description.
Other enhancements

- `DataFrame.to_string()` added the `max_colwidth` parameter to control when wide columns are truncated (GH9784)
- Added the `na_value` argument to `Series.to_numpy()`, `Index.to_numpy()` and `DataFrame.to_numpy()` to control the value used for missing data (GH30322)
- `MultiIndex.from_product()` infers level names from inputs if not explicitly provided (GH27292)
- `DataFrame.to_latex()` now accepts `caption` and `label` arguments (GH25436)
- DataFrames with `nullable integer`, the `new string dtype` and period data type can now be converted to pyarrow (>=0.15.0), which means that it is supported in writing to the Parquet file format when using the pyarrow engine (GH28368). Full roundtrip to parquet (writing and reading back in with `to_parquet()` / `read_parquet()`) is supported starting with pyarrow >= 0.16 (GH20612).
- `to_parquet()` now appropriately handles the `schema` argument for user defined schemas in the pyarrow engine. (GH30270)
- `DataFrame.to_json()` now accepts an `indent` integer argument to enable pretty printing of JSON output (GH12004)
- `read_stata()` can read Stata 119 dta files. (GH28250)
- Implemented pandas.core.window.Window.var() and pandas.core.window.Window.std() functions (GH26597)
- Added encoding argument to `DataFrame.to_string()` for non-ascii text (GH28766)
- Added encoding argument to `DataFrame.to_html()` for non-ascii text (GH28663)
- `Styler.background_gradient()` now accepts vmin and vmax arguments (GH12145)
- `Styler.format()` added the `na_rep` parameter to help format the missing values (GH21527, GH28358)
- `read_excel()` now can read binary Excel (.xlsb) files by passing engine='pyxlsb'. For more details and example usage, see the Binary Excel files documentation. Closes GH8540.
- The `partition_cols` argument in `DataFrame.to_parquet()` now accepts a string (GH27117)
- `pandas.read_json()` now parses NaN, Infinity and -Infinity (GH12213)
- DataFrame constructor preserve ExtensionArray dtype with ExtensionArray (GH11363)
- `DataFrame.sort_values()` and `Series.sort_values()` have gained `ignore_index` keyword to be able to reset index after sorting (GH30114)
- `DataFrame.sort_index()` and `Series.sort_index()` have gained `ignore_index` keyword to reset index (GH30114)
- `DataFrame.drop_duplicates()` has gained `ignore_index` keyword to reset index (GH30114)
- Added new writer for exporting Stata dta files in versions 118 and 119, `StataWriterUTF8`. These files formats support exporting strings containing Unicode characters. Format 119 supports data sets with more than 32,767 variables (GH23573, GH30959)
- `Series.map()` now accepts collections.abc.Mapping subclasses as a mapper (GH29733)
- Added an experimental `attrs` for storing global metadata about a dataset (GH29062)
- `Timestamp.fromisocalendar()` is now compatible with python 3.8 and above (GH28115)
- `DataFrame.to_pickle()` and `read_pickle()` now accept URL (GH30163)
Backwards incompatible API changes

Avoid using names from MultiIndex.levels

As part of a larger refactor to MultiIndex the level names are now stored separately from the levels (GH27242). We recommend using MultiIndex.names to access the names, and Index.set_names() to update the names.

For backwards compatibility, you can still access the names via the levels.

```
In [24]: mi = pd.MultiIndex.from_product([[1, 2], ['a', 'b']], names=['x', 'y'])
In [25]: mi.levels[0].name
Out[25]: 'x'
```

However, it is no longer possible to update the names of the MultiIndex via the level.

```
In [26]: mi.levels[0].name = "new name"
---------------------------------------------------------------------------
RuntimeError                               Traceback (most recent call last)
<ipython-input-26-65f4400a0c97> in <module>
----> 1 mi.levels[0].name = "new name"
/pandas-release/pandas/pandas/core/indexes/base.py in name(self, value)
    1178         # Used in MultiIndex.levels to avoid silently ignoring name_
    1179         if self._no_setting_name:
-> 1180             raise RuntimeError(
    1181             "Cannot set name on a level of a MultiIndex. Use 
    1182             'MultiIndex.set_names' instead."

RuntimeError: Cannot set name on a level of a MultiIndex. Use 'MultiIndex.set_names' instead.
```

To update, use MultiIndex.set_names, which returns a new MultiIndex.

```
In [28]: mi2 = mi.set_names("new name", level=0)
In [29]: mi2.names
Out[29]: FrozenList(['new name', 'y'])
```

New repr for IntervalArray

pandas.arrays.IntervalArray adopts a new __repr__ in accordance with other array classes (GH25022)

pandas 0.25.x

```
In [1]: pd.arrays.IntervalArray.from_tuples([(0, 1), (2, 3)])
Out[2]:
IntervalArray([(0, 1), (2, 3)],
               closed='right',
               dtype='interval[int64]')
```

pandas 1.0.0
Dataframe.rename now only accepts one positional argument

`DataFrame.rename()` would previously accept positional arguments that would lead to ambiguous or undefined behavior. From pandas 1.0, only the very first argument, which maps labels to their new names along the default axis, is allowed to be passed by position (GH29136).

---

For example, with pandas 0.25.x:

```python
>>> df = pd.DataFrame([[1]])
>>> df.rename((0: 1), {0: 2})
FutureWarning: ...
2
1 1
```

And with pandas 1.0:

```python
>>> df.rename((0: 1), {0: 2})
Traceback (most recent call last):
... TypeError: rename() takes from 1 to 2 positional arguments but 3 were given
```

Note that errors will now be raised when conflicting or potentially ambiguous arguments are provided.

---

For example, with pandas 0.25.x:

```python
>>> df.rename((0: 1), index={0: 2})
0
1 1
>>> df.rename(mapper={0: 1}, index={0: 2})
0
2 1
```

And with pandas 1.0:

```python
>>> df.rename((0: 1), index={0: 2})
Traceback (most recent call last):
... TypeError: Cannot specify both 'mapper' and any of 'index' or 'columns'
>>> df.rename(mapper={0: 1}, index={0: 2})
Traceback (most recent call last):
... TypeError: Cannot specify both 'mapper' and any of 'index' or 'columns'
```

You can still change the axis along which the first positional argument is applied by supplying the axis keyword argument.

---

```python
In [31]: df.rename({0: 1})
Out[31]:
```

(continues on next page)
If you would like to update both the index and column labels, be sure to use the respective keywords.

```python
In [33]: df.rename(index={0: 1}, columns={0: 2})
Out[33]:
   2
0  1
[1 rows x 1 columns]
```

**Extended verbose info output for DataFrame**

`DataFrame.info()` now shows line numbers for the columns summary (GH17304)

**pandas 0.25.x**

```python
>>> df = pd.DataFrame({"int_col": [1, 2, 3],
... "text_col": ["a", "b", "c"],
... "float_col": [0.0, 0.1, 0.2]})
>>> df.info(verbos=True)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3 entries, 0 to 2
Data columns (total 3 columns):
  # Column Non-Null Count Dtype
  --- ------ -------------- -----  
  0 int_col 3 non-null int64
  1 text_col 3 non-null object
  2 float_col 3 non-null float64
memory usage: 152.0+ bytes
```

**pandas 1.0.0**

```python
In [34]: df = pd.DataFrame({"int_col": [1, 2, 3],
... "text_col": ["a", "b", "c"],
... "float_col": [0.0, 0.1, 0.2]})
...:
In [35]: df.info(verbos=True)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3 entries, 0 to 2
Data columns (total 3 columns):
  # Column  Non-Null Count Dtype
  --- ------ -------------- ----- 
  0 int_col 3 non-null int64
  1 text_col 3 non-null object
```

(continues on next page)
2 float_col 3 non-null float64
dtypes: float64(1), int64(1), object(1)
memory usage: 200.0+ bytes

```
pandas.array() inference changes

pandas.array() now infers pandas’ new extension types in several cases (GH29791):

1. String data (including missing values) now returns a arrays.StringArray.
2. Integer data (including missing values) now returns a arrays.IntegerArray.
3. Boolean data (including missing values) now returns the new arrays.BooleanArray
```

```
pandas 0.25.x

```36``` pd.array(['a', None])
<PandasArray>
['a', None]
Length: 2, dtype: object
```37``` pd.array([1, None])
<PandasArray>
[1, None]
Length: 2, dtype: object

pandas 1.0.0

```36``` pd.array(['a', None])
<StringArray>
['a', <NA>]
Length: 2, dtype: string
```37``` pd.array([1, None])
<IntegerArray>
[1, <NA>]
Length: 2, dtype: Int64

As a reminder, you can specify the dtype to disable all inference.

arrays.IntegerArray now uses pandas.NA

arrays.IntegerArray now uses pandas.NA rather than numpy.nan as its missing value marker (GH29964).
```
pandas 0.25.x

```37``` a = pd.array([1, 2, None], dtype="Int64")
```38``` a
<IntegerArray>
[1, 2, NaN]
Length: 3, dtype: Int64
```39``` a[2]
nan

5.2. Version 1.0
This has a few API-breaking consequences.

**Converting to a NumPy ndarray**

When converting to a NumPy array missing values will be `pd.NA`, which cannot be converted to a float. So calling `np.asarray(integer_array, dtype="float")` will now raise.

### pandas 0.25.x

```python
>>> np.asarray(a, dtype="float")
array([ 1. , 2. , nan])
```

### pandas 1.0.0

```python
In [41]: np.asarray(a, dtype="float")
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-41-4578f04da2b3> in
     1 np.asarray(a, dtype="float")
/opt/conda/envs/pandas/lib/python3.8/site-packages/numpy/core/_asarray.py in
     85     return array(a, dtype, copy=False, order=order)
86
87
/pandas-release/pandas/pandas/core/arrays/masked.py in __array__(self, dtype)
   217     We return an object array here to preserve our scalar values
   218     """
--> 219     return self.to_numpy(dtype=dtype)
   220
   221     def __arrow_array__(self, type=None):
/pandas-release/pandas/pandas/core/arrays/masked.py in to_numpy(self, dtype, copy, na_value)
   198     and na_value is libmissing.NA
   199     :
--> 200     raise ValueError(  
   201     f"cannot convert to '{dtype}'-dtype NumPy array "
   202     "with missing values. Specify an appropriate 'na_value' "

ValueError: cannot convert to 'float64'-dtype NumPy array with missing values. Specify an appropriate 'na_value' for this dtype.
```

Use `arrays.IntegerArray.to_numpy()` with an explicit `na_value` instead.
Reductions can return `pd.NA`

When performing a reduction such as a sum with `skipna=False`, the result will now be `pd.NA` instead of `np.nan` in presence of missing values (GH30958).

pandas 0.25.x

```python
>>> pd.Series(a).sum(skipna=False)
nan
```

pandas 1.0.0

```python
In [43]: pd.Series(a).sum(skipna=False)
Out[43]: <NA>
```

value_counts returns a nullable integer dtype

`Series.value_counts()` with a nullable integer dtype now returns a nullable integer dtype for the values.

pandas 0.25.x

```python
>>> pd.Series([2, 1, 1, None], dtype="Int64").value_counts().dtype
dtype('int64')
```

pandas 1.0.0

```python
In [44]: pd.Series([2, 1, 1, None], dtype="Int64").value_counts().dtype
Out[44]: Int64Dtype()
```

See [Experimental NA scalar to denote missing values](#) for more on the differences between `pandas.NA` and `numpy.nan`.

arrays.IntegerArray comparisons return arrays.BooleanArray

Comparison operations on an `arrays.IntegerArray` now returns an `arrays.BooleanArray` rather than a NumPy array (GH29964).

pandas 0.25.x

```python
>>> a = pd.array([1, 2, None], dtype="Int64")
>>> a
<IntegerArray>
[1, 2, NaN]
Length: 3, dtype: Int64

>>> a > 1
array([False, True, False])
```

pandas 1.0.0

```python
In [45]: a = pd.array([1, 2, None], dtype="Int64")

In [46]: a > 1
Out[46]:
```
Note that missing values now propagate, rather than always comparing unequal like `numpy.nan`. See *Experimental NA scalar to denote missing values* for more.

**By default Categorical.min() now returns the minimum instead of np.nan**

When `Categorical` contains `np.nan`, `Categorical.min()` no longer return `np.nan` by default (skipna=True) (GH25303)

```python
pandas 0.25.x
In [1]: pd.Categorical([1, 2, np.nan], ordered=True).min()
Out[1]: nan

pandas 1.0.0
In [47]: pd.Categorical([1, 2, np.nan], ordered=True).min()
Out[47]: 1
```

**Default dtype of empty pandas.Series**

Initialising an empty `pandas.Series` without specifying a dtype will raise a *DeprecationWarning* now (GH17261). The default dtype will change from `float64` to `object` in future releases so that it is consistent with the behaviour of `DataFrame` and `Index`.

```python
pandas 1.0.0
In [1]: pd.Series()
Out[2]:
DeprecationWarning: The default dtype for empty Series will be 'object' instead of 'float64' in a future version. Specify a dtype explicitly to silence this warning.
Series([], dtype: float64)
```

**Result dtype inference changes for resample operations**

The rules for the result dtype in `DataFrame.resample()` aggregations have changed for extension types (GH31359). Previously, pandas would attempt to convert the result back to the original dtype, falling back to the usual inference rules if that was not possible. Now, pandas will only return a result of the original dtype if the scalar values in the result are instances of the extension dtype’s scalar type.

```python
In [48]: df = pd.DataFrame({"A": ['a', 'b']}, dtype='category',
                   ....: index=pd.date_range('2000', periods=2))

In [49]: df
Out[49]:
        A
2000-01-01  a
```

(continues on next page)
pandas 0.25.x

```python
>>> df.resample("2D").agg(lambda x: 'a').A.dtype
CategoricalDtype(categories=['a', 'b'], ordered=False)
```

pandas 1.0.0

```python
In [50]: df.resample("2D").agg(lambda x: 'a').A.dtype
Out[50]: dtype('O')
```

This fixes an inconsistency between `resample` and `groupby`. This also fixes a potential bug, where the values of the result might change depending on how the results are cast back to the original dtype.

pandas 0.25.x

```python
>>> df.resample("2D").agg(lambda x: 'c')
   A
0  NaN
```

pandas 1.0.0

```python
In [51]: df.resample("2D").agg(lambda x: 'c')
Out[51]:
    A  
2000-01-01  c
[1 rows x 1 columns]
```

Increased minimum version for Python

Pandas 1.0.0 supports Python 3.6.1 and higher (GH29212).

Increased minimum versions for dependencies

Some minimum supported versions of dependencies were updated (GH29766, GH29723). If installed, we now require:

<table>
<thead>
<tr>
<th>Package</th>
<th>Minimum Version</th>
<th>Required</th>
<th>Changed</th>
</tr>
</thead>
<tbody>
<tr>
<td>numpy</td>
<td>1.13.3</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>pytz</td>
<td>2015.4</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>python-dateutil</td>
<td>2.6.1</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>bottleneck</td>
<td>1.2.1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>numexpr</td>
<td>2.6.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>pytest (dev)</td>
<td>4.0.2</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

For optional libraries the general recommendation is to use the latest version. The following table lists the lowest version per library that is currently being tested throughout the development of pandas. Optional libraries below the lowest tested version may still work, but are not considered supported.
Build changes

Pandas has added a pyproject.toml file and will no longer include cythonized files in the source distribution uploaded to PyPI (GH28341, GH20775). If you’re installing a built distribution (wheel) or via conda, this shouldn’t have any effect on you. If you’re building pandas from source, you should no longer need to install Cython into your build environment before calling pip install pandas.

Other API changes

- core.groupby.GroupBy.transform now raises on invalid operation names (GH27489)
- pandas.api.types.infer_dtype() will now return “integer-na” for integer and np.nan mix (GH27283)
- MultiIndex.from_arrays() will no longer infer names from arrays if names=None is explicitly provided (GH27292)
- In order to improve tab-completion, Pandas does not include most deprecated attributes when introspecting a pandas object using dir (e.g. dir(df)). To see which attributes are excluded, see an object’s _deprecations attribute, for example pd.DataFrame._deprecations (GH28805).
- The returned dtype of unique() now matches the input dtype. (GH27874)
- Changed the default configuration value for options.matplotlib.register_converters from True to "auto" (GH18720). Now, pandas custom formatters will only be applied to plots created by pandas, through plot(). Previously, pandas’ formatters would be applied to all plots created after a plot(). See units registration for more.
- Series.dropna() has dropped its **kwargs argument in favor of a single how parameter. Supplying anything else than how to **kwargs raised a TypeError previously (GH29388)
- When testing pandas, the new minimum required version of pytest is 5.0.1 (GH29664)
• `Series.str.__iter__()` was deprecated and will be removed in future releases (GH28277).

• Added `<NA>` to the list of default NA values for `read_csv()` (GH30821)

Documentation improvements

• Added new section on *Scaling to large datasets* (GH28315).

• Added sub-section on *Query MultiIndex* for HDF5 datasets (GH28791).

Deprecations

• `Series.item()` and `Index.item()` have been _undeprecated_ (GH29250)

• `Index.set_value` has been deprecated. For a given index `idx`, array `arr`, value in `idx` of `idx_val` and a new value of `val`, `idx.set_value(arr, idx_val, val)` is equivalent to `arr[idx.get_loc(idx_val)] = val`, which should be used instead (GH28621).

• `is_extension_type()` is deprecated, `is_extension_array_dtype()` should be used instead (GH29457)

• `eval()` keyword argument “truediv” is deprecated and will be removed in a future version (GH29812)

• `DateOffset.isAnchored()` and `DatetOffset.onOffset()` are deprecated and will be removed in a future version, use `DateOffset.is_anchored()` and `DateOffset.is_on_offset()` instead (GH30340)

• `pandas.tseries.frequencies.get_offset` is deprecated and will be removed in a future version, use `pandas.tseries.frequencies.to_offset` instead (GH4205)

• `Categorical.take_nd()` and `CategoricalIndex.take_nd()` are deprecated, use `Categorical.take()` and `CategoricalIndex.take()` instead (GH27745)

• The parameter `numeric_only` of `Categorical.min()` and `Categorical.max()` is deprecated and replaced with `skipna` (GH25303)

• The parameter `label` in `lreshape()` has been deprecated and will be removed in a future version (GH29742)

• `pandas.core.index` has been deprecated and will be removed in a future version, the public classes are available in the top-level namespace (GH19711)

• `pandas.json_normalize()` is now exposed in the top-level namespace. Usage of `json_normalize` as `pandas.io.json.json_normalize` is now deprecated and it is recommended to use `json_normalize` as `pandas.json_normalize()` instead (GH27586).

• The `numpy` argument of `pandas.read_json()` is deprecated (GH28512).

• `DataFrame.to_stata()`, `DataFrame.to_feather()`, and `DataFrame.to_parquet()` argument “frame” is deprecated, use “path” instead (GH23574)

• The deprecated internal attributes `_start`, `_stop` and `_step` of `RangeIndex` now raise a `FutureWarning` instead of a `DeprecationWarning` (GH26581)

• The `pandas.util.testing` module has been deprecated. Use the public API in `pandas.testing` documented at `Testing functions` (GH16232).

• `pandas.SparseArray` has been deprecated. Use `pandas.arrays.SparseArray` instead (arrays.SparseArray) (GH30642)
• The parameter `is_copy` of `Series.take()` and `DataFrame.take()` has been deprecated and will be removed in a future version. (GH27357)

• Support for multi-dimensional indexing (e.g. `index[:, None]`) on a `Index` is deprecated and will be removed in a future version, convert to a numpy array before indexing instead (GH30588)

• The `pandas.np` submodule is now deprecated. Import numpy directly instead (GH30296)

• The `pandas.datetime` class is now deprecated. Import from `datetime` instead (GH30610)

• `diff` will raise a `TypeError` rather than implicitly losing the dtype of extension types in the future. Convert to the correct dtype before calling `diff` instead (GH31025)

### Selecting Columns from a Grouped DataFrame

When selecting columns from a `DataFrameGroupBy` object, passing individual keys (or a tuple of keys) inside single brackets is deprecated, a list of items should be used instead. (GH23566) For example:

```python
df = pd.DataFrame({
    "A": ["foo", "bar", "foo", "bar", "foo", "bar", "foo", "foo"],
    "B": np.random.randn(8),
    "C": np.random.randn(8),
})
g = df.groupby('A')
# single key, returns SeriesGroupBy
g["B"]
# tuple of single key, returns SeriesGroupBy
g[['B',]]
# tuple of multiple keys, returns DataFrameGroupBy, raises FutureWarning
g[['B', 'C']]
# multiple keys passed directly, returns DataFrameGroupBy, raises FutureWarning
# (implicitly converts the passed strings into a single tuple)
g["B", 'C']
# proper way, returns DataFrameGroupBy
g[['B', 'C']]
```

### Removal of prior version deprecations/changes

**Removed SparseSeries and SparseDataFrame**

SparseSeries, SparseDataFrame and the `DataFrame.to_sparse` method have been removed (GH28425). We recommend using a Series or DataFrame with sparse values instead. See Migrating for help with migrating existing code.

**Matplotlib unit registration**

Previously, pandas would register converters with matplotlib as a side effect of importing pandas (GH18720). This changed the output of plots made via matplotlib plots after pandas was imported, even if you were using matplotlib directly rather than `plot()`.

To use pandas formatters with a matplotlib plot, specify

```python
>>> import pandas as pd
>>> pd.options.plotting.matplotlib.register_converters = True
```
Note that plots created by `DataFrame.plot()` and `Series.plot()` do register the converters automatically. The only behavior change is when plotting a date-like object via `matplotlib.pyplot.plot` or `matplotlib.Axes.plot`. See `Custom formatters for timeseries plots` for more.

Other removals

- Removed the previously deprecated keyword “index” from `read_stata()`, `StataReader`, and `StataReader.read()`, use “index_col” instead (GH17328)
- Removed `StataReader.data` method, use `StataReader.read()` instead (GH9493)
- Removed `pandas.plotting._matplotlib.tsplot` and `Series.plot()` instead (GH19980)
- `pandas.tseries.converter.register` has been moved to `pandas.plotting.register_matplotlib_converters()` (GH18307)
- `Series.plot()` no longer accepts positional arguments, pass keyword arguments instead (GH30003)
- `DataFrame.hist()` and `Series.hist()` no longer allows `figsize="default"`, specify figure size by passing a tuple instead (GH30003)
- Floordiv of integer-dtyped array by `Timedelta` now raises `TypeError` (GH21036)
- `TimedeltaIndex` and `DatetimeIndex` no longer accept non-nanosecond dtype strings like “timedelta64” or “datetime64”, use “timedelta64[ns]” and “datetime64[ns]” instead (GH24806)
- Changed the default “skipna” argument in `pandas.api.types.infer_dtype()` from False to True (GH24050)
- Removed `Series.ix` and `DataFrame.ix` (GH26438)
- Removed `Index.summary` (GH18217)
- Removed the previously deprecated keyword “fastpath” from the `Index` constructor (GH23110)
- Removed `Series.get_value`, `Series.set_value`, `DataFrame.get_value`, `DataFrame.set_value` (GH17739)
- Removed `Series.compound` and `DataFrame.compound` (GH26405)
- Changed the default “inplace” argument in `DataFrame.set_index()` and `Series.set_axis()` from None to False (GH27600)
- Removed `Series.cat.categorical`, `Series.cat.index`, `Series.cat.name` (GH24751)
- Removed the previously deprecated keyword “box” from `to_datetime()` and `to_timedelta()`; in addition these now always returns `DatetimeIndex`, `TimedeltaIndex`, `Index`, `Series`, or `DataFrame` (GH24486)
- `to_timedelta()`, `Timedelta`, and `TimedeltaIndex` no longer allow “M”, “y”, or “Y” for the “unit” argument (GH23264)
- Removed the previously deprecated keyword “time_rule” from (non-public) `offsets.generate_range`, which has been moved to `core.arrays._ranges.generate_range()` (GH24157)
- `DataFrame.loc()` or `Series.loc()` with listlike indexers and missing labels will no longer reindex (GH17295)
- `DataFrame.to_excel()` and `Series.to_excel()` with non-existent columns will no longer reindex (GH17295)
- Removed the previously deprecated keyword “join_axes” from `concat()`; use `reindex_like` on the result instead (GH22318)
- Removed the previously deprecated keyword “by” from `DataFrame.sort_index()`, use `DataFrame.sort_values()` instead (GH10726)
• Removed support for nested renaming in DataFrame.aggregate(), Series.aggregate(), core.groupby.DataFrameGroupBy.aggregate(), core.groupby.SeriesGroupBy.aggregate(), core.window.rolling.Rolling.aggregate() (GH18529)

• Passing datetime64 data to TimedeltaIndex or timedelta64 data to DatetimeIndex now raises TypeError (GH23539, GH23937)

• Passing int64 values to DatetimeIndex and a timezone now interprets the values as nanosecond timestamps in UTC, not wall times in the given timezone (GH24559)

• A tuple passed to DataFrame.groupby() is now exclusively treated as a single key (GH18314)

• Removed Index.contains, use key in index instead (GH30103)

• Addition and subtraction of int or integer-arrays is no longer allowed in Timestamp, DatetimeIndex, TimedeltaIndex, use obj + n * obj.freq instead of obj + n (GH22535)

• Removed Series.ptp (GH21614)

• Removed Series.from_array (GH18258)

• Removed DataFrame.from_items (GH18458)

• Removed DataFrame.as_matrix, Series.as_matrix (GH18458)

• Removed Series.asobject (GH18477)

• Removed DataFrame.as_blocks, Series.as_blocks, DataFrame.blocks, Series.blocks (GH17656)

• pandas.Series.str.cat() now defaults to aligning others, using join='left' (GH27611)

• pandas.Series.str.cat() does not accept list-likes within list-likes anymore (GH27611)

• Series.where() with Categorical dtype (or DataFrame.where() with Categorical column) no longer allows setting new categories (GH24114)

• Removed the previously deprecated keywords “start”, “end”, and “periods” from the DatetimeIndex, TimedeltaIndex, and PeriodIndex constructors; use date_range(), timedelta_range(), and period_range() instead (GH23919)

• Removed the previously deprecated keyword “verify_integrity” from the DatetimeIndex and TimedeltaIndex constructors (GH23919)

• Removed the previously deprecated keyword “fastpath” from pandas.core.internals.blocks.make_block (GH19265)

• Removed the previously deprecated keyword “dtype” from Block.make_block_same_class() (GH19434)

• Removed ExtensionArray._formatting_values. Use ExtensionArray._formatter instead. (GH23601)

• Removed MultiIndex.to_hierarchical (GH21613)

• Removed MultiIndex.labels, use MultiIndex.codes instead (GH23752)

• Removed the previously deprecated keyword “labels” from the MultiIndex constructor, use “codes” instead (GH23752)

• Removed MultiIndex.set_labels, use MultiIndex.set_codes() instead (GH23752)

• Removed the previously deprecated keyword “labels” from MultiIndex.set_codes(), MultiIndex.copy(), MultiIndex.drop(), use “codes” instead (GH23752)

• Removed support for legacy HDF5 formats (GH29787)
• Passing a dtype alias (e.g. ‘datetime64[ns, UTC]’) to DatetimeTZDtype is no longer allowed, use DatetimeTZDtype.construct_from_string() instead (GH23990)

• Removed the previously deprecated keyword “skip_footer” from read_excel(); use “skipfooter” instead (GH18836)

• read_excel() no longer allows an integer value for the parameter usecols, instead pass a list of integers from 0 to usecols inclusive (GH23635)

• Removed the previously deprecated keyword “convert_datetime64” from DataFrame.to_records() (GH18902)

• Removed IntervalIndex.from_intervals in favor of the IntervalIndex constructor (GH19263)

• Changed the default “keep_tz” argument in DatetimeIndex.to_series() from None to True (GH23739)

• Removed api.types.is_period and api.types.is_datetimetz (GH23917)

• Ability to read pickles containing Categorical instances created with pre-0.16 version of pandas has been removed (GH27538)

• Removed pandas.tseries.plotting.tsplot (GH18627)

• Removed the previously deprecated keywords “reduce” and “broadcast” from DataFrame.apply() (GH18577)

• Removed the previously deprecated assert_raises_regex function in pandas._testing (GH29174)

• Removed the previously deprecated FrozenNDArray class in pandas.core.indexes.frozen (GH29335)

• Removed the previously deprecated keyword “nthreads” from read_feather(), use “use_threads” instead (GH23053)

• Removed Index.is_lexsorted_for_tuple (GH29305)

• Removed support for nested renaming in DataFrame.aggregate(), Series.aggregate(), core.groupby.DataFrameGroupBy.aggregate(), core.groupby.SeriesGroupBy.aggregate(), core.window.rolling.Rolling.aggregate() (GH29608)

• Removed Series.valid; use Series.dropna() instead (GH18800)

• Removed DataFrame.is_copy, Series.is_copy (GH18812)

• Removed DataFrame.get_ftype_counts, Series.get_ftype_counts (GH18243)

• Removed DataFrame.ftypes, Series.ftypes (GH26744)

• Removed Index.get_duplicates, use idx[idx.duplicated()].unique() instead (GH20239)

• Removed Series.clip_upper, Series.clip_lower, DataFrame.clip_upper, DataFrame.clip_lower (GH24203)

• Removed the ability to alter DatetimeIndex.freq, TimedeltaIndex.freq, or PeriodIndex.freq (GH20772)

• Removed DatetimeIndex.offset (GH20730)

• Removed DatetimeIndex.asobject, TimedeltaIndex.asobject, PeriodIndex.asobject, use astype(object) instead (GH29801)

• Removed the previously deprecated keyword “order” from factorize() (GH19751)

• Removed the previously deprecated keyword “encoding” from read_stata() and DataFrame.to_stata() (GH21400)
• Changed the default “sort” argument in `concat()` from `None` to `False` (GH20613)

• Removed the previously deprecated keyword “raise_conflict” from `DataFrame.update()`, use “errors” instead (GH23585)

• Removed the previously deprecated keyword “n” from `DateTimeIndex.shift()`, `TimedeltaIndex.shift()`, `PeriodIndex.shift()` , use “periods” instead (GH22458)

• Removed the previously deprecated keywords “how”, “fill_method”, and “limit” from `DataFrame.resample()` (GH30139)

• Passing an integer to `Series.fillna()` or `DataFrame.fillna()` with `timedelta64[ns]` dtype now raises `TypeError` (GH24694)

• Passing multiple axes to `DataFrame.dropna()` is no longer supported (GH20995)

• Removed `Series.nonzero`, use `to_numpy().nonzero()` instead (GH24048)

• Passing floating dtype codes to `Categorical.from_codes()` is no longer supported, pass `codes.astype(np.int64)` instead (GH21775)

• Removed the previously deprecated keyword “pat” from `Series.str.partition()` and `Series.str.rpartition()`, use “sep” instead (GH23767)

• Removed `Series.put` (GH27106)

• Removed `Series.real, Series.imag` (GH27106)

• Removed `Series.to_dense, DataFrame.to_dense` (GH26684)

• Removed `Index.dtype_str, use str(index.dtype)` instead (GH27106)

• `Categorical.ravel()` returns a `Categorical` instead of a ndarray (GH27199)

• The ‘outer’ method on Numpy ufuncs, e.g. `np.subtract.outer` operating on `Series` objects is no longer supported, and will raise `NotImplementedError` (GH27198)

• Removed `Series.get_dtype_counts` and `DataFrame.get_dtype_counts` (GH27145)

• Changed the default “fill_value” argument in `Categorical.take()` from `True` to `False` (GH20841)

• Changed the default value for the `raw` argument in `Series.rolling().apply()`, `DataFrame.rolling().apply()`, `Series.expanding().apply()`, and `DataFrame.expanding().apply()` from `None` to `False` (GH20584)

• Removed deprecated behavior of `Series.argmin()` and `Series.argmax()`, use `Series.idxmin()` and `Series.idxmax()` for the old behavior (GH16955)

• Passing a tz-aware `datetime.datetime` or `Timestamp` into the `Timestamp` constructor with the `tz` argument now raises a `ValueError` (GH23621)

• Removed `Series.base, Index.base, Categorical.base, Series.flags, Index.flags, PeriodArray.flags, Series.strides, Index.strides, Series.itemsize, Index.itemsize, Series.data, Index.data` (GH20721)

• Changed `Timedelta.resolution()` to match the behavior of the standard library `datetime.timedelta.resolution`, for the old behavior, use `Timedelta.resolution_string()` (GH26839)

• Removed `Timestamp.weekday_name, DatetimeIndex.weekday_name, and Series.dt.weekday_name` (GH18164)

• Removed the previously deprecated keyword “errors” in `Timestamp.tz_localize()`, `DatetimeIndex.tz_localize()`, and `Series.tz_localize()` (GH22644)

• Changed the default “ordered” argument in `CategoricalDtype` from `None` to `False` (GH26336)
• *Series.set_axis()* and *DataFrame.set_axis()* now require “labels” as the first argument and “axis” as an optional named parameter (GH30089)

• Removed `to_msgpack`, `read_msgpack`, `DataFrame.to_msgpack`, `Series.to_msgpack` (GH27103)

• Removed `Series.compress` (GH21930)

• Removed the previously deprecated keyword “fill_value” from `Categorical.fillna()`, use “value” instead (GH19269)

• Removed the previously deprecated keyword “data” from `andrews_curves()`, use “frame” instead (GH6956)

• Removed the previously deprecated keyword “data” from `parallel_coordinates()`, use “frame” instead (GH6956)

• Removed the previously deprecated keyword “colors” from `parallel_coordinates()`, use “color” instead (GH6956)

• Removed the previously deprecated keywords “verbose” and “private_key” from `read_gbq()` (GH30200)

• Calling `np.array` and `np.asarray` on tz-aware `Series` and `DatetimeIndex` will now return an object array of tz-aware `Timestamp` (GH24596)

Performance improvements

• Performance improvement in *DataFrame* arithmetic and comparison operations with scalars (GH24990, GH29853)

• Performance improvement in indexing with a non-unique `IntervalIndex` (GH27489)

• Performance improvement in `MultiIndex.is_monotonic` (GH27495)

• Performance improvement in `cut()` when `bins` is an `IntervalIndex` (GH27668)

• Performance improvement when initializing a `DataFrame` using a range (GH30171)

• Performance improvement in `DataFrame.corr()` when method is "spearman" (GH28139)

• Performance improvement in `DataFrame.replace()` when provided a list of values to replace (GH28099)

• Performance improvement in `DataFrame.select_dtypes()` by using vectorization instead of iterating over a loop (GH28317)

• Performance improvement in `Categorical.searchsorted()` and `CategoricalIndex.searchsorted()` (GH28795)

• Performance improvement when comparing a `Categorical` with a scalar and the scalar is not found in the categories (GH29750)

• Performance improvement when checking if values in a `Categorical` are equal, equal or larger or larger than a given scalar. The improvement is not present if checking if the `Categorical` is less than or less than or equal than the scalar (GH29820)

• Performance improvement in `Index.equals()` and `MultiIndex.equals()` (GH29134)

• Performance improvement in `infer_dtype()` when `skipna` is True (GH28814)
Bug fixes

Categorical

- Added test to assert the `fillna()` raises the correct `ValueError` message when the value isn’t a value from categories (GH13628)
- Bug in `Categorical.astype()` where NaN values were handled incorrectly when casting to int (GH28406)
- `DataFrame.reindex()` with a `CategoricalIndex` would fail when the targets contained duplicates, and wouldn’t fail if the source contained duplicates (GH28107)
- Bug in `Categorical.astype()` not allowing for casting to extension dtypes (GH28668)
- Bug where `merge()` was unable to join on categorical and extension dtype columns (GH28668)
- `Categorical.searchsorted()` and `CategoricalIndex.searchsorted()` now work on unordered categories also (GH21667)
- Added test to assert roundtripping to parquet with `DataFrame.to_parquet()` or `read_parquet()` will preserve Categorical dtypes for string types (GH27955)
- Changed the error message in `Categorical.remove_categories()` to always show the invalid removals as a set (GH28669)
- Using date accessors on a categorical typed `Series` of datetimes was not returning an object of the same type as if one used the `str()` / `dt()` on a `Series` of that type. E.g. when accessing `Series.dt.tz_localize()` on a `Categorical` with duplicate entries, the accessor was skipping duplicates (GH27952)
- Bug in `DataFrame.replace()` and `Series.replace()` that would give incorrect results on categorical data (GH26988)
- Bug where calling `Categorical.min()` or `Categorical.max()` on an empty Categorical would raise a numpy exception (GH30227)
- The following methods now also correctly output values for unobserved categories when called through `groupby(..., observed=False)` (GH17605) *
  * `core.groupby.SeriesGroupBy.count()` *
  * `core.groupby.SeriesGroupBy.size()` *
  * `core.groupby.SeriesGroupBy.nunique()` *
  * `core.groupby.SeriesGroupBy.nth()` *

Datetimelike

- Bug in `Series.__setitem__()` incorrectly casting `np.timedelta64("NaT")` to `np.datetime64("NaT")` when inserting into a `Series` with datetime64 dtype (GH27311)
- Bug in `Series.dt()` property lookups when the underlying data is read-only (GH27529)
- Bug in `HDFStore.__getitem__` incorrectly reading tz attribute created in Python 2 (GH26443)
- Bug in `to_datetime()` where passing arrays of malformed `str` with errors=“coerce” could incorrectly lead to raise `ValueError` (GH28299)
- Bug in `core.groupby.SeriesGroupBy.nunique()` where `NaT` values were interfering with the count of unique values (GH27951)
- Bug in `Timestamp` subtraction when subtracting a `Timestamp` from a `np.datetime64` object incorrectly raising `TypeError` (GH28286)
• Addition and subtraction of integer or integer-dtype arrays with `Timestamp` will now raise `NullFrequencyError` instead of `ValueError` (GH28268)
• Bug in `Series` and `DataFrame` with integer dtype failing to raise `TypeError` when adding or subtracting a `np.datetime64` object (GH28080)
• Bug in `Series.astype()`, `Index.astype()`, and `DataFrame.astype()` failing to handle `NaT` when casting to an integer dtype (GH28492)
• Bug in `Week` with weekday incorrectly raising `AttributeError` instead of `TypeError` when adding or subtracting an invalid type (GH28530)
• Bug in `DataFrame` arithmetic operations when operating with a Series with dtype `timedelta64[ns]` (GH28049)
• Bug in `core.groupby.generic.SeriesGroupBy.apply()` raising `ValueError` when a column in the original DataFrame is a datetime and the column labels are not standard integers (GH28247)
• Bug in `pandas._config.localization.get_locales()` where the locales `-a` encodes the locales list as `windows-1252` (GH23638, GH24760, GH27368)
• Bug in `Series.var()` failing to raise `TypeError` when called with `timedelta64[ns]` dtype (GH28289)
• Bug in `DatetimeIndex.strftime()` and `Series.dt.strftime()` where `NaT` was converted to the string 'NaT' instead of `np.nan` (GH29578)
• Bug in masking datetime-like arrays with a boolean mask of an incorrect length not raising an `IndexError` (GH30308)
• Bug in `Timestamp.resolution` being a property instead of a class attribute (GH29910)
• Bug in `pandas.to_datetime()` when called with `None` raising `TypeError` instead of returning `NaT` (GH30011)
• Bug in `pandas.to_datetime()` failing for `deque`s when using `cache=True` (the default) (GH29403)
• Bug in `Series.item()` with datetime64 or timedelta64 dtype, `DatetimeIndex.item()`, and `TimedeltaIndex.item()` returning an integer instead of a `Timestamp` or `Timedelta` (GH30175)
• Bug in `DatetimeIndex` addition when adding a non-optimized `DateOffset` incorrectly dropping timezone information (GH30336)
• Bug in `DataFrame.drop()` where attempting to drop non-existent values from a DatetimeIndex would yield a confusing error message (GH30399)
• Bug in `DataFrame.append()` would remove the timezone-awareness of new data (GH30238)
• Bug in `Series.cummin()` and `Series.cummax()` with timezone-aware dtype incorrectly dropping its timezone (GH15553)
• Bug in `DatetimeArray`, `TimedeltaArray`, and `PeriodArray` where inplace addition and subtraction did not actually operate inplace (GH24115)
• Bug in `pandas.to_datetime()` when called with Series storing `IntegerArray` raising `TypeError` instead of returning Series (GH30050)
• Bug in `date_range()` with custom business hours as `freq` and given number of `periods` (GH30593)
• Bug in `PeriodIndex` comparisons with incorrectly casting integers to `Period` objects, inconsistent with the `Period` comparison behavior (GH30722)
• Bug in `DatetimeIndex.insert()` raising a `ValueError` instead of a `TypeError` when trying to insert a timezone-aware `Timestamp` into a timezone-naive `DatetimeIndex`, or vice-versa (GH30806)
pandas: powerful Python data analysis toolkit, Release 1.1.1

Timedelta

- Bug in subtracting a TimedeltaIndex or TimedeltaArray from a np.datetime64 object (GH29558)
- 

Timezones

- 
- 

Numeric

- Bug in DataFrame.quantile() with zero-column DataFrame incorrectly raising (GH23925)
- DataFrame flex inequality comparisons methods (DataFrame.lt(), DataFrame.le(), DataFrame.gt(), DataFrame.ge()) with object-dtype and complex entries failing to raise TypeError like their Series counterparts (GH28079)
- Bug in DataFrame logical operations (&, |, ^) not matching Series behavior by filling NA values (GH28741)
- Bug in DataFrame.interpolate() where specifying axis by name references variable before it is assigned (GH29142)
- Bug in Series.var() not computing the right value with a nullable integer dtype series not passing through ddof argument (GH29128)
- Improved error message when using frac > 1 and replace = False (GH27451)
- Bug in numeric indexes resulted in it being possible to instantiate an Int64Index, UInt64Index, or Float64Index with an invalid dtype (e.g. datetime-like) (GH29539)
- Bug in UInt64Index precision loss while constructing from a list with values in the np.uint64 range (GH29526)
- Bug in NumericIndex construction that caused indexing to fail when integers in the np.uint64 range were used (GH28023)
- Bug in NumericIndex construction that caused UInt64Index to be casted to Float64Index when integers in the np.uint64 range were used to index a DataFrame (GH28279)
- Bug in Series.interpolate() when using method='index' with an unsorted index, would previously return incorrect results. (GH21037)
- Bug in DataFrame.round() where a DataFrame with a CategoricalIndex of IntervalIndex columns would incorrectly raise a TypeError (GH30063)
- Bug in Series.pct_change() and DataFrame.pct_change() when there are duplicated indices (GH30463)
- Bug in DataFrame cumulative operations (e.g. cumsum, cummax) incorrect casting to object-dtype (GH19296)
- Bug in diff losing the dtype for extension types (GH30889)
- Bug in DataFrame.diff raising an IndexError when one of the columns was a nullable integer dtype (GH30967)
pandas: powerful Python data analysis toolkit, Release 1.1.1

Conversion

•

Strings

• Calling `Series.str.isalnum()` (and other “ismethods”) on an empty Series would return an object dtype instead of bool (GH29624)

Interval

• Bug in `IntervalIndex.get_indexer()` where a Categorical or CategoricalIndex target would incorrectly raise a TypeError (GH30063)

• Bug in `pandas.core.dtypes.cast.infer_dtype_from_scalar` where passing pandas_dtype=True did not infer IntervalDtype (GH30337)

• Bug in `Series` constructor where constructing a Series from a list of Interval objects resulted in object dtype instead of IntervalDtype (GH23563)

• Bug in IntervalDtype where the kind attribute was incorrectly set as None instead of "O" (GH30568)

• Bug in `IntervalIndex`, `IntervalArray`, and `Series` with interval data where equality comparisons were incorrect (GH24112)

Indexing

• Bug in assignment using a reverse slicer (GH26939)

• Bug in `DataFrame.explode()` would duplicate frame in the presence of duplicates in the index (GH28010)

• Bug in reindexing a PeriodIndex() with another type of index that contained a Period (GH28323)

• Fix assignment of column via .loc with numpy non-ns datetime type (GH27395)

• Bug in Float64Index.astype() where np.inf was not handled properly when casting to an integer dtype (GH28475)

• Index.union() could fail when the left contained duplicates (GH28257)

• Bug when indexing with .loc where the index was a CategoricalIndex with non-string categories didn’t work (GH17569, GH30225)

• Index.get_indexer_non_unique() could fail with TypeError in some cases, such as when searching for ints in a string index (GH28257)

• Bug in Float64Index.get_loc() incorrectly raising TypeError instead of KeyError (GH29189)

• Bug in DataFrame.loc() with incorrect dtype when setting Categorical value in 1-row DataFrame (GH25495)

• MultiIndex.get_loc() can’t find missing values when input includes missing values (GH19132)
• Bug in Series.__setitem__() incorrectly assigning values with boolean indexer when the length of new data matches the number of True values and new data is not a Series or an np.array (GH30567)

• Bug in indexing with a PeriodIndex incorrectly accepting integers representing years, use e.g. ser.loc["2007"] instead of ser.loc[2007] (GH30763)

Missing

•

MultiIndex

• Constructor for MultiIndex verifies that the given sortorder is compatible with the actual lexsort_depth if verify_integrity parameter is True (the default) (GH28735)

• Series and MultiIndex.drop with MultiIndex raise exception if labels not in given in level (GH8594)

I/O

• read_csv() now accepts binary mode file buffers when using the Python csv engine (GH23779)

• Bug in DataFrame.to_json() where using a Tuple as a column or index value and using orient="columns" or orient="index" would produce invalid JSON (GH20500)

• Improve infinity parsing. read_csv() now interprets Infinity, +Infinity, -Infinity as floating point values (GH10065)

• Bug in DataFrame.to_csv() where values were truncated when the length of na_rep was shorter than the text input data. (GH25099)

• Bug in DataFrame.to_string() where values were truncated using display options instead of outputting the full content (GH9784)

• Bug in DataFrame.to_json() where a datetime column label would not be written out in ISO format with orient="table" (GH28130)

• Bug in DataFrame.to_parquet() where writing to GCS would fail with engine='fastparquet' if the file did not already exist (GH28326)

• Bug in read_hdf() closing stores that it didn’t open when Exceptions are raised (GH28699)

• Bug in DataFrame.read_json() where using orient="index" would not maintain the order (GH28557)

• Bug in DataFrame.to_html() where the length of the formatters argument was not verified (GH28469)

• Bug in DataFrame.read_excel() with engine='ods' when sheet_name argument references a non-existent sheet (GH27676)

• Bug in pandas.io.formats.style.Styler() formatting for floating values not displaying decimals correctly (GH13257)

• Bug in DataFrame.to_html() when using formatters=<list> and max_cols together. (GH25955)
- Bug in `Styler.background_gradient()` not able to work with dtype `Int64` (GH28869)
- Bug in `DataFrame.to_clipboard()` which did not work reliably in ipython (GH22707)
- Bug in `read_json()` where default encoding was not set to `utf-8` (GH29565)
- Bug in `read_gbq()` now accepts `progress_bar_type` to display progress bar while the data downloads. (GH29857)
- Bug in `pandas.io.json.json_normalize()` where a missing value in the location specified by `record_path` would raise a `TypeError` (GH30148)
- Bug in `read_excel()` now accepts binary data (GH15914)
- Bug in `read_csv()` in which encoding handling was limited to just the string `utf-16` for the C engine (GH24130)

**Plotting**

- Bug in `Series.plot()` not able to plot boolean values (GH23719)
- Bug in `DataFrame.plot()` not able to plot when no rows (GH27758)
- Bug in `DataFrame.plot()` producing incorrect legend markers when plotting multiple series on the same axis (GH18222)
- Bug in `DataFrame.plot()` when `kind='box'` and data contains datetime or timedelta data. These types are now automatically dropped (GH22799)
- Bug in `DataFrame.plot.line()` and `DataFrame.plot.area()` produce wrong xlim in x-axis (GH27686, GH25160, GH24784)
- Bug where `DataFrame.boxplot()` would not accept a `color` parameter like `DataFrame.plot.box()` (GH26214)
- Bug in the `xticks` argument being ignored for `DataFrame.plot.bar()` (GH14119)
- `set_option()` now validates that the plot backend provided to 'plotting.backend' implements the backend when the option is set, rather than when a plot is created (GH28163)
- `DataFrame.plot()` now allow a `backend` keyword argument to allow changing between backends in one session (GH28619).
- Bug in color validation incorrectly raising for non-color styles (GH29122).
- Allow `DataFrame.plot.scatter()` to plot objects and datetime type data (GH18755, GH30391)
- Bug in `DataFrame.hist()`, `xrot=0` does not work with `by` and subplots (GH30288).

**Groupby/resample/rolling**

- Bug in `core.groupby.DataFrameGroupBy.apply()` only showing output from a single group when function returns an `Index` (GH28652)
- Bug in `DataFrame.groupby()` with multiple groups where an `IndexError` would be raised if any group contained all NA values (GH20519)
- Bug in `pandas.core.resample.Resampler.size()` and `pandas.core.resample.Resampler.count()` returning wrong dtype when used with an empty `Series` or `DataFrame` (GH28427)
• Bug in `DataFrame.rolling()` not allowing for rolling over datetimes when axis=1 (GH28192)
• Bug in `DataFrame.rolling()` not allowing rolling over multi-index levels (GH15584).
• Bug in `DataFrame.rolling()` not allowing rolling on monotonic decreasing time indexes (GH19248).
• Bug in `DataFrame.groupby()` not offering selection by column name when axis=1 (GH27614)
• Bug in `core.groupby.DataFrameGroupby.agg()` not able to use lambda function with named aggregation (GH27519)
• Bug in `DataFrame.groupby()` losing column name information when grouping by a categorical column (GH28787)
• Remove error raised due to duplicated input functions in named aggregation in `DataFrame.groupby()` and `Series.groupby()`. Previously error will be raised if the same function is applied on the same column and now it is allowed if new assigned names are different. (GH28426)
• `core.groupby.SeriesGroupBy.value_counts()` will be able to handle the case even when the Grouper makes empty groups (GH28479)
• Bug in `core.window.rolling.Rolling.quantile()` ignoring interpolation keyword argument when used within a groupby (GH28779)
• Bug in `DataFrame.groupby()` where any, all, nunique and transform functions would incorrectly handle duplicate column labels (GH21668)
• Bug in `core.groupby.DataFrameGroupBy.agg()` with timezone-aware datetime64 column incorrectly casting results to the original dtype (GH29641)
• Bug in `DataFrame.groupby()` when using axis=1 and having a single level columns index (GH30208)
• Bug in `DataFrame.groupby()` when using nunique on axis=1 (GH30253)
• Bug in `GroupBy.quantile()` with multiple list-like q value and integer column names (GH30289)
• `GroupBy.pct_change()` and `core.groupby.SeriesGroupBy.pct_change()` causes TypeError when fill_method is None (GH30463)
• Bug in `Rolling.count()` and `Expanding.count()` argument where min_periods was ignored (GH26996)

Reshaping

• Bug in `DataFrame.apply()` that caused incorrect output with empty `DataFrame` (GH28202, GH21959)
• Bug in `DataFrame.stack()` not handling non-unique indexes correctly when creating MultiIndex (GH28301)
• Bug in `pivot_table()` not returning correct type float when margins=True and aggfunc='mean' (GH24893)
• Bug `merge_asof()` could not use `datetime.timedelta` for tolerance kwarg (GH28098)
• Bug in `merge()`, did not append suffixes correctly with MultiIndex (GH28518)
• `qcut()` and `cut()` now handle boolean input (GH20303)
• Fix to ensure all int dtypes can be used in `merge_asof()` when using a tolerance value. Previously every non-int64 type would raise an erroneous `MergeError` (GH28870).
• Better error message in `get_dummies()` when `columns` isn’t a list-like value (GH28383)
pandas: powerful Python data analysis toolkit, Release 1.1.1

- Bug in `Index.join()` that caused infinite recursion error for mismatched MultiIndex name orders. (GH25760, GH28956)
- Bug in `Series.pct_change()` where supplying an anchored frequency would throw a ValueError (GH28664)
- Bug where `DataFrame.equals()` returned True incorrectly in some cases when two DataFrames had the same columns in different orders (GH28839)
- Bug in `DataFrame.replace()` that caused non-numeric replacer's dtype not respected (GH26632)
- Bug in `melt()` where supplying mixed strings and numeric values for `id_vars` or `value_vars` would incorrectly raise a ValueError (GH29718)
- Dtypes are now preserved when transposing a DataFrame where each column is the same extension dtype (GH30091)
- Bug in `merge_asof()` merging on a tz-aware left_index and right_on a tz-aware column (GH29864)
- Improved error message and docstring in `cut()` and `qcut()` when `labels=True` (GH13318)
- Bug in missing `fill_na` parameter to `DataFrame.unstack()` with list of levels (GH30740)

Sparse

- Bug in `SparseDataFrame` arithmetic operations incorrectly casting inputs to float (GH28107)
- Bug in `DataFrame.sparse` returning a Series when there was a column named `sparse` rather than the accessor (GH30758)
- Fixed `operator.xor()` with a boolean-dtype `SparseArray`. Now returns a sparse result, rather than object dtype (GH31025)

ExtensionArray

- Bug in `arrays.PandasArray` when setting a scalar string (GH28118, GH28150).
- Bug where nullable integers could not be compared to strings (GH28930)
- Bug where `DataFrame` constructor raised `ValueError` with list-like data and dtype specified (GH30280)

Other

- Trying to set the `display.precision`, `display.max_rows` or `display.max_columns` using `set_option()` to anything but a None or a positive int will raise a `ValueError` (GH23348)
- Using `DataFrame.replace()` with overlapping keys in a nested dictionary will no longer raise, now matching the behavior of a flat dictionary (GH27660)
- `DataFrame.to_csv()` and `Series.to_csv()` now support dicts as compression argument with key 'method' being the compression method and others as additional compression options when the compression method is 'zip'. (GH26023)
- Bug in `Series.diff()` where a boolean series would incorrectly raise a `TypeError` (GH17294)
- `Series.append()` will no longer raise a `TypeError` when passed a tuple of `Series` (GH28410)
- Fix corrupted error message when calling `pandas.libs._json.encode()` on a 0d array (GH18878)
pandas: powerful Python data analysis toolkit, Release 1.1.1

- Backtick quoting in `DataFrame.query()` and `DataFrame.eval()` can now also be used to use invalid identifiers like names that start with a digit, are python keywords, or are using single character operators. (GH27017)
- Bug in `pd.core.util.hashing.hash_pandas_object` where arrays containing tuples were incorrectly treated as non-hashable (GH28969)
- Bug in `DataFrame.append()` that raised `IndexError` when appending with empty list (GH28769)
- Fix `AbstractHolidayCalendar` to return correct results for years after 2030 (now goes up to 2200) (GH27790)
- Fixed `IntegerArray` returning `inf` rather than `NaN` for operations dividing by 0 (GH27398)
- Fixed `pow` operations for `IntegerArray` when the other value is 0 or 1 (GH29997)
- Bug in `Series.count()` raises if `use_inf_as_na` is enabled (GH29478)
- Bug in `Index` where a non-hashable name could be set without raising `TypeError` (GH29069)
- Bug in `DataFrame` constructor when passing a 2D `ndarray` and an extension dtype (GH12513)
- Bug in `DataFrame.to_csv()` when supplied a series with a `dtype="string"` and a `na_rep`, the `na_rep` was being truncated to 2 characters. (GH29975)
- Bug where `DataFrame.itertuples()` would incorrectly determine whether or not namedtuples could be used for dataframes of 255 columns (GH28282)
- Handle nested NumPy object arrays in `testing.assert_series_equal()` for `ExtensionArray` implementations (GH30841)
- Bug in `Index` constructor incorrectly allowing 2-dimensional input arrays (GH13601, GH27125)

Contributors

A total of 308 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Aaditya Panikath +
- Abdullah Ihsan Seçer
- Abhijeet Krishnan +
- Adam J. Stewart
- Adam Klaum +
- Addison Lynch
- Aivengoe +
- Alastair James +
- Albert Villanova del Moral
- Alex Kirko +
- Alfredo Granja +
- Allen Downey
- Alp Arbal +
- Andreas Buhr +
- Andrew Munch +
- Andy
- Angela Ambroz +
- Aniruddha Bhattacharjee +
- Ankit Dhankhar +
- Antonio Andraues Jr +
- Arda Kosar +
- Asish Mahapatra +
- Austin Hackett +
- Avi Kelman +
- AyowoleT +
- Bas Nijholt +
- Ben Thayer
- Bharat Raghunathan
- Bhavani Ravi
- Bhuvana KA +
- Big Head
- Blake Hawkins +
- Bobae Kim +
- Brett Naul
- Brian Wignall
- Bruno P. Kinoshita +
- Bryant Moscon +
- Cesar H +
- Chris Stadler
- Chris Zimmerman +
- Christopher Whelan
- Clemens Brunner
- Clemens Tolboom +
- Connor Charles +
- Daniel Hähnke +
- Daniel Saxton
- Darin Plutchok +
- Dave Hughes
- David Stansby
- DavidRosen +
- Dean +
pandas: powerful Python data analysis toolkit, Release 1.1.1

- Deepan Das +
- Deepyaman Datta
- DorAmram +
- Dorothy Kabarozi +
- Drew Heenan +
- Eliza Mae Saret +
- Elle +
- Endre Mark Borza +
- Eric Brassell +
- Eric Wong +
- Eunseop Jeong +
- Eyden Villanueva +
- Felix Divo
- ForTimeBeing +
- Francesco Truzzi +
- Gabriel Corona +
- Gabriel Monteiro +
- Galuh Sahid +
- Georgi Baychev +
- Gina
- GiuPassarelli +
- Grigorios Giannakopoulos +
- Guilherme Leite +
- Guilherme Salomé +
- Gyeongjae Choi +
- Harshavardhan Bachina +
- Harutaka Kawamura +
- Hassan Kibirige
- Hielke Walinga
- Hubert
- Hugh Kelley +
- Ian Eaves +
- Ignacio Santolin +
- Igor Filippov +
- Irv Lustig
- Isaac Virshup +
• Ivan Bessarabov +
• JMBurley +
• Jack Bicknell +
• Jacob Buckheit +
• Jan Koch
• Jan Pipek +
• Jan Škoda +
• Jan-Philip Gehrcke
• Jasper J.F. van den Bosch +
• Javad +
• Jeff Reback
• Jeremy Schendel
• Jeroen Kant +
• Jesse Pardue +
• Jethro Cao +
• Jiang Yue
• Jiaxiang +
• Jihyung Moon +
• Jimmy Callin
• Jinyang Zhou +
• Joao Victor Martinelli +
• Joaq Almirante +
• John G Evans +
• John Ward +
• Jonathan Larkin +
• Joris Van den Bossche
• Josh Dimarsky +
• Joshua Smith +
• Josiah Baker +
• Julia Signell +
• Jung Dong Ho +
• Justin Cole +
• Justin Zheng
• Kaiqi Dong
• Karthigeyan +
• Katherine Younglove +
• Katrin Leinweber
• Kee Chong Tan +
• Keith Kraus +
• Kevin Nguyen +
• Kevin Sheppard
• Kisekka David +
• Koushik +
• Kyle Boone +
• Kyle McCahill +
• Laura Collard, PhD +
• LiuSeeker +
• Louis Huynh +
• Lucas Scarlato Astur +
• Luiz Gustavo +
• Luke +
• Luke Shepard +
• MKhalusova +
• Mabel Villalba
• Maciej J +
• Mak Sze Chun
• Manu NALEPA +
• Marc
• Marc Garcia
• Marco Gorelli +
• Marco Neumann +
• Martin Winkel +
• Martina G. Vilas +
• Mateusz +
• Matthew Roeschke
• Matthew Tan +
• Max Bolingbroke
• Max Chen +
• MeeseeksMachine
• Miguel +
• MinGyo Jung +
• Mohamed Amine ZGHAL +
• Mohit Anand +
• MomIsBestFriend +
• Naomi Bonnin +
• Nathan Abel +
• Nico Cernek +
• Nigel Markey +
• Noritada Kobayashi +
• Oktay Sabak +
• Oliver Hofkens +
• Oluokun Adedayo +
• Osman +
• Oğuzhan Öğreden +
• Pandas Development Team +
• Patrik Hlobil +
• Paul Lee +
• Paul Siegel +
• Petr Baev +
• Pietro Battiston
• Prakhar Pandey +
• Puneeth K +
• Raghav +
• Rajat +
• Rajhans Jadhao +
• Rajiv Bharadwaj +
• Rik-de-Kort +
• Roei.r
• Rohit Sanjay +
• Ronan Lamy +
• Roshni +
• Roymprog +
• Rushabh Vasani +
• Ryan Grout +
• Ryan Nazareth
• Samesh Lakhota +
• Samuel Sinayoko
• Samyak Jain +
• Sarah Donehower +
• Sarah Masud +
• Saul Shanabrook +
• Scott Cole +
• SdgJlbl +
• Seb +
• Sergei Ivko +
• Shadi Akiki
• Shorokhov Sergey
• Siddhesh Poyarekar +
• Sidharthan Nair +
• Simon Gibbons
• Simon Hawkins
• Simon-Martin Schröder +
• Sofiane Mahiou +
• Sourav kumar +
• Souvik Mandal +
• Soyoun Kim +
• Sparkle Russell-Puleri +
• Srinivas Reddy Thatiparthi ( )
• Stuart Berg +
• Sumanau Sareen
• Szymon Bednarek +
• Tambe Tabitha Achere +
• Tan Tran
• Tang Heyi +
• Tanmay Daripa +
• Tanya Jain
• Terji Petersen
• Thomas Li +
• Tirth Jain +
• Tola A +
• Tom Augspurger
• Tommy Lynch +
• Tomoyuki Suzuki +
• Tony Lorenzo
- Unprocessable +
- Uwe L. Korn
- Vaibhav Vishal
- Victoria Zdanovskaya +
- Vijayant +
- Vishwak Srinivasan +
- WANG Aiyong
- Wenhuan
- Wes McKinney
- Will Ayd
- Will Holmgren
- William Ayd
- William Blan +
- Wouter Overmeire
- Wuraola Oyewusi +
- YaOzI +
- Yash Shukla +
- Yu Wang +
- Yusei Tahara +
- alexander135 +
- alimcmaster1
- avelineg +
- bganglia +
- bolkedebuvin
- bravech +
- chinhwee +
- cruuzzoe +
- dalgarno +
- daniellebrown +
- danielplawrence
- est271 +
- francisco souza +
- ganevgv +
- garanews +
- gfyoun
- h-vetinari
• hasnain2808 +
• ianzur +
• jalbritt +
• jbrockmendel
• jeschwar +
• jlamborn324 +
• joy-rosie +
• kernc
• killerontherun1
• krey +
• lexy-lixinyu +
• lucyleeow +
• lukasbk +
• maheshbapatu +
• mck619 +
• nathalier
• naveenkaushik2504 +
• nlepleux +
• nreben
• ohad83 +
• pilkibun
• pqzx +
• proost +
• pv8493013j +
• quade +
• rhstanton +
• rmunjal29 +
• sangarshanan +
• sardonick +
• saskakarsi +
• shaido987 +
• ssikdar1
• steveayers124 +
• taddressgaki +
• timcera +
• tlaytongoogle +
5.3 Version 0.25

5.3.1 What’s new in 0.25.3 (October 31, 2019)

These are the changes in pandas 0.25.3. See Release notes for a full changelog including other versions of pandas.

Bug fixes

Groupby/resample/rolling

- Bug in DataFrameGroupBy.quantile() where NA values in the grouping could cause segfaults or incorrect results (GH28882)

Contributors

A total of 2 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Will Ayd
- William Ayd

5.3.2 What’s new in 0.25.2 (October 15, 2019)

These are the changes in pandas 0.25.2. See Release notes for a full changelog including other versions of pandas.

Note: Pandas 0.25.2 adds compatibility for Python 3.8 (GH28147).

Bug fixes

Indexing

- Fix regression in DataFrame.reindex() not following the limit argument (GH28631).
- Fix regression in RangeIndex.get_indexer() for decreasing RangeIndex where target values may be improperly identified as missing/present (GH28678)
pandas: powerful Python data analysis toolkit, Release 1.1.1

I/O

- Fix regression in notebook display where `<th>` tags were missing for `DataFrame.index` values (GH28204).
- Regression in `to_csv()` where writing a Series or DataFrame indexed by an `IntervalIndex` would incorrectly raise a `TypeError` (GH28210).
- Fix `to_csv()` with `ExtensionArray` with list-like values (GH28840).

Groupby/resample/rolling

- Bug incorrectly raising an `IndexError` when passing a list of quantiles to `pandas.core.groupby.DataFrameGroupBy.quantile()` (GH28113).
- Bug in `pandas.core.groupby.GroupBy.shift()`, `pandas.core.groupby.GroupBy.bfill()` and `pandas.core.groupby.GroupBy.ffill()` where timezone information would be dropped (GH19995, GH27992).

Other

- Compatibility with Python 3.8 in `DataFrame.query()` (GH27261).
- Fix to ensure that tab-completions in an IPython console does not raise warnings for deprecated attributes (GH27900).

Contributors

A total of 6 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Felix Divo +
- Jeremy Schendel
- Joris Van den Bossche
- MeeseeksMachine
- Tom Augspurger
- jbrockmendel

5.3.3 What’s new in 0.25.1 (August 21, 2019)

These are the changes in pandas 0.25.1. See Release notes for a full changelog including other versions of pandas.
I/O and LZMA

Some users may unknowingly have an incomplete Python installation lacking the `lzma` module from the standard library. In this case, `import pandas` failed due to an `ImportError` (GH27575). Pandas will now warn, rather than raising an `ImportError` if the `lzma` module is not present. Any subsequent attempt to use `lzma` methods will raise a `RuntimeError`. A possible fix for the lack of the `lzma` module is to ensure you have the necessary libraries and then re-install Python. For example, on MacOS installing Python with `pyenv` may lead to an incomplete Python installation due to unmet system dependencies at compilation time (like `xz`). Compilation will succeed, but Python might fail at run time. The issue can be solved by installing the necessary dependencies and then re-installing Python.

Bug fixes

Categorical

- Bug in `Categorical.fillna()` that would replace all values, not just those that are `NaN` (GH26215)

Datetimelike

- Bug in `to_datetime()` where passing a timezone-naive `DatetimeArray` or `DatetimeIndex` and `utc=True` would incorrectly return a timezone-naive result (GH27733)
- Bug in `Period.to_timestamp()` where a `Period` outside the `Timestamp` implementation bounds (roughly 1677-09-21 to 2262-04-11) would return an incorrect `Timestamp` instead of raising `OutOfBoundsDatetime` (GH19643)
- Bug in iterating over `DatetimeIndex` when the underlying data is read-only (GH28055)

Timezones

- Bug in `Index` where a numpy object array with a timezone aware `Timestamp` and `np.nan` would not return a `DatetimeIndex` (GH27011)

Numeric

- Bug in `Series.interpolate()` when using a timezone aware `DatetimeIndex` (GH27548)
- Bug when printing negative floating point complex numbers would raise an `IndexError` (GH27484)
- Bug where `DataFrame` arithmetic operators such as `DataFrame.mul()` with a `Series` with `axis=1` would raise an `AttributeError` on `DataFrame` larger than the minimum threshold to invoke `numexpr` (GH27636)
- Bug in `DataFrame` arithmetic where missing values in results were incorrectly masked with `NaN` instead of `Inf` (GH27464)
Conversion

- Improved the warnings for the deprecated methods `Series.real()` and `Series.imag()` (GH27610)

Interval

- Bug in `IntervalIndex` where `dir(obj)` would raise `ValueError` (GH27571)

Indexing

- Bug in partial-string indexing returning a NumPy array rather than a `Series` when indexing with a scalar like `.loc['2015']` (GH27516)
- Break reference cycle involving `Index` and other index classes to allow garbage collection of index objects without running the GC. (GH27585, GH27840)
- Fix regression in assigning values to a single column of a `DataFrame` with a `MultiIndex` columns (GH27841).
- Fix regression in `.ix` fallback with an `IntervalIndex` (GH27865).

Missing

- Bug in `pandas.isnull()` or `pandas.isna()` when the input is a type e.g. `type(pandas.Series())` (GH27482)

I/O

- Avoid calling `S3File.s3` when reading parquet, as this was removed in s3fs version 0.3.0 (GH27756)
- Better error message when a negative header is passed in `pandas.read_csv()` (GH27779)
- Follow the `min_rows` display option (introduced in v0.25.0) correctly in the HTML repr in the notebook (GH27991).

Plotting

- Added a `pandas_plotting_backends` entrypoint group for registering plot backends. See `Plotting backends` for more (GH26747).
- Fixed the re-instatement of Matplotlib datetime converters after calling `pandas.plotting.deregister_matplotlib_converters()` (GH27481).
- Fix compatibility issue with matplotlib when passing a pandas `Index` to a plot call (GH27775).
Groupby/resample/rolling

- Fixed regression in `pandas.core.groupby.DataFrameGroupBy.quantile()` raising when multiple quantiles are given (GH27526)
- Bug in `pandas.core.groupby.DataFrameGroupBy.transform()` where applying a timezone conversion lambda function would drop timezone information (GH27496)
- Bug in `pandas.core.groupby.GroupBy.nth()` where `observed=False` was being ignored for Categorical groupers (GH26385)
- Bug in windowing over read-only arrays (GH27766)
- Fixed segfault in `pandas.core.groupby.DataFrameGroupBy.quantile` when an invalid quantile was passed (GH27470)

Reshaping

- A `KeyError` is now raised if `.unstack()` is called on a `Series` or `DataFrame` with a flat `Index` passing a name which is not the correct one (GH18303)
- Bug `merge_asof()` could not merge `Timedelta` objects when passing `tolerance` kwarg (GH27642)
- Bug in `DataFrame.crosstab()` when `margins` set to `True` and `normalize` is not `False`, an error is raised. (GH27500)
- `DataFrame.join()` now suppresses the `FutureWarning` when the `sort` parameter is specified (GH21952)
- Bug in `DataFrame.join()` raising with readonly arrays (GH27943)

Sparse

- Bug in reductions for `Series` with Sparse dtypes (GH27080)

Other

- Bug in `Series.replace()` and `DataFrame.replace()` when replacing timezone-aware timestamps using a dict-like replacer (GH27720)
- Bug in `Series.rename()` when using a custom type indexer. Now any value that isn’t callable or dict-like is treated as a scalar. (GH27814)

Contributors

A total of 5 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Jeff Reback
- Joris Van den Bossche
- MeeseeksMachine +
- Tom Augspurger
- jbrockmendel
5.3.4 What’s new in 0.25.0 (July 18, 2019)

Warning: Starting with the 0.25.x series of releases, pandas only supports Python 3.5.3 and higher. See Dropping Python 2.7 for more details.

Warning: The minimum supported Python version will be bumped to 3.6 in a future release.

Warning: Panel has been fully removed. For N-D labeled data structures, please use xarray

Warning: read_pickle() and read_msgpack() are only guaranteed backwards compatible back to pandas version 0.20.3 (GH27082)

These are the changes in pandas 0.25.0. See Release notes for a full changelog including other versions of pandas.

Enhancements

Groupby aggregation with relabeling

Pandas has added special groupby behavior, known as “named aggregation”, for naming the output columns when applying multiple aggregation functions to specific columns (GH18366, GH26512).

In [1]: animals = pd.DataFrame({'kind': ['cat', 'dog', 'cat', 'dog'],
                             'height': [9.1, 6.0, 9.5, 34.0],
                             'weight': [7.9, 7.5, 9.9, 198.0]})

In [2]: animals.groupby("kind").agg(
   ...:     min_height=pd.NamedAgg(column='height', aggfunc='min'),
   ...:     max_height=pd.NamedAgg(column='height', aggfunc='max'),
   ...:     average_weight=pd.NamedAgg(column='weight', aggfunc=np.mean),
   ...: )

Out[3]:

    min_height  max_height  average_weight
kind      kind
  cat      9.1          9.5          8.90
  dog      6.0          34.0         102.75

(continues on next page)
Pass the desired column names as the \texttt{**kwargs} to \texttt{.agg}. The values of \texttt{**kwargs} should be tuples where the first element is the column selection, and the second element is the aggregation function to apply. Pandas provides the pandas.NamedAgg namedtuple to make it clearer what the arguments to the function are, but plain tuples are accepted as well.

\begin{Verbatim}
In [4]: animals.groupby("kind").agg(
    ...:     min_height=('height', 'min'),
    ...:     max_height=('height', 'max'),
    ...:     average_weight=('weight', np.mean),
    ...: )
Out[4]:
     min_height  max_height  average_weight
    kind
    cat     9.1       9.5            8.90
    dog     6.0      34.0           102.75
\end{Verbatim}

Named aggregation is the recommended replacement for the deprecated “dict-of-dicts” approach to naming the output of column-specific aggregations (\textit{Deprecate groupby.agg() with a dictionary when renaming}).

A similar approach is now available for Series groupby objects as well. Because there’s no need for column selection, the values can just be the functions to apply.

\begin{Verbatim}
In [5]: animals.groupby("kind").height.agg(
    ...:     min_height="min",
    ...:     max_height="max",
    ...: )
Out[5]:
     min_height  max_height
    kind
    cat        9.1        9.5
    dog        6.0       34.0
\end{Verbatim}

This type of aggregation is the recommended alternative to the deprecated behavior when passing a dict to a Series groupby aggregation (\textit{Deprecate groupby.agg() with a dictionary when renaming}).

See \texttt{Named aggregation} for more.
Groupby aggregation with multiple lambdas

You can now provide multiple lambda functions to a list-like aggregation in `pandas.core.groupby.GroupBy.agg` (GH26430).

```python
In [6]: animals.groupby('kind').height.agg([  
...: lambda x: x.iloc[0], lambda x: x.iloc[-1]  
...: ])
```

```bash
Out[6]:
<lambda_0> <lambda_1>
kind  
cat    9.1    9.5
dog    6.0  34.0
```

Previously, these raised a `SpecificationError`.

Better repr for MultiIndex

Printing of `MultiIndex` instances now shows tuples of each row and ensures that the tuple items are vertically aligned, so it’s now easier to understand the structure of the `MultiIndex`. (GH13480):

```python
In [8]: pd.MultiIndex.from_product([[a, 'abc'], range(500)])
```

```bash
Out[8]:
MultiIndex([('a', 0),  
('a', 1),  
('a', 2),  
('a', 3),  
('a', 4),  
('a', 5),  
('a', 6),  
('a', 7),  
('a', 8),  
('a', 9),  
...'abc', 490),  
('abc', 491),  
('abc', 492),  
('a', 490),  
...]  
...  
(continues on next page)
```
Previously, outputting a `MultiIndex` printed all the levels and codes of the `MultiIndex`, which was visually unappealing and made the output more difficult to navigate. For example (limiting the range to 5):

```python
In [1]: pd.MultiIndex.from_product([['a', 'abc'], range(5)])
Out[1]: MultiIndex(levels=[['a', 'abc'], [0, 1, 2, 3]],
...: codes=[[0, 0, 0, 0, 1, 1, 1, 1], [0, 1, 2, 3, 0, 1, 2, 3]])
```

In the new repr, all values will be shown, if the number of rows is smaller than `options.display.max_seq_items` (default: 100 items). Horizontally, the output will truncate, if it’s wider than `options.display.width` (default: 80 characters).

### Shorter truncated repr for Series and DataFrame

Currently, the default display options of pandas ensure that when a Series or DataFrame has more than 60 rows, its repr gets truncated to this maximum of 60 rows (the `display.max_rows` option). However, this still gives a repr that takes up a large part of the vertical screen estate. Therefore, a new option `display.min_rows` is introduced with a default of 10 which determines the number of rows showed in the truncated repr:

- For small Series or DataFrames, up to `max_rows` number of rows is shown (default: 60).
- For larger Series of DataFrame with a length above `max_rows`, only `min_rows` number of rows is shown (default: 10, i.e. the first and last 5 rows).

This dual option allows to still see the full content of relatively small objects (e.g. `df.head(20)` shows all 20 rows), while giving a brief repr for large objects.

To restore the previous behaviour of a single threshold, set `pd.options.display.min_rows = None`.

### Json normalize with max_level param support

`json_normalize()` normalizes the provided input dict to all nested levels. The new `max_level` parameter provides more control over which level to end normalization (GH23843):

The repr now looks like this:

```python
from pandas.io.json import json_normalize
data = [{
    'CreatedBy': {'Name': 'User001'},
    'Lookup': {'TextField': 'Some text',
               'UserField': {'Id': 'ID001', 'Name': 'Name001'}},
    'Image': {'a': 'b'}
}]
json_normalize(data, max_level=1)
```
Series.explode to split list-like values to rows

Series and DataFrame have gained the DataFrame.explode() methods to transform list-likes to individual rows. See section on Exploding list-like column in docs for more information (GH16538, GH10511)

Here is a typical use case. You have comma separated string in a column.

```python
In [9]: df = pd.DataFrame([{'var1': 'a,b,c', 'var2': 1},
                         {'var1': 'd,e,f', 'var2': 2}])

In [10]: df
Out[10]:
    var1 var2
   0  a,b,c    1
   1  d,e,f    2
[2 rows x 2 columns]
```

Creating a long form DataFrame is now straightforward using chained operations

```python
In [11]: df.assign(var1=df.var1.str.split(',')).explode('var1')
Out[11]:
    var1  var2
   0 a   1
   1 b   1
   0 c   1
   1 d   2
   1 e   2
   1 f   2
[6 rows x 2 columns]
```

Other enhancements

- DataFrame.plot() keywords logy, logx and loglog can now accept the value 'sym' for symlog scaling. (GH24867)
- Added support for ISO week year format (‘%G-%V-%u’) when parsing datetimes using to_datetime() (GH16607)
- Indexing of DataFrame and Series now accepts zerodim np.ndarray (GH24919)
- Timestamp.replace() now supports the fold argument to disambiguate DST transition times (GH25017)
- DataFrame.at_time() and Series.at_time() now support datetime.time objects with time-zones (GH24043)
- DataFrame.pivot_table() now accepts an observed parameter which is passed to underlying calls to DataFrame.groupby() to speed up grouping categorical data. (GH24923)
- Series.str has gained Series.str.casefold() method to removes all case distinctions present in a string (GH25405)
- DataFrame.set_index() now works for instances of abc.Iterator, provided their output is of the same length as the calling frame (GH22484, GH24984)
• `DatetimeIndex.union()` now supports the `sort` argument. The behavior of the sort parameter matches that of `Index.union()` (GH24994)

• `RangeIndex.union()` now supports the `sort` argument. If `sort=False` an unsorted `Int64Index` is always returned. `sort=None` is the default and returns a monotonically increasing `RangeIndex` if possible or a sorted `Int64Index` if not (GH24471)

• `TimedeltaIndex.intersection()` now also supports the `sort` keyword (GH24471)

• `DataFrame.rename()` now supports the `errors` argument to raise errors when attempting to rename nonexistent keys (GH13473)

• Added `Sparse accessor` for working with a DataFrame whose values are sparse (GH25681)

• `RangeIndex` has gained `start`, `stop`, and `step` attributes (GH25710)

• `datetime.timezone` objects are now supported as arguments to timezone methods and constructors (GH25065)

• `DataFrame.query()` and `DataFrame.eval()` now supports quoting column names with backticks to refer to names with spaces (GH6508)

• `merge_asof()` now gives a more clear error message when merge keys are categoricals that are not equal (GH26136)

• `pandas.core.window.Rolling()` supports exponential (or Poisson) window type (GH21303)

• Error message for missing required imports now includes the original import error’s text (GH23868)

• `DatetimeIndex` and `TimedeltaIndex` now have a `mean` method (GH24757)

• `DataFrame.describe()` now formats integer percentiles without decimal point (GH26660)

• Added support for reading SPSS .sav files using `read_spss()` (GH26537)

• Added new option `plotting.backend` to be able to select a plotting backend different than the existing `matplotlib` one. Use `pandas.set_option('plotting.backend', '<backend-module>')` where `<backend-module>` is a library implementing the pandas plotting API (GH14130)

• `pandas.offsets.BusinessHour` supports multiple opening hours intervals (GH15481)

• `read_excel()` can now use `openpyxl` to read Excel files via the `engine='openpyxl'` argument. This will become the default in a future release (GH11499)

• `pandas.io.excel.read_excel()` supports reading OpenDocument tables. Specify `engine='odf'` to enable. Consult the `IO User Guide` for more details (GH9070)

• `Interval`, `IntervalIndex`, and `IntervalArray` have gained an `is_empty` attribute denoting if the given interval(s) are empty (GH27219)

Backwards incompatible API changes

Indexing with date strings with UTC offsets

Indexing a `DataFrame` or `Series` with a `DatetimeIndex` with a date string with a UTC offset would previously ignore the UTC offset. Now, the UTC offset is respected in indexing. (GH24076, GH16785)

```python
In [12]: df = pd.DataFrame([0], index=pd.DatetimeIndex(['2019-01-01'], tz='US/Pacific'))
In [13]: df
Out[13]:
```

(continues on next page)
Previous behavior:

In [3]: df['2019-01-01 00:00:00+04:00':'2019-01-01 01:00:00+04:00']
Out[3]:
0
2019-01-01 00:00:00-08:00 0
[1 rows x 1 columns]

New behavior:

In [14]: df['2019-01-01 12:00:00+04:00':'2019-01-01 13:00:00+04:00']
Out[14]:
0
2019-01-01 00:00:00-08:00 0
[1 rows x 1 columns]

MultiIndex constructed from levels and codes

Constructing a MultiIndex with NaN levels or codes value < -1 was allowed previously. Now, construction with codes value < -1 is not allowed and NaN levels’ corresponding codes would be reassigned as -1. (GH19387)

Previous behavior:

In [1]: pd.MultiIndex(levels=[[np.nan, None, pd.NaT, 128, 2]],
                   codes=[[0, -1, 1, 2, 3, 4]])
   ...:
Out[1]: MultiIndex(levels=[nan, None, NaT, 128, 2],
                   codes=[[0, -1, 1, 2, 3, 4]])
In [2]: pd.MultiIndex(levels=[[1, 2]], codes=[[0, -2]])
Out[2]: MultiIndex(levels=[[1, 2]],
                   codes=[[0, -2]])

New behavior:

In [15]: pd.MultiIndex(levels=[[np.nan, None, pd.NaT, 128, 2]],
                   codes=[[0, -1, 1, 2, 3, 4]])
   ...:
Out[15]: MultiIndex([(nan,),
                    (nan,),
                    (nan,),
                    (nan,),
                    (128,),
                    ( 2,)])
In [16]: pd.MultiIndex(levels=[[1, 2]], codes=[[0, -2]])
---------------------------------------------------------------------------
ValueError Traceback (most recent call last)

Groupby.apply on DataFrame evaluates first group only once

The implementation of DataFrameGroupBy.apply() previously evaluated the supplied function consistently twice on the first group to infer if it is safe to use a fast code path. Particularly for functions with side effects, this was an undesired behavior and may have led to surprises. (GH2936, GH2656, GH7739, GH10519, GH12155, GH20084, GH21417)

Now every group is evaluated only a single time.

Previous behavior:

In [3]: df.groupby('a').apply(func)
   x
   x
   y
Out[3]:
   a  b

New behavior:

```
In [20]: df.groupby("a").apply(func)
  
Out[20]:
         a  b
0       0  1
1       1  2
[2 rows x 2 columns]
```

**Concatenating sparse values**

When passed DataFrames whose values are sparse, `concat()` will now return a `Series` or `DataFrame` with sparse values, rather than a `SparseDataFrame` (GH25702).

```
In [21]: df = pd.DataFrame({"A": pd.SparseArray([0, 1])})

Previous behavior:

```
In [2]: type(pd.concat([df, df]))
pandas.core.sparse.frame.SparseDataFrame
```

New behavior:

```
In [22]: type(pd.concat([df, df]))
Out[22]: pandas.core.frame.DataFrame
```

This now matches the existing behavior of `concat` on `Series` with sparse values. `concat()` will continue to return a `SparseDataFrame` when all the values are instances of `SparseDataFrame`.

This change also affects routines using `concat()` internally, like `get_dummies()`, which now returns a `DataFrame` in all cases (previously a `SparseDataFrame` was returned if all the columns were dummy encoded, and a `DataFrame` otherwise).

Providing any `SparseSeries` or `SparseDataFrame` to `concat()` will cause a `SparseSeries` or `SparseDataFrame` to be returned, as before.

**The `.str`-accessor performs stricter type checks**

Due to the lack of more fine-grained dtypes, `Series.str` so far only checked whether the data was of `object` dtype. `Series.str` will now infer the dtype data within the `Series`; in particular, 'bytes'-only data will raise an exception (except for `Series.str.decode()`, `Series.str.get()`, `Series.str.len()`, `Series.str.slice()`), see GH23163, GH23011, GH23551.

Previous behavior:

```
In [1]: s = pd.Series(np.array(['a', 'ba', 'cba'], 'S'), dtype=object)
```
In [2]: s
Out[2]:
0   b'a'
1   b'ba'
2   b'cba'
dtype: object

In [3]: s.str.startswith(b'a')
Out[3]:
0   True
1   False
2   False
dtype: bool

New behavior:

In [23]: s = pd.Series(np.array(\['a', 'ba', 'cba',\], 'S'), dtype=object)
In [24]: s
Out[24]:
0   b'a'
1   b'ba'
2   b'cba'
Length: 3, dtype: object
In [25]: s.str.startswith(b'a')
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-25-ac784692b361> in                                          
----> 1 s.str.startswith(b'a')
/pandas-release/pandas/pandas/core/strings.py in wrapper(self, *args, **kwargs)
    1998   f"inferred dtype '{self._inferred_dtype}'."
    1999        raise
 1999    raise TypeError(msg)
2000   return func(self, *args, **kwargs)
2001
2002
TypeError: Cannot use .str.startswith with values of inferred dtype 'bytes'.

Categorical dtypes are preserved during groupby

Previously, columns that were categorical, but not the groupby key(s) would be converted to object dtype during groupby operations. Pandas now will preserve these dtypes. (GH18502)

In [26]: cat = pd.Categorical(["foo", "bar", "bar", "qux"], ordered=True)
In [27]: df = pd.DataFrame({'payload': [-1, -2, -1, -2], 'col': cat})
In [28]: df
Out[28]:
payload  col
0   -1  foo
1   -2  bar
2   -1  bar
pandas: powerful Python data analysis toolkit, Release 1.1.1

(continued from previous page)

3   -2   qux
[4 rows x 2 columns]

In [29]: df.dtypes
Out[29]:
payload   int64
col        category
Length: 2, dtype: object

Previous Behavior:

In [5]: df.groupby('payload').first().col.dtype
Out[5]: dtype('O')

New Behavior:

In [30]: df.groupby('payload').first().col.dtype
Out[30]: CategoricalDtype(categories=['bar', 'foo', 'qux'], ordered=True)

Incompatible Index type unions

When performing `Index.union()` operations between objects of incompatible dtypes, the result will be a base `Index` of dtype object. This behavior holds true for unions between `Index` objects that previously would have been prohibited. The dtype of empty `Index` objects will now be evaluated before performing union operations rather than simply returning the other `Index` object. `Index.union()` can now be considered commutative, such that `A.union(B) == B.union(A)` (GH23525).

Previous behavior:

In [1]: pd.period_range('19910905', periods=2).union(pd.Int64Index([1, 2, 3]))
...  
ValueError: can only call with other PeriodIndex-ed objects

In [2]: pd.Index([], dtype=object).union(pd.Index([1, 2, 3]))
Out[2]: Int64Index([1, 2, 3], dtype='int64')

New behavior:

In [31]: pd.period_range('19910905', periods=2).union(pd.Int64Index([1, 2, 3]))
Out[31]: Index(['1991-09-05', '1991-09-06', 1, 2, 3], dtype='object')

In [32]: pd.Index([], dtype=object).union(pd.Index([1, 2, 3]))
Out[32]: Index([1, 2, 3], dtype='object')

Note that integer- and floating-dtype indexes are considered “compatible”. The integer values are coerced to floating point, which may result in loss of precision. See Set operations on Index objects for more.
DataFrame groupby ffill/bfill no longer return group labels

The methods ffill, bfill, pad and backfill of DataFrameGroupBy previously included the group labels in the return value, which was inconsistent with other groupby transforms. Now only the filled values are returned. (GH21521)

```
In [33]: df = pd.DataFrame({"a": ["x", "y"], "b": [1, 2]})

In [34]: df
Out[34]:
   a  b
0  x  1
1  y  2
[2 rows x 2 columns]

Previous behavior:

In [3]: df.groupby("a").ffill()
Out[3]:
   a  b
0  x  1
1  y  2

New behavior:

In [35]: df.groupby("a").ffill()
Out[35]:
   b
0  1
1  2
[2 rows x 1 columns]
```

DataFrame describe on an empty categorical / object column will return top and freq

When calling DataFrame.describe() with an empty categorical / object column, the ‘top’ and ‘freq’ columns were previously omitted, which was inconsistent with the output for non-empty columns. Now the ‘top’ and ‘freq’ columns will always be included, with numpy.nan in the case of an empty DataFrame (GH26397)

```
In [36]: df = pd.DataFrame({"empty_col": pd.Categorical([])})

In [37]: df
Out[37]:
Empty DataFrame
Columns: [empty_col]
Index: []
[0 rows x 1 columns]

Previous behavior:

In [3]: df.describe()
Out[3]:
   empty_col
       None

(continues on next page)
New behavior:

```
In [38]: df.describe()
Out[38]:
   empty_col
      count   0
      unique  0
   top     NaN
   freq    NaN
[4 rows x 1 columns]
```

__str__ methods now call __repr__ rather than vice versa

Pandas has until now mostly defined string representations in a Pandas object's __str__/__unicode__/__bytes__ methods, and called __str__ from the __repr__ method, if a specific __repr__ method is not found. This is not needed for Python3. In Pandas 0.25, the string representations of Pandas objects are now generally defined in __repr__, and calls to __str__ in general now pass the call on to the __repr__, if a specific __str__ method doesn't exist, as is standard for Python. This change is backward compatible for direct usage of Pandas, but if you subclass Pandas objects and give your subclasses specific __str__/__repr__ methods, you may have to adjust your __str__/__repr__ methods (GH26495).

Indexing an IntervalIndex with Interval objects

Indexing methods for IntervalIndex have been modified to require exact matches only for Interval queries. IntervalIndex methods previously matched on any overlapping Interval. Behavior with scalar points, e.g. querying with an integer, is unchanged (GH16316).

```
In [39]: ii = pd.IntervalIndex.from_tuples([(0, 4), (1, 5), (5, 8)])
In [40]: ii
Out[40]:
IntervalIndex([(0, 4], (1, 5], (5, 8]
             closed='right',
             dtype='interval[int64]'
```

The in operator (__contains__) now only returns True for exact matches to Intervals in the IntervalIndex, whereas this would previously return True for any Interval overlapping an Interval in the IntervalIndex.

Previous behavior:

```
In [4]: pd.Interval(1, 2, closed='neither') in ii
Out[4]: True

In [5]: pd.Interval(-10, 10, closed='both') in ii
Out[5]: True
```

New behavior:
The `get_loc()` method now only returns locations for exact matches to `Interval` queries, as opposed to the previous behavior of returning locations for overlapping matches. A `KeyError` will be raised if an exact match is not found.

### Previous behavior:

```python
In [6]: ii.get_loc(pd.Interval(1, 5))
Out[6]: array([0, 1])

In [7]: ii.get_loc(pd.Interval(2, 6))
Out[7]: array([0, 1, 2])
```

### New behavior:

```python
In [6]: ii.get_loc(pd.Interval(1, 5))
Out[6]: 1

In [7]: ii.get_loc(pd.Interval(2, 6))
KeyError: Interval(2, 6, closed='right')
```

Likewise, `get_indexer()` and `get_indexer_non_unique()` will also only return locations for exact matches to `Interval` queries, with -1 denoting that an exact match was not found.

These indexing changes extend to querying a `Series` or `DataFrame` with an `IntervalIndex` index.

```python
In [43]: s = pd.Series(list('abc'), index=ii)
In [44]: s
Out[44]:
      0          4  a
      1          5  b
   5          8  c
Length: 3, dtype: object
```

Selecting from a `Series` or `DataFrame` using `[]` (`__getitem__`) or `loc` now only returns exact matches for `Interval` queries.

### Previous behavior:

```python
In [8]: s[pd.Interval(1, 5)]
Out[8]:
      0          4  a
      1          5  b
dtype: object

In [9]: s.loc[pd.Interval(1, 5)]
Out[9]:
      0          4  a
      1          5  b
dtype: object
```

### New behavior:

```python
In [8]: s[pd.Interval(1, 5)]
Out[8]:
      0          4  a
      1          5  b
dtype: object

In [9]: s.loc[pd.Interval(1, 5)]
KeyError: Interval(1, 6, closed='right')
```
Similarly, a `KeyError` will be raised for non-exact matches instead of returning overlapping matches.

**Previous behavior:**

```
In [9]: s[pd.Interval(2, 3)]
Out[9]:
(0, 4]  a
(1, 5]  b
dtype: object
```

```
In [10]: s.loc[pd.Interval(2, 3)]
Out[10]:
(0, 4]  a
(1, 5]  b
dtype: object
```

**New behavior:**

```
In [6]: s[pd.Interval(2, 3)]
---------------------------------------------------------------------------
KeyError: Interval(2, 3, closed='right')
```

```
In [7]: s.loc[pd.Interval(2, 3)]
---------------------------------------------------------------------------
KeyError: Interval(2, 3, closed='right')
```

The `overlaps()` method can be used to create a boolean indexer that replicates the previous behavior of returning overlapping matches.

**New behavior:**

```
In [47]: idxr = s.index.overlaps(pd.Interval(2, 3))
In [48]: idxr
Out[48]: array([ True,  True, False])
```

```
In [49]: s[idxr]
Out[49]:
(0, 4]  a
(1, 5]  b
Length: 2, dtype: object
```

```
In [50]: s.loc[idxr]
Out[50]:
(0, 4]  a
(1, 5]  b
Length: 2, dtype: object
```
Binary ufuncs on Series now align

Applying a binary ufunc like `numpy.power()` now aligns the inputs when both are `Series` (GH23293).

```python
In [51]: s1 = pd.Series([1, 2, 3], index=['a', 'b', 'c'])
In [52]: s2 = pd.Series([3, 4, 5], index=['d', 'c', 'b'])

In [53]: s1
Out[53]:
          a  1
          b  2
          c  3
Length: 3, dtype: int64

In [54]: s2
Out[54]:
          d  3
          c  4
          b  5
Length: 3, dtype: int64

Previous behavior

```python
In [5]: np.power(s1, s2)
Out[5]:
          a   1
          b  16
          c 243
dtype: int64

New behavior

```python
In [55]: np.power(s1, s2)
Out[55]:
          a  1.0
          b 32.0
          c 81.0
d   NaN
Length: 4, dtype: float64

This matches the behavior of other binary operations in pandas, like `Series.add()`. To retain the previous behavior, convert the other `Series` to an array before applying the ufunc.

```python
In [56]: np.power(s1, s2.array)
Out[56]:
          a  1
          b 16
          c 243
Length: 3, dtype: int64
```
Categorical.argsort now places missing values at the end

Categorical.argsort() now places missing values at the end of the array, making it consistent with NumPy and the rest of pandas (GH21801).

Previous behavior

New behavior

Column order is preserved when passing a list of dicts to DataFrame

Starting with Python 3.7 the key-order of dict is guaranteed. In practice, this has been true since Python 3.6. The DataFrame constructor now treats a list of dicts in the same way as it does a list of OrderedDict, i.e. preserving the order of the dicts. This change applies only when pandas is running on Python>=3.6 (GH27309).

Previous Behavior:
The columns were lexicographically sorted previously.

New Behavior:
The column order now matches the insertion-order of the keys in the `dict`, considering all the records from top to bottom. As a consequence, the column order of the resulting DataFrame has changed compared to previous pandas versions.

```
In [61]: pd.DataFrame(data)
Out[61]:
   name state  age  hobby  finances
0   Joe   NY   18     NaN       NaN
1  Jane   KY   19  Minecraft       NaN
2  Jean   OK   20       NaN      good
[3 rows x 5 columns]
```

**Increased minimum versions for dependencies**

Due to dropping support for Python 2.7, a number of optional dependencies have updated minimum versions (GH25725, GH24942, GH25752). Independently, some minimum supported versions of dependencies were updated (GH23519, GH25554). If installed, we now require:

<table>
<thead>
<tr>
<th>Package</th>
<th>Minimum Version</th>
<th>Required</th>
</tr>
</thead>
<tbody>
<tr>
<td>numpy</td>
<td>1.13.3</td>
<td>X</td>
</tr>
<tr>
<td>pytz</td>
<td>2015.4</td>
<td>X</td>
</tr>
<tr>
<td>python-dateutil</td>
<td>2.6.1</td>
<td>X</td>
</tr>
<tr>
<td>bottleneck</td>
<td>1.2.1</td>
<td></td>
</tr>
<tr>
<td>numexpr</td>
<td>2.6.2</td>
<td></td>
</tr>
<tr>
<td>pytest (dev)</td>
<td>4.0.2</td>
<td></td>
</tr>
</tbody>
</table>

For optional libraries the general recommendation is to use the latest version. The following table lists the lowest version per library that is currently being tested throughout the development of pandas. Optional libraries below the lowest tested version may still work, but are not considered supported.

<table>
<thead>
<tr>
<th>Package</th>
<th>Minimum Version</th>
</tr>
</thead>
<tbody>
<tr>
<td>beautifulsoup4</td>
<td>4.6.0</td>
</tr>
<tr>
<td>fastparquet</td>
<td>0.2.1</td>
</tr>
<tr>
<td>gcsfs</td>
<td>0.2.2</td>
</tr>
<tr>
<td>lxml</td>
<td>3.8.0</td>
</tr>
<tr>
<td>matplotlib</td>
<td>2.2.2</td>
</tr>
<tr>
<td>openpyxl</td>
<td>2.4.8</td>
</tr>
<tr>
<td>pyarrow</td>
<td>0.9.0</td>
</tr>
<tr>
<td>pymysql</td>
<td>0.7.1</td>
</tr>
<tr>
<td>pytables</td>
<td>3.4.2</td>
</tr>
<tr>
<td>scipy</td>
<td>0.19.0</td>
</tr>
<tr>
<td>sqlalchemwy</td>
<td>1.1.4</td>
</tr>
<tr>
<td>xarray</td>
<td>0.8.2</td>
</tr>
<tr>
<td>xlrd</td>
<td>1.1.0</td>
</tr>
<tr>
<td>xlsxwriter</td>
<td>0.9.8</td>
</tr>
<tr>
<td>xlwt</td>
<td>1.2.0</td>
</tr>
</tbody>
</table>

See Dependencies and Optional dependencies for more.
Other API changes

- **DatetimeTZDtype** will now standardize pytz time zones to a common timezone instance (GH24713)
- **Timestamp** and **Timedelta** scalars now implement the `to_numpy()` method as aliases to `Timestamp.to_datetime64()` and `Timedelta.to_timedelta64()`, respectively. (GH24653)
- **Timestamp.strptime()** will now raise a `NotImplementedError` (GH25016)
- Comparing **Timestamp** with unsupported objects now returns `NotImplemented` instead of raising `TypeError`. This implies that unsupported rich comparisons are delegated to the other object, and are now consistent with Python 3 behavior for `datetime` objects (GH24011)
- Bug in **DatetimeIndex.snap()** which didn’t preserving the name of the input `Index` (GH25575)
- The `arg` argument in `pandas.core.groupby.DataFrameGroupBy.agg()` has been renamed to `func` (GH26089)
- The `arg` argument in `pandas.core.window._Window.aggregate()` has been renamed to `func` (GH26372)
- Most Pandas classes had a `__bytes__` method, which was used for getting a python2-style bytestring representation of the object. This method has been removed as a part of dropping Python2 (GH26447)
- The `.str`-accessor has been disabled for 1-level **MultiIndex**, use `MultiIndex.to_flat_index()` if necessary (GH23679)
- Removed support of gtk package for clipboards (GH26563)
- Using an unsupported version of Beautiful Soup 4 will now raise an `ImportError` instead of a `ValueError` (GH27063)
- **Series.to_excel()** and **DataFrame.to_excel()** will now raise a `ValueError` when saving timezone aware data. (GH27008, GH7056)
- **ExtensionArray.argsort()** places NA values at the end of the sorted array. (GH21801)
- **DataFrame.to_hdf()** and **Series.to_hdf()** will now raise a `NotImplementedError` when saving a **MultiIndex** with extension data types for a fixed format. (GH7775)
- Passing duplicate names in `read_csv()` will now raise a `ValueError` (GH17346)

Deprecations

Sparse subclasses

The **SparseSeries** and **SparseDataFrame** subclasses are deprecated. Their functionality is better-provided by a **Series** or **DataFrame** with sparse values.

Previous way

```python
df = pd.SparseDataFrame({"A": [0, 0, 1, 2]})
df.dtypes
```

New way

```python
In [62]: df = pd.DataFrame({"A": pd.SparseArray([0, 0, 1, 2])})
In [63]: df.dtypes
Out[63]:
```

(continues on next page)
A Sparse[int64, 0]
Length: 1, dtype: object

The memory usage of the two approaches is identical. See Migrating for more (GH19239).

msgpack format

The msgpack format is deprecated as of 0.25 and will be removed in a future version. It is recommended to use pyarrow for on-the-wire transmission of pandas objects. (GH27084)

Other deprecations

- The deprecated .ix[] indexer now raises a more visible FutureWarning instead of DeprecationWarning (GH26438).
- Deprecated the units=M (months) and units=Y (year) parameters for units of pandas.to_timedelta(), pandas.Timedelta() and pandas.TimedeltaIndex() (GH16344)
- pandas.concat() has deprecated the join_axes-keyword. Instead, use DataFrame.reindex() or DataFrame.reindex_like() on the result or on the inputs (GH21951)
- The SparseArray.values attribute is deprecated. You can use np.asarray(...) or the SparseArray.to_dense() method instead (GH26421).
- The functions pandas.to_datetime() and pandas.to_timedelta() have deprecated the box keyword. Instead, use to_numpy() or Timestamp.to_datetime64() or Timedelta.to_timedelta64() (GH24416)
- The DataFrame.compound() and Series.compound() methods are deprecated and will be removed in a future version (GH26405).
- The internal attributes _start, _stop and _step attributes of RangeIndex have been deprecated. Use the public attributes start, stop and step instead (GH26581).
- The Series.ftype(), Series.ftypes() and DataFrame.ftypes() methods are deprecated and will be removed in a future version. Instead, use Series.dtype() and DataFrame.dtypes() (GH26705).
- The Series.get_values(), DataFrame.get_values(), Index.get_values(), SparseArray.get_values() and Categorical.get_values() methods are deprecated. One of np.asarray(...) or to_numpy() can be used instead (GH19617).
- The ‘outer’ method on NumPy ufuncs, e.g. np.subtract.outer has been deprecated on Series objects. Convert the input to an array with Series.array first (GH27186)
- Timedelta.resolution() is deprecated and replaced with Timedelta.resolution_string(). In a future version, Timedelta.resolution() will be changed to behave like the standard library datetime.timedelta.resolution (GH21344)
- read_table() has been undeprecated. (GH25220)
- Index.dtype_str is deprecated. (GH18262)
- Series.imag and Series.real are deprecated. (GH18262)
- Series.put() is deprecated. (GH18262)
- Index.item() and Series.item() is deprecated. (GH18262)
The default value `ordered=None` in `CategoricalDtype` has been deprecated in favor of `ordered=False`. When converting between categorical types `ordered=True` must be explicitly passed in order to be preserved. (GH26336)

- `Index.contains()` is deprecated. Use `key in index (__contains__)` instead (GH17753).
- `DataFrame.get_dtype_counts()` is deprecated. (GH18262)
- `Categorical.ravel()` will return a `Categorical` instead of a `np.ndarray` (GH27199)

### Removal of prior version deprecations/changes

- Removed Panel (GH25047, GH25191, GH25231)
- Removed the previously deprecated `sheetname` keyword in `read_excel()` (GH16442, GH20938)
- Removed the previously deprecated `TimeGrouper` (GH16942)
- Removed the previously deprecated `parse_cols` keyword in `read_excel()` (GH16488)
- Removed the previously deprecated `pd.options.html.border` (GH16970)
- Removed the previously deprecated `convert_objects` (GH11221)
- Removed the previously deprecated `select` method of `DataFrame` and `Series` (GH17633)
- Removed the previously deprecated behavior of `Series` treated as list-like in `rename_categories()` (GH17982)
- Removed the previously deprecated `DataFrame.reindex_axis` and `Series.reindex_axis` (GH17842)
- Removed the previously deprecated behavior of altering column or index labels with `Series.rename_axis()` or `DataFrame.rename_axis()` (GH17842)
- Removed the previously deprecated `tupleize_cols` keyword argument in `read_html()`, `read_csv()`, and `DataFrame.to_csv()` (GH17877, GH17820)
- Removed the previously deprecated `DataFrame.from.csv` and `Series.from_csv` (GH17812)
- Removed the previously deprecated `raise_on_error` keyword argument in `DataFrame.where()` and `DataFrame.mask()` (GH17744)
- Removed the previously deprecated `ordered` and `categories` keyword arguments in `astype` (GH17742)
- Removed the previously deprecated `cdate_range` (GH17691)
- Removed the previously deprecated `True` option for the `dropna` keyword argument in `SeriesGroupBy.nth()` (GH17493)
- Removed the previously deprecated `convert` keyword argument in `Series.take()` and `DataFrame.take()` (GH17352)
- Removed the previously deprecated behavior of arithmetic operations with `datetime.date` objects (GH21152)
Performance improvements

- Significant speedup in SparseArray initialization that benefits most operations, fixing performance regression introduced in v0.20.0 (GH24985)
- DataFrame.to_stata() is now faster when outputting data with any string or non-native endian columns (GH25045)
- Improved performance of Series.searchsorted(). The speedup is especially large when the dtype is int8/int16/int32 and the searched key is within the integer bounds for the dtype (GH22034)
- Improved performance of pandas.core.groupby.GroupBy.quantile() (GH20405)
- Improved performance of slicing and other selected operation on a RangeIndex (GH26565, GH26617, GH26722)
- RangeIndex now performs standard lookup without instantiating an actual hashtable, hence saving memory (GH16685)
- Improved performance of read_csv() by faster tokenizing and faster parsing of small float numbers (GH25784)
- Improved performance of read_csv() by faster parsing of N/A and boolean values (GH25804)
- Improved performance of IntervalIndex.is_monotonic, IntervalIndex.is_monotonic_increasing and IntervalIndex.is_monotonic_decreasing by removing conversion to MultiIndex (GH24813)
- Improved performance of DataFrame.to_csv() when writing datetime dtypes (GH25708)
- Improved performance of read_csv() by much faster parsing of MM/YYYY and DD/MM/YYYY datetime formats (GH25922)
- Improved performance of nanops for dtypes that cannot store NaNs. Speedup is particularly prominent for Series.all() and Series.any() (GH25070)
- Improved performance of Series.map() for dictionary mappers on categorical series by mapping the categories instead of mapping all values (GH23785)
- Improved performance of IntervalIndex.intersection() (GH24813)
- Improved performance of read_csv() by faster concatenating date columns without extra conversion to string for integer/float zero and float NaN; by faster checking the string for the possibility of being a date (GH25754)
- Improved performance of IntervalIndex.is_unique by removing conversion to MultiIndex (GH24813)
- Restored performance of DatetimeIndex.__iter__() by re-enabling specialized code path (GH26702)
- Improved performance when building MultiIndex with at least one CategoricalIndex level (GH22044)
- Improved performance by removing the need for a garbage collect when checking for SettingWithCopyWarning (GH27031)
- For to_datetime() changed default value of cache parameter to True (GH26043)
- Improved performance of DatetimeIndex and PeriodIndex slicing given non-unique, monotonic data (GH27136).
- Improved performance of pd.read_json() for index-oriented data. (GH26773)
- Improved performance of MultiIndex.shape() (GH27384).
Bug fixes

Categorical

- Bug in `DataFrame.at()` and `Series.at()` that would raise exception if the index was a `CategoricalIndex` (GH20629)
- Fixed bug in comparison of ordered `Categorical` that contained missing values with a scalar which sometimes incorrectly resulted in `True` (GH26504)
- Bug in `DataFrame.dropna()` when the DataFrame has a `CategoricalIndex` containing `Interval` objects incorrectly raised a `TypeError` (GH25087)

Datetimelike

- Bug in `to_datetime()` which would raise an (incorrect) `ValueError` when called with a date far into the future and the `format` argument specified instead of raising `OutOfBoundsDatetime` (GH23830)
- Bug in `to_datetime()` which would raise `InvalidIndexError`: Reindexing only valid uniquely valued Index objects when called with `cache=True`, with `arg` including at least two different elements from the set `{None, numpy.nan, pandas.NaT}` (GH22305)
- Bug in `DataFrame` and `Series` where timezone aware data with `dtype='datetime64[ns]` was not cast to naive (GH25843)
- Improved `Timestamp` type checking in various datetime functions to prevent exceptions when using a subclassed datetime (GH25851)
- Bug in `Series` and `DataFrame` repr where `np.datetime64('NaT')` and `np.timedelta64('NaT')` with `dtype=object` would be represented as `NaN` (GH25445)
- Bug in `to_datetime()` which does not replace the invalid argument with `NaT` when error is set to coerce (GH26122)
- Bug in adding `DateOffset` with nonzero month to `DatetimeIndex` would raise `ValueError` (GH26258)
- Bug in `to_datetime()` which raises unhandled `OverflowError` when called with mix of invalid dates and `NaN` values with `format='%Y%m%d' and error='coerce'` (GH25512)
- Bug in `isin()` for datetimelike indexes; `DatetimeIndex`, `TimedeltaIndex` and `PeriodIndex` where the `levels` parameter was ignored. (GH26675)
- Bug in `to_datetime()` which raises `TypeError` for `format='%Y%m%d'` when called for invalid integer dates with length >= 6 digits with `errors='ignore'` (GH26689)
- Bug when comparing a `PeriodIndex` against a zero-dimensional numpy array (GH26689)
- Bug in constructing a `Series` or `DataFrame` from a numpy `datetime64` array with a non-ns unit and out-of-bound timestamps generating rubbish data, which will now correctly raise an `OutOfBoundsDatetime` error (GH26206).
- Bug in `date_range()` with unnecessary `OverflowError` being raised for very large or very small dates (GH26651)
- Bug where adding `Timestamp` to a `np.timedelta64` object would raise instead of returning a `Timestamp` (GH24775)
- Bug where comparing a zero-dimensional numpy array containing a `np.datetime64` object to a `Timestamp` would incorrect raise `TypeError` (GH26916)
• Bug in `to_datetime()` which would raise `ValueError`: Tz-aware datetime.datetime cannot be converted to datetime64 unless utc=True when called with cache=True, with arg including datetime strings with different offset (GH26097)

Timedelta

• Bug in `TimedeltaIndex.intersection()` where for non-monotonic indices in some cases an empty Index was returned when in fact an intersection existed (GH25913)

• Bug with comparisons between `Timedelta` and `NaT` raising `TypeError` (GH26039)

• Bug when adding or subtracting a `BusinessHour` to a `Timestamp` with the resulting time landing in a following or prior day respectively (GH26381)

• Bug when comparing a `TimedeltaIndex` against a zero-dimensional numpy array (GH26689)

Timezones

• Bug in `DatetimeIndex.to_frame()` where timezone aware data would be converted to timezone naive data (GH25809)

• Bug in `to_datetime()` with utc=True and datetime strings that would apply previously parsed UTC offsets to subsequent arguments (GH24992)

• Bug in `Timestamp.tz_localize()` and `Timestamp.tz_convert()` does not propagate freq (GH25241)

• Bug in `Series.at()` where setting `Timestamp` with timezone raises `TypeError` (GH25506)

• Bug in `DataFrame.update()` when updating with timezone aware data would return timezone naive data (GH25807)

• Bug in `to_datetime()` where an uninformative `RuntimeError` was raised when passing a naive `Timestamp` with datetime strings with mixed UTC offsets (GH25978)

• Bug in `to_datetime()` with unit='ns' would drop timezone information from the parsed argument (GH26168)

• Bug in `DataFrame.join()` where joining a timezone aware index with a timezone aware column would result in a column of NaN (GH26335)

• Bug in `date_range()` where ambiguous or nonexistent start or end times were not handled by the ambiguous or nonexistent keywords respectively (GH27088)

• Bug in `DatetimeIndex.union()` when combining a timezone aware and timezone unaware `DatetimeIndex` (GH21671)

• Bug when applying a numpy reduction function (e.g. `numpy.minimum()`) to a timezone aware `Series` (GH15552)
Numeric

- Bug in `to_numeric()` in which large negative numbers were being improperly handled (GH24910)
- Bug in `to_numeric()` in which numbers were being coerced to float, even though `errors` was not `coerce` (GH24910)
- Bug in `to_numeric()` in which invalid values for `errors` were being allowed (GH26466)
- Bug in `format` in which floating point complex numbers were not being formatted to proper display precision and trimming (GH25514)
- Bug in error messages in `DataFrame.corr()` and `Series.corr()`. Added the possibility of using a callable. (GH25729)
- Bug in `Series.divmod()` and `Series.rdivmod()` which would raise an (incorrect) `ValueError` rather than return a pair of `Series` objects as result (GH25557)
- Raises a helpful exception when a non-numeric index is sent to `interpolate()` with methods which require numeric index. (GH21662)
- Bug in `eval()` when comparing floats with scalar operators, for example: `x < -0.1` (GH25928)
- Fixed bug where casting all-boolean array to integer extension array failed (GH25211)
- Bug in `divmod` with a `Series` object containing zeros incorrectly raising `AttributeError` (GH26987)
- Inconsistency in `Series` floor-division (`//`) and `divmod` filling positive//zero with `NaN` instead of `Inf` (GH27321)

Conversion

- Bug in `DataFrame.astype()` when passing a dict of columns and types the `errors` parameter was ignored. (GH25905)

Strings

- Bug in the `__name__` attribute of several methods of `Series.str`, which were set incorrectly (GH23551)
- Improved error message when passing `Series` of wrong dtype to `Series.str.cat()` (GH22722)
Interval

- Construction of *Interval* is restricted to numeric, *Timestamp* and *Timedelta* endpoints (GH23013)
- Fixed bug in *Series*/*DataFrame* not displaying NaN in *IntervalIndex* with missing values (GH25984)
- Bug in *IntervalIndex.get_loc()* where a *KeyError* would be incorrectly raised for a decreasing *IntervalIndex* (GH25860)
- Bug in *Index* constructor where passing mixed closed *Interval* objects would result in a *ValueError* instead of an object dtype *Index* (GH27172)

Indexing

- Improved exception message when calling *DataFrame.iloc()* with a list of non-numeric objects (GH25753).
- Improved exception message when calling .iloc or .loc with a boolean indexer with different length (GH26658).
- Bug in *KeyError* exception message when indexing a *MultiIndex* with a non-existent key not displaying the original key (GH27250).
- Bug in .iloc and .loc with a boolean indexer not raising an *IndexError* when too few items are passed (GH26658).
- Bug in *DataFrame.loc()* and *Series.loc()* where *KeyError* was not raised for a *MultiIndex* when the key was less than or equal to the number of levels in the *MultiIndex* (GH14885).
- Bug in which *DataFrame.append()* produced an erroneous warning indicating that a *KeyError* will be thrown in the future when the data to be appended contains new columns (GH22252).
- Bug in which *DataFrame.to_csv()* caused a segfault for a reindexed data frame, when the indices were single-level *MultiIndex* (GH26303).
- Fixed bug where assigning a *arrays.PandasArray* to a *pandas.core.frame.DataFrame* would raise error (GH26390)
- Allow keyword arguments for callable local reference used in the *DataFrame.query()* string (GH26426)
- Fixed a *KeyError* when indexing a *MultiIndex*’ level with a list containing exactly one label, which is missing (GH27148)
- Bug which produced *AttributeError* on partial matching *Timestamp* in a *MultiIndex* (GH26944)
- Bug in *Categorical* and *CategoricalIndex* with *Interval* values when using the in operator (__contains__) with objects that are not comparable to the values in the Interval (GH23705)
- Bug in *DataFrame.loc()* and *DataFrame.iloc()* on a *DataFrame* with a single timezone-aware datetime64[ns] column incorrectly returning a scalar instead of a *Series* (GH27110)
- Bug in *CategoricalIndex* and *Categorical* incorrectly raising *ValueError* instead of *TypeError* when a list is passed using the in operator (__contains__) (GH21729)
- Bug in setting a new value in a *Series* with a *Timedelta* object incorrectly casting the value to an integer (GH22717)
- Bug in *Series* setting a new key (__setitem__) with a timezone-aware datetime incorrectly raising *ValueError* (GH12862)
- Bug in *DataFrame.iloc()* when indexing with a read-only indexer (GH17192)
• Bug in `Series` setting an existing tuple key (`__setitem__`) with timezone-aware datetime values incorrectly raising `TypeError` (GH20441)

**Missing**

• Fixed misleading exception message in `Series.interpolate()` if argument `order` is required, but omitted (GH10633, GH24014).

• Fixed class type displayed in exception message in `DataFrame.dropna()` if invalid `axis` parameter passed (GH25555)

• A `ValueError` will now be thrown by `DataFrame.fillna()` when `limit` is not a positive integer (GH27042)

**MultiIndex**

• Bug in which incorrect exception raised by `Timedelta` when testing the membership of `MultiIndex` (GH24570)

**I/O**

• Bug in `DataFrame.to_html()` where values were truncated using display options instead of outputting the full content (GH17004)

• Fixed bug in missing text when using `to_clipboard()` if copying utf-16 characters in Python 3 on Windows (GH25040)

• Bug in `read_json()` for `orient='table'` when it tries to infer dtypes by default, which is not applicable as dtypes are already defined in the JSON schema (GH21345)

• Bug in `read_json()` for `orient='table'` and float index, as it infers index dtype by default, which is not applicable because index dtype is already defined in the JSON schema (GH25433)

• Bug in `read_json()` for `orient='table'` and string of float column names, as it makes a column name type conversion to `Timestamp`, which is not applicable because column names are already defined in the JSON schema (GH25435)

• Bug in `json_normalize()` for `errors='ignore'` where missing values in the input data, were filled in resulting `DataFrame` with the string "nan" instead of `numpy.nan` (GH25468)

• `DataFrame.to_html()` now raises `TypeError` when using an invalid type for the `classes` parameter instead of `AssertionError` (GH25608)

• Bug in `DataFrame.to_string()` and `DataFrame.to_latex()` that would lead to incorrect output when the `header` keyword is used (GH16718)

• Bug in `read_csv()` not properly interpreting the UTF8 encoded filenames on Windows on Python 3.6+ (GH15086)

• Improved performance in `pandas.read_stata()` and `pandas.io.stata.StataReader` when converting columns that have missing values (GH25772)

• Bug in `DataFrame.to_html()` where header numbers would ignore display options when rounding (GH17280)
• Bug in `read_hdf()` where reading a table from an HDF5 file written directly with PyTables fails with a ValueError when using a sub-selection via the `start` or `stop` arguments (GH11188)

• Bug in `read_hdf()` not properly closing store after a KeyError is raised (GH25766)

• Improved the explanation for the failure when value labels are repeated in Stata dta files and suggested workarounds (GH25772)

• Improved `pandas.read_stata()` and `pandas.io.stata.StataReader` to read incorrectly formatted 118 format files saved by Stata (GH25960)

• Improved the `col_space` parameter in `DataFrame.to_html()` to accept a string so CSS length values can be set correctly (GH25941)

• Fixed bug in loading objects from S3 that contain # characters in the URL (GH25945)

• Adds `use_bqstorage_api` parameter to `read_gbq()` to speed up downloads of large data frames. This feature requires version 0.10.0 of the pandas-gbq library as well as the google-cloud-bigquery-storage and fastavro libraries. (GH26104)

• Fixed memory leak in `DataFrame.to_json()` when dealing with numeric data (GH24889)

• Added `cache_dates=True` parameter to `read_csv()`, which allows to cache unique dates when they are parsed (GH25990)

• `DataFrame.to_excel()` now raises a ValueError when the caller’s dimensions exceed the limitations of Excel (GH26051)

• Fixed bug in `pandas.read_csv()` where a BOM would result in incorrect parsing using `engine='python'` (GH26545)

• `read_excel()` now raises a ValueError when input is of type `pandas.io.excel.ExcelFile` and `engine` param is passed since `pandas.io.excel.ExcelFile` has an engine defined (GH26566)

• Bug while selecting from HDFStore with `where=''` specified (GH26610).

• Fixed bug in `DataFrame.to_excel()` where custom objects (i.e. `PeriodIndex`) inside merged cells were not being converted into types safe for the Excel writer (GH27006)

• Bug in `read_hdf()` where reading a timezone aware `DatetimeIndex` would raise a TypeError (GH11926)

• Bug in `to_msgpack()` and `read_msgpack()` which would raise a ValueError rather than a FileNotFoundError for an invalid path (GH27160)

• Fixed bug in `DataFrame.to_parquet()` which would raise a ValueError when the dataframe had no columns (GH27339)

• Allow parsing of `PeriodDtype` columns when using `read_csv()` (GH26934)

**Plotting**

• Fixed bug where `api.extensions.ExtensionArray` could not be used in matplotlib plotting (GH25587)

• Bug in an error message in `DataFrame.plot()`. Improved the error message if non-numerics are passed to `DataFrame.plot()` (GH25481)

• Bug in incorrect ticklabel positions when plotting an index that are non-numeric / non-datetime (GH7612, GH15912, GH22334)
• Fixed bug causing plots of PeriodIndex timeseries to fail if the frequency is a multiple of the frequency rule code (GH14763)
• Fixed bug when plotting a DatetimeIndex with datetime.timezone.utc timezone (GH17173)

Groupby/resample/rolling

• Bug in pandas.core.resample.Resampler.agg() with a timezone aware index where OverflowError would raise when passing a list of functions (GH22660)
• Bug in pandas.core.groupby.DataFrameGroupBy.nunique() in which the names of column levels were lost (GH23222)
• Bug in pandas.core.groupby.GroupBy.agg() when applying an aggregation function to timezone aware data (GH23683)
• Bug in pandas.core.groupby.GroupBy.first() and pandas.core.groupby.GroupBy.last() where timezone information would be dropped (GH21603)
• Bug in pandas.core.groupby.GroupBy.size() when grouping only NA values (GH23050)
• Bug in Series.groupby() where observed kwarg was previously ignored (GH24880)
• Bug in Series.groupby() where using groupby with a MultiIndex Series with a list of labels equal to the length of the series caused incorrect grouping (GH25704)
• Ensured that ordering of outputs in groupby aggregation functions is consistent across all versions of Python (GH25692)
• Ensured that result group order is correct when grouping on an ordered Categorical and specifying observed=True (GH25871, GH25167)
• Bug in pandas.core.window.Rolling.min() and pandas.core.window.Rolling.max() that caused a memory leak (GH25893)
• Bug in pandas.core.window.Rolling.count() and pandas.core.window.Expanding.count was previously ignoring the axis keyword (GH13503)
• Bug in pandas.core.groupby.GroupBy.idmax() and pandas.core.groupby.GroupBy.idmin() with datetime column would return incorrect dtype (GH25444, GH15306)
• Bug in pandas.core.groupby.GroupBy.cumsum(), pandas.core.groupby.GroupBy.cumprod(), pandas.core.groupby.GroupBy.cummin() and pandas.core.groupby.GroupBy.cummax() with categorical column having absent categories, would return incorrect result or segfault (GH16771)
• Bug in pandas.core.groupby.GroupBy.nth() where NA values in the grouping would return incorrect results (GH26011)
• Bug in pandas.core.groupby.SeriesGroupBy.transform() where transforming an empty group would raise a ValueError (GH26208)
• Bug in pandas.core.frame.DataFrame.groupby() where passing a pandas.core.groupby.grouper.Grouper would return incorrect groups when using the .groups accessor (GH26326)
• Bug in pandas.core.groupby.GroupBy.agg() where incorrect results are returned for uint64 columns. (GH26310)
- Bug in `pandas.core.window.Rolling.median()` and `pandas.core.window.Rolling.quantile()` where MemoryError is raised with empty window (GH26005)
- Bug in `pandas.core.window.Rolling.median()` and `pandas.core.window.Rolling.quantile()` where incorrect results are returned with closed='left' and closed='neither' (GH26005)
- Improved `pandas.core.window.Rolling`, `pandas.core.window.Window` and `pandas.core.window.ExponentialMovingWindow` functions to exclude nuisance columns from results instead of raising errors and raise a `DataError` only if all columns are nuisance (GH12537)
- Bug in `pandas.core.window.Rolling.max()` and `pandas.core.window.Rolling.min()` where incorrect results are returned with an empty variable window (GH26005)
- Raise a helpful exception when an unsupported weighted window function is used as an argument of `pandas.core.window.Window.aggregate()` (GH26597)

**Reshaping**

- Bug in `pandas.merge()` adds a string of None, if None is assigned in suffixes instead of remain the column name as-is (GH24782).
- Bug in `merge()` when merging by index name would sometimes result in an incorrectly numbered index (missing index values are now assigned NA) (GH24212, GH25009)
- `to_records()` now accepts dtypes to its `column_dtypes` parameter (GH24895)
- Bug in `concat()` where order of `OrderedDict` (and `dict` in Python 3.6+) is not respected, when passed in as `objs` argument (GH21510)
- Bug in `pivot_table()` where columns with NaN values are dropped even if dropna argument is False, when the aggfunc argument contains a list (GH22159)
- Bug in `concat()` where the resulting freq of two `DatetimeIndex` with the same freq would be dropped (GH3232).
- Bug in `merge()` where merging with equivalent Categorical dtypes was raising an error (GH22501)
- Bug in `DataFrame` instantiating with a dict of iterators or generators (e.g. `pd.DataFrame({'A': reversed(range(3))})`) raised an error (GH26349).
- Bug in `DataFrame` instantiating with a range (e.g. `pd.DataFrame(range(3))`) raised an error (GH26342).
- Bug in `DataFrame` constructor when passing non-empty tuples would cause a segmentation fault (GH25691)
- Bug in `Series.apply()` failed when the series is a timezone aware `DatetimeIndex` (GH25959)
- Bug in `pandas.cut()` where large bins could incorrectly raise an error due to an integer overflow (GH26045)
- Bug in `DataFrame.sort_index()` where an error is thrown when a multi-indexed DataFrame is sorted on all levels with the initial level sorted last (GH26053)
- Bug in `Series.nlargest()` treats True as smaller than False (GH26154)
- Bug in `DataFrame.pivot_table()` with a `IntervalIndex` as pivot index would raise `TypeError` (GH25814)
- Bug in which `DataFrame.from_dict()` ignored order of `OrderedDict` when orient='index' (GH8425).
- Bug in `DataFrame.transpose()` where transposing a DataFrame with a timezone-aware datetime column would incorrectly raise `ValueError` (GH26825)
• Bug in `pivot_table()` when pivoting a timezone aware column as the values would remove timezone information (GH14948)
• Bug in `merge_asof()` when specifying multiple by columns where one is `datetime64[ns, tz]` dtype (GH26649)

Sparse

• Significant speedup in `SparseArray` initialization that benefits most operations, fixing performance regression introduced in v0.20.0 (GH24985)
• Bug in `SparseFrame` constructor where passing `None` as the data would cause `default_fill_value` to be ignored (GH16807)
• Bug in `SparseDataFrame` when adding a column in which the length of values does not match length of index, `AssertionError` is raised instead of raising `ValueError` (GH25484)
• Introduce a better error message in `Series.sparse.from_coo()` so it returns a `TypeError` for inputs that are not `coo` matrices (GH26554)
• Bug in `numpy.modf()` on a `SparseArray`. Now a tuple of `SparseArray` is returned (GH26946).

Build changes

• Fix install error with PyPy on macOS (GH26536)

ExtensionArray

• Bug in `factorize()` when passing an `ExtensionArray` with a custom `na_sentinel` (GH25696).
• `Series.count()` miscounts NA values in ExtensionArrays (GH26835)
• Added `Series.__array_ufunc__` to better handle NumPy ufuncs applied to Series backed by extension arrays (GH23293).
• Keyword argument `deep` has been removed from `ExtensionArray.copy()` (GH27083)

Other

• Removed unused C functions from vendored UltraJSON implementation (GH26198)
• Allow `Index` and `RangeIndex` to be passed to `numpy min` and `max` functions (GH26125)
• Use actual class name in repr of empty objects of a `Series` subclass (GH27001).
• Bug in `DataFrame` where passing an object array of timezone-aware `datetime` objects would incorrectly raise `ValueError` (GH13287)
Contributors

A total of 231 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- l_x7 +
- Abdullah İhsan Seçer +
- Adam Bull +
- Adam Hooper
- Albert Villanova del Moral
- Alex Watt +
- AlexTereshenkov +
- Alexander Buchkovsky
- Alexander Hendorf +
- Alexander Nordin +
- Alexander Ponomaroff
- Alexandre Batisse +
- Alexandre Decan +
- Allen Downey +
- Alyssa Fu Ward +
- Andrew Gaspari +
- Andrew Wood +
- Antoine Viscardi +
- Antonio Gutierrez +
- Arno Veenstra +
- ArtinSarraf
- Batalex +
- Baurzhan Muftakhidinov
- Benjamin Rowell
- Bharat Raghunathan +
- Bhavani Ravi +
- Big Head +
- Brett Randall +
- Bryan Cutler +
- C John Klehm +
- Caleb Braun +
- Cecilia +
- Chris Bertinato +
pandas: powerful Python data analysis toolkit, Release 1.1.1

- Chris Stadler +
- Christian Haege +
- Christian Hudon
- Christopher Whelan
- Chuanzhu Xu +
- Clemens Brunner
- Damian Kula +
- Daniel Hrisca +
- Daniel Luis Costa +
- Daniel Saxton
- DanielFEvans +
- David Liu +
- Deepyaman Datta +
- Denis Belavin +
- Devin Petersohn +
- Diane Trout +
- EdAbati +
- Enrico Rotundo +
- EternalLearner42 +
- Evan +
- Evan Livelo +
- Fabian Rost +
- Flavien Lambert +
- Florian Rathgeber +
- Frank Hoang +
- Gaibo Zhang +
- Gioia Ballin
- Giuseppe Romagnuolo +
- Gordon Blackadder +
- Gregory Rome +
- Guillaume Gay
- HHest +
- Hielke Walinga +
- How Si Wei +
- Hubert
- Huize Wang +
• Hyukjin Kwon +
• Ian Dunn +
• Inevitable-Marzipan +
• Irv Lustig
• JElfner +
• Jacob Bundgaard +
• James Cobon-Kerr +
• Jan-Philip Gehrcke +
• Jarrod Millman +
• Jayanth Katuri +
• Jeff Reback
• Jeremy Schendel
• Jiang Yue +
• Joel Ostblom
• Johan von Forstner +
• Johnny Chiu +
• Jonas +
• Jonathon Vandezande +
• Jop Vermeer +
• Joris Van den Bossche
• Josh
• Josh Friedlander +
• Justin Zheng
• Kaiqi Dong
• Kane +
• Kapil Patel +
• Kara de la Marck +
• Katherine Surta +
• Katrin Leinweber +
• Kendall Masse
• Kevin Sheppard
• Kyle Kosic +
• Lorenzo Stella +
• Maarten Rietbergen +
• Mak Sze Chun
• Marc Garcia
pandas: powerful Python data analysis toolkit, Release 1.1.1

- Mateusz Woś
- Matias Heikkilä
- Mats Maiwald +
- Matthew Roeschke
- Max Bolingbroke +
- Max Kovalovs +
- Max van Deursen +
- Michael
- Michael Davis +
- Michael P. Moran +
- Mike Cramblett +
- Min ho Kim +
- Misha Veldhoen +
- Mukul Ashwath Ram +
- MusTheDataGuy +
- Nanda H Krishna +
- Nicholas Musolino
- Noam Hershtig +
- Noora Husseini +
- Paul
- Paul Reidy
- Pauli Virtanen
- Pav A +
- Peter Leimbigler +
- Philippe Ombredanne +
- Pietro Battiston
- Richard Eames +
- Roman Yurchak
- Ruijing Li
- Ryan
- Ryan Joyce +
- Ryan Nazareth
- Ryan Rehman +
- Sakar Panta +
- Samuel Sinayoko
- Sandeep Pathak +
• Sangwoong Yoon
• Saurav Chakravorty
• Scott Talbert +
• Sergey Kopylov +
• Shantanu Gontia +
• Shivam Rana +
• Shorokhov Sergey +
• Simon Hawkins
• Soyoun(Rose) Kim
• Stephan Hoyer
• Stephen Cowley +
• Stephen Rauch
• Sterling Paramore +
• Steven +
• Stijn Van Hoey
• Sumanau Sareen +
• Takuya N +
• Tan Tran +
• Tao He +
• Tarbo Fukazawa
• Terji Petersen +
• Thein Oo
• ThibTrip +
• Thijs Damsma +
• Thiviyan Thanapalasingam
• Thomas A Caswell
• Thomas Kluiters +
• Tin Kusterle +
• Tim Gates +
• Tim Hoffmann
• Tim Swast
• Tom Augspurger
• Tom Neep +
• Tomáš Chvátal +
• Tyler Reddy
• Vaibhav Vishal +
• Vasily Litvinov +
• Vibhu Agarwal +
• Vikramjeet Das +
• Vladislav +
• Víctor Moron Tejero +
• Wenhuan
• Will Ayd +
• William Ayd
• Wouter De Coster +
• Yoann Goular +
• Zach Angell +
• alimcmaster1
• anmyachev +
• chris-b1
• danielplawrence +
• endenis +
• enisnazif +
• ezcitron +
• fjetter
• froessler
• gfyounh
• gwrome +
• h-vetinari
• haison +
• hannah-c +
• heckeo +
• iamshwin +
• jamesoliverh +
• jbrockmendel
• jkovacevic +
• killerontherrun1 +
• knuu +
• kpapdac +
• kpflugshaupt +
• krnik93 +
• leerssej +
5.4 Version 0.24

5.4.1 What’s new in 0.24.2 (March 12, 2019)

**Warning:** The 0.24.x series of releases will be the last to support Python 2. Future feature releases will support Python 3 only. See [Dropping Python 2.7](#) for more.

These are the changes in pandas 0.24.2. See [Release notes](#) for a full changelog including other versions of pandas.

**Fixed regressions**

- Fixed regression in `DataFrame.all()` and `DataFrame.any()` where `bool_only=True` was ignored (GH25101)
- Fixed issue in `DataFrame` construction with passing a mixed list of mixed types could segfault. (GH25075)
- Fixed regression in `DataFrame.apply()` causing `RecursionError` when dict-like classes were passed as argument. (GH25196)
- Fixed regression in `DataFrame.replace()` where `regex=True` was only replacing patterns matching the start of the string (GH25259)
- Fixed regression in `DataFrame.duplicated()`, where empty dataframe was not returning a boolean dtyped Series. (GH25184)
• Fixed regression in `Series.min()` and `Series.max()` where numeric_only=True was ignored when the Series contained Categorical data (GH25299)
• Fixed regression in subtraction between `Series` objects with datetime64[ns] dtype incorrectly raising OverflowError when the Series on the right contains null values (GH25317)
• Fixed regression in `TimedeltaIndex` where np.sum(index) incorrectly returned a zero-dimensional object instead of a scalar (GH25282)
• Fixed regression in `IntervalDtype` construction where passing an incorrect string with ‘Interval’ as a prefix could result in a RecursionError. (GH25338)
• Fixed regression in creating a period-dtype array from a read-only NumPy array of period objects. (GH25403)
• Fixed regression in `Categorical`, where constructing it from a categorical Series and an explicit categories= that differed from that in the Series created an invalid object which could trigger segfaults. (GH25318)
• Fixed regression in `to_timedelta()` losing precision when converting floating data to Timedelta data (GH25077).
• Fixed pip installing from source into an environment without NumPy (GH25193)
• Fixed regression in `DataFrame.replace()` where large strings of numbers would be coerced into int64, causing an OverflowError (GH25616)
• Fixed regression in `factorize()` when passing a custom na_sentinel value with sort=True (GH25409).
• Fixed regression in `DataFrame.to_csv()` writing duplicate line endings with gzip compress (GH25311)

### Bug fixes

#### I/O

• Better handling of terminal printing when the terminal dimensions are not known (GH25080)
• Bug in reading a HDF5 table-format `DataFrame` created in Python 2, in Python 3 (GH24925)
• Bug in reading a JSON with orient='table' generated by `DataFrame.to_json()` with index=False (GH25170)
• Bug where float indexes could have misaligned values when printing (GH25061)

#### Categorical

• Bug where calling `Series.replace()` on categorical data could return a Series with incorrect dimensions (GH24971)
  ...
  ...

#### Reshaping

• Bug in `transform()` where applying a function to a timezone aware column would return a timezone naive result (GH24198)
• Bug in `DataFrame.join()` when joining on a timezone aware `DatetimeIndex` (GH23931)

#### Visualization

• Bug in `Series.plot()` where a secondary y axis could not be set to log scale (GH25545)

#### Other

...
• Bug in `Series.is_unique()` where single occurrences of NaN were not considered unique (GH25180)
• Bug in `merge()` when merging an empty `DataFrame` with an `Int64` column or a non-empty `DataFrame` with an `Int64` column that is all NaN (GH25183)
• Bug in `IntervalTree` where a `RecursionError` occurs upon construction due to an overflow when adding endpoints, which also causes `IntervalIndex` to crash during indexing operations (GH25485)
• Bug in `Series.size` raising for some extension-array-backed `Series`, rather than returning the size (GH25580)
• Bug in resampling raising for nullable integer-dtype columns (GH25580)

Contributors

A total of 25 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

• Albert Villanova del Moral
• Arno Veenstra +
• chris-b1
• Devin Petersohn +
• EternalLearner42 +
• Flavien Lambert +
• gyoung
• Gioia Ballin
• jbrockmendel
• Jeff Reback
• Jeremy Schendel
• Johan von Forstner +
• Joris Van den Bossche
• Josh
• Justin Zheng
• Kendall Masse
• Matthew Roeschke
• Max Bolingbroke +
• rbenes +
• Sterling Paramore +
• Tao He +
• Thomas A Caswell
• Tom Augspurger
• Vibhu Agarwal +
• William Ayd
These are the changes in pandas 0.24.1. See Release notes for a full changelog including other versions of pandas. See What's new in 0.24.0 (January 25, 2019) for the 0.24.0 changelog.

## API changes

### Changing the sort parameter for Index set operations

The default sort value for `Index.union()` has changed from True to None (GH24959). The default behavior, however, remains the same: the result is sorted, unless

1. self and other are identical
2. self or other is empty
3. self or other contain values that can not be compared (a RuntimeWarning is raised).

This change will allow sort=True to mean “always sort” in a future release.

The same change applies to `Index.difference()` and `Index.symmetric_difference()`, which would not sort the result when the values could not be compared.

The `sort` option for `Index.intersection()` has changed in three ways.

1. The default has changed from True to False, to restore the pandas 0.23.4 and earlier behavior of not sorting by default.
2. The behavior of sort=True can now be obtained with sort=None. This will sort the result only if the values in self and other are not identical.
3. The value sort=True is no longer allowed. A future version of pandas will properly support sort=True meaning “always sort”.

### Fixed regressions

- Fixed regression in `DataFrame.to_dict()` with records orient raising an AttributeError when the DataFrame contained more than 255 columns, or wrongly converting column names that were not valid python identifiers (GH24939, GH24940).
- Fixed regression in `read_sql()` when passing certain queries with MySQL/pymysql (GH24988).
- Fixed regression in `Index.intersection` incorrectly sorting the values by default (GH24959).
- Fixed regression in `merge()` when merging an empty DataFrame with multiple timezone-aware columns on one of the timezone-aware columns (GH25014).
- Fixed regression in `Series.rename_axis()` and `DataFrame.rename_axis()` where passing None failed to remove the axis name (GH25034).
- Fixed regression in `to_timedelta()` with box=False incorrectly returning a datetime64 object instead of a timedelta64 object (GH24961)
• Fixed regression where custom hashable types could not be used as column keys in `DataFrame.set_index()` (GH24969)

**Bug fixes**

**Reshaping**

• Bug in `DataFrame.groupby()` with `Grouper` when there is a time change (DST) and grouping frequency is '1d' (GH24972)

**Visualization**

• Fixed the warning for implicitly registered matplotlib converters not showing. See Restore Matplotlib datetime converter registration for more (GH24963).

**Other**

• Fixed AttributeError when printing a DataFrame’s HTML repr after accessing the IPython config object (GH25036)

**Contributors**

A total of 7 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

• Alex Buchkovsky
• Roman Yurchak
• h-vetinari
• jbrockmendel
• Jeremy Schendel
• Joris Van den Bossche
• Tom Augspurger

5.4.3 What’s new in 0.24.0 (January 25, 2019)

**Warning:** The 0.24.x series of releases will be the last to support Python 2. Future feature releases will support Python 3 only. See Dropping Python 2.7 for more details.

This is a major release from 0.23.4 and includes a number of API changes, new features, enhancements, and performance improvements along with a large number of bug fixes.

Highlights include:

• *Optional Integer NA Support*
• *New APIs for accessing the array backing a Series or Index*
• *A new top-level method for creating arrays*
• *Store Interval and Period data in a Series or DataFrame*
• *Support for joining on two MultiIndexes*
Check the **API Changes** and **deprecations** before updating.

These are the changes in pandas 0.24.0. See **Release notes** for a full changelog including other versions of pandas.

### Enhancements

#### Optional integer NA support

Pandas has gained the ability to hold integer dtypes with missing values. This long requested feature is enabled through the use of **extension types**.

**Note:** IntegerArray is currently experimental. Its API or implementation may change without warning.

We can construct a **Series** with the specified dtype. The dtype string **Int64** is a pandas **ExtensionDtype**. Specifying a list or array using the traditional missing value marker of **np.nan** will infer to integer dtype. The display of the **Series** will also use the **NaN** to indicate missing values in string outputs.  (GH20700, GH20747, GH22441, GH21789, GH22346)

```python
In [1]: s = pd.Series([1, 2, np.nan], dtype='Int64')
In [2]: s
Out[2]:
0    1
1    2
2   <NA>
Length: 3, dtype: Int64
```

Operations on these dtypes will propagate **NaN** as other pandas operations.

```python
# arithmetic
In [3]: s + 1
Out[3]:
0    2
1    3
2   <NA>
Length: 3, dtype: Int64

# comparison
In [4]: s == 1
Out[4]:
0   True
1  False
2   <NA>
Length: 3, dtype: boolean

# indexing
In [5]: s.iloc[1:3]
Out[5]:
1    2
2   <NA>
Length: 2, dtype: Int64

# operate with other dtypes
In [6]: s + s.iloc[1:3].astype('Int8')
Out[6]:
```

(continues on next page)
0  <NA>  
1   4  
2  <NA>  
Length: 3, dtype: Int64
# coerce when needed
In [7]: s + 0.01  
Out[7]:  
0   1.01  
1   2.01  
2  NaN  
Length: 3, dtype: float64

These dtypes can operate as part of a DataFrame.

In [8]: df = pd.DataFrame({'A': s, 'B': [1, 1, 3], 'C': list('aab')})  
In [9]: df  
Out[9]:  
   A  B  C  
0  1  1  a  
1  2  1  a  
2 <NA> 3  b  
[3 rows x 3 columns]  
In [10]: df.dtypes  
Out[10]:  
       A   Int64  
       B   int64  
       C   object  
Length: 3, dtype: object

These dtypes can be merged, reshaped, and casted.

In [11]: pd.concat([df[['A']], df[['B', 'C']]], axis=1).dtypes  
Out[11]:  
       A   Int64  
       B   int64  
       C   object  
Length: 3, dtype: object  
In [12]: df['A'].astype(float)  
Out[12]:  
0  1.0  
1  2.0  
2  NaN  
Name: A, Length: 3, dtype: float64

Reduction and groupby operations such as sum work.

In [13]: df.sum()  
Out[13]:  
       A   3  
       B   5  
       C  aab  
Length: 3, dtype: object  
(continues on next page)
In [14]: df.groupby('B').A.sum()
Out[14]:
B
1 3
3 0
Name: A, Length: 2, dtype: Int64

**Warning:** The Integer NA support currently uses the capitalized dtype version, e.g. `Int8` as compared to the traditional `int8`. This may be changed at a future date.

See [Nullable integer data type](#) for more.

### Accessing the values in a Series or Index

`Series.array` and `Index.array` have been added for extracting the array backing a `Series` or `Index`. (GH19954, GH23623)

In [15]: idx = pd.period_range('2000', periods=4)
In [16]: idx.array
Out[16]:
<PeriodArray>
Length: 4, dtype: period[D]
In [17]: pd.Series(idx).array
Out[17]:
<PeriodArray>
Length: 4, dtype: period[D]

Historically, this would have been done with `series.values`, but with `.values` it was unclear whether the returned value would be the actual array, some transformation of it, or one of pandas custom arrays (like `Categorical`). For example, with `PeriodIndex`, `.values` generates a new ndarray of period objects each time.

In [18]: idx.values
Out[18]:
array([Period('2000-01-01', 'D'), Period('2000-01-02', 'D'),
       Period('2000-01-03', 'D'), Period('2000-01-04', 'D')], dtype=object)
In [19]: id(idx.values)
Out[19]: 140610594519520
In [20]: id(idx.values)
Out[20]: 140610658538880

If you need an actual NumPy array, use `Series.to_numpy()` or `Index.to_numpy()`.

In [21]: idx.to_numpy()
For Series and Indexes backed by normal NumPy arrays, `Series.array` will return a new array. `PandasArray`, which is a thin (no-copy) wrapper around a `numpy.ndarray`. `PandasArray` isn’t especially useful on its own, but it does provide the same interface as any extension array defined in pandas or by a third-party library.

```
In [23]: ser = pd.Series([1, 2, 3])
In [24]: ser.array
Out[24]:
<PandasArray>
[1, 2, 3]
Length: 3, dtype: int64
In [25]: ser.to_numpy()
Out[25]:
array([1, 2, 3])
```

We haven’t removed or deprecated `Series.values` or `DataFrame.values`, but we highly recommend and using `.array` or `.to_numpy()` instead.

See `Dtypes` and `Attributes and Underlying Data` for more.

**pandas.array: a new top-level method for creating arrays**

A new top-level method `array()` has been added for creating 1-dimensional arrays (GH22860). This can be used to create any extension array, including extension arrays registered by 3rd party libraries. See the `dtypes docs` for more on extension arrays.

```
In [26]: pd.array([1, 2, np.nan], dtype='Int64')
Out[26]:
<IntegerArray>
[1, 2, <NA>]
Length: 3, dtype: Int64
In [27]: pd.array(['a', 'b', 'c'], dtype='category')
Out[27]:
['a', 'b', 'c']
Categories (3, object): ['a', 'b', 'c']
```

Passing data for which there isn’t dedicated extension type (e.g. float, integer, etc.) will return a new array. `PandasArray`, which is just a thin (no-copy) wrapper around a `numpy.ndarray` that satisfies the pandas extension array interface.

```
In [28]: pd.array([1, 2, 3])
Out[28]:
<IntegerArray>
[1, 2, 3]
Length: 3, dtype: Int64
```
On their own, a PandasArray isn’t a very useful object. But if you need write low-level code that works generically for any ExtensionArray, PandasArray satisfies that need.

Notice that by default, if no dtype is specified, the dtype of the returned array is inferred from the data. In particular, note that the first example of [1, 2, np.nan] would have returned a floating-point array, since NaN is a float.

```py
In [29]: pd.array([1, 2, np.nan])
Out[29]:
<IntegerArray>
[1, 2, <NA>]
Length: 3, dtype: Int64
```

### Storing Interval and Period data in Series and DataFrame

Interval and Period data may now be stored in a Series or DataFrame, in addition to an IntervalIndex and PeriodIndex like previously (GH19453, GH22862).

```py
In [30]: ser = pd.Series(pd.interval_range(0, 5))
In [31]: ser
Out[31]:
0 (0, 1]
1 (1, 2]
2 (2, 3]
3 (3, 4]
4 (4, 5]
Length: 5, dtype: interval

In [32]: ser.dtype
Out[32]: interval[int64]
```

For periods:

```py
In [33]: pser = pd.Series(pd.period_range("2000", freq="D", periods=5))
In [34]: pser
Out[34]:
0 2000-01-01
1 2000-01-02
2 2000-01-03
3 2000-01-04
4 2000-01-05
Length: 5, dtype: period[D]

In [35]: pser.dtype
Out[35]: period[D]
```

Previously, these would be cast to a NumPy array with object dtype. In general, this should result in better performance when storing an array of intervals or periods in a Series or column of a DataFrame.

Use Series.array to extract the underlying array of intervals or periods from the Series:

```py
In [36]: ser.array
Out[36]:
<IntervalArray>
[(0, 1], [1, 2], [2, 3], [3, 4], [4, 5]]
```

(continues on next page)
These return an instance of `arrays.IntervalArray` or `arrays.PeriodArray`, the new extension arrays that back interval and period data.

**Warning:** For backwards compatibility, `Series.values` continues to return a NumPy array of objects for Interval and Period data. We recommend using `Series.array` when you need the array of data stored in the `Series`, and `Series.to_numpy()` when you know you need a NumPy array.

See [Dtypes](#) and [Attributes and Underlying Data](#) for more.

### Joining with two multi-indexes

`DataFrame.merge()` and `DataFrame.join()` can now be used to join multi-indexed `DataFrame` instances on the overlapping index levels (GH6360)

See the [Merge, join, and concatenate](#) documentation section.

```python
In [38]: index_left = pd.MultiIndex.from_tuples([ ('K0', 'X0'), ('K0', 'X1'), ('K1', 'X2') ], names=['key', 'X'])

In [39]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2'], 
                       'B': ['B0', 'B1', 'B2']}, index=index_left)

In [40]: index_right = pd.MultiIndex.from_tuples([ ('K0', 'Y0'), ('K1', 'Y1'), ('K2', 'Y2'), ('K2', 'Y3') ], names=['key', 'Y'])

In [41]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'], 
                        'D': ['D0', 'D1', 'D2', 'D3']}, index=index_right)

In [42]: left.join(right)
Out[42]:
   A  B  C  D
key X  Y
K0  X0 Y0 A0 B0 C0 D0
    X1 Y0 A1 B1 C0 D0
K1  X2 Y1 A2 B2 C1 D1
```

For earlier versions this can be done using the following.
In [43]: 

```python
pd.merge(left.reset_index(), right.reset_index(),
    ....:     on=['key'], how='inner').set_index(['key', 'X', 'Y'])
```

Out[43]:
```
    A   B   C   D
key X  Y
K0 A0 B0 C0 D0
  X1 A1 B1 C0 D0
K1 X2 Y1 A2 B2 C1 D1
```

[3 rows x 4 columns]

---

**read_html Enhancements**

`read_html()` previously ignored `colspan` and `rowspan` attributes. Now it understands them, treating them as sequences of cells with the same value. (GH17054)

In [44]: 

```python
result = pd.read_html('""
    ....:     <table>
    ....:     <thead>
    ....:     <tr>
    ....:         <th>A</th><th>B</th><th>C</th>
    ....:     </tr>
    ....:     </thead>
    ....:     <tbody>
    ....:         <tr>
    ....:             <td colspan="2">1</td><td>2</td>
    ....:         </tr>
    ....:     </tbody>
    ....:     <table>"
```

---

**Previous behavior:**

In [13]: result
Out [13]:
```
[ A B C
  0 1 2 NaN]
```

**New behavior:**

In [45]: result
Out[45]:
```
[ A B C
  0 1 1 2
  [1 rows x 3 columns]]
```
New Styler.pipe() method

The Styler class has gained a pipe() method. This provides a convenient way to apply users' predefined styling functions, and can help reduce "boilerplate" when using DataFrame styling functionality repeatedly within a notebook. (GH23229)

```python
In [46]: df = pd.DataFrame({'N': [1250, 1500, 1750], 'X': [0.25, 0.35, 0.50]})
In [47]: def format_and_align(styler):
   ....:     return (styler.format({'N': '{:,}', 'X': '{:.1%}'})
   ....:         .set_properties(**{'text-align': 'right'})
   ....:
In [48]: df.style.pipe(format_and_align).set_caption('Summary of results.')
Out[48]: <pandas.io.formats.style.Styler at 0x7fe1fd440280>
```

Similar methods already exist for other classes in pandas, including DataFrame.pipe(), GroupBy.pipe(), and Resampler.pipe().

Renaming names in a MultiIndex

DataFrame.rename_axis() now supports index and columns arguments and Series.rename_axis() supports index argument (GH19978). This change allows a dictionary to be passed so that some of the names of a MultiIndex can be changed.

Example:

```python
In [49]: mi = pd.MultiIndex.from_product([list('AB'), list('CD'), list('EF')], names=['AB', 'CD', 'EF'])
In [50]: df = pd.DataFrame(list(range(len(mi))), index=mi, columns=['N'])
In [51]: df
Out[51]:
      N
AB CD EF
A  C  E  0
     F  1
     D  2
     F  3
B  C  E  4
     F  5
     D  6
     F  7
[8 rows x 1 columns]
In [52]: df.rename_axis(index={'CD': 'New'})
Out[52]:
     N
AB New EF
A  C  E  0
     F  1
     D  2
```

(continues on next page)
F 3
B C E 4
F 5
D E 6
F 7
[8 rows x 1 columns]

See the Advanced documentation on renaming for more details.

Other enhancements

- `merge()` now directly allows merge between objects of type DataFrame and named Series, without the need to convert the Series object into a DataFrame beforehand (GH21220)
- ExcelWriter now accepts mode as a keyword argument, enabling append to existing workbooks when using the openpyxl engine (GH3441)
- FrozenList has gained the .union() and .difference() methods. This functionality greatly simplifies groupby's that rely on explicitly excluding certain columns. See Splitting an object into groups for more information (GH15475, GH15506).
- `DataFrame.to_parquet()` now accepts index as an argument, allowing the user to override the engine’s default behavior to include or omit the dataframe’s indexes from the resulting Parquet file. (GH20768)
- `read_feather()` now accepts columns as an argument, allowing the user to specify which columns should be read. (GH24025)
- `DataFrame.corr()` and `Series.corr()` now accept a callable for generic calculation methods of correlation, e.g. histogram intersection (GH22684)
- `DataFrame.to_string()` now accepts decimal as an argument, allowing the user to specify which decimal separator should be used in the output. (GH23614)
- `DataFrame.to_html()` now accepts render_links as an argument, allowing the user to generate HTML with links to any URLs that appear in the DataFrame. See the section on writing HTML in the IO docs for example usage. (GH2679)
- `pandas.read_csv()` now supports pandas extension types as an argument to dtype, allowing the user to use pandas extension types when reading CSVs. (GH23228)
- The `shift()` method now accepts fill_value as an argument, allowing the user to specify a value which will be used instead of NA/NaT in the empty periods. (GH15486)
- `to_datetime()` now supports the %Z and %z directive when passed into format (GH13486)
- `Series.mode()` and `DataFrame.mode()` now support the dropna parameter which can be used to specify whether NaN/NaT values should be considered (GH17534)
- `DataFrame.to_csv()` and `Series.to_csv()` now support the compression keyword when a file handle is passed. (GH21227)
- `Index.droplevel()` is now implemented also for flat indexes, for compatibility with MultiIndex (GH21115)
- `Series.droplevel()` and `DataFrame.droplevel()` are now implemented (GH20342)
- Added support for reading from/writing to Google Cloud Storage via the gcsfs library (GH19454, GH23094)
• **DataFrame.to_gbq()** and **read_gbq()** signature and documentation updated to reflect changes from the Pandas-GBQ library version 0.8.0. Adds a credentials argument, which enables the use of any kind of google-auth credentials. (GH21627, GH22557, GH23662)

• New method **HDFStore.walk()** will recursively walk the group hierarchy of an HDF5 file (GH10932)

• **read_html()** copies cell data across colspan and rowspan, and it treats all-th table rows as headers if header kwarg is not given and there is no thead (GH17054)

• **Series.nlargest()**, **Series.nsmallest()**, **DataFrame.nlargest()**, and **DataFrame.nsmallest()** now accept the value "all" for the keep argument. This keeps all ties for the nth largest/smallest value (GH16818)

• **IntervalIndex** has gained the **set_closed()** method to change the existing closed value (GH21670)

• **to_csv(), to_csv(), to_json(), and to_json()** now support compression='infer' to infer compression based on filename extension (GH15008). The default compression for to_csv, to_json, and to_pickle methods has been updated to 'infer' (GH22004).

• **DataFrame.to_sql()** now supports writing **TIMESTAMP WITH TIME ZONE** types for supported databases. For databases that don’t support timezones, datetime data will be stored as timezone unaware local timestamps. See the **Datetime data types** for implications (GH9086).

• **to_timedelta()** now supports iso-formatted timedelta strings (GH21877)

• **Series** and **DataFrame** now support **Iterable** objects in the constructor (GH2193)

• **DatetimeIndex** has gained the **DatetimeIndex.timetz** attribute. This returns the local time with timezone information. (GH21358)

• **round()**, **ceil()**, and **floor()** for **DatetimeIndex** and **Timestamp** now support an ambiguous argument for handling datetimes that are rounded to ambiguous times (GH18946) and a nonexistent argument for handling datetimes that are rounded to nonexistent times. See **Nonexistent times when localizing** (GH22647)

• The result of **resample()** is now iterable similar to **groupby()** (GH15314).

• **Series.resample()** and **DataFrame.resample()** have gained the **pandas.core.resample.Resampler.quantile()** (GH15023).

• **DataFrame.resample()** and **Series.resample()** with a **PeriodIndex** will now respect the base argument in the same fashion as with a **DatetimeIndex**. (GH23882)

• **pandas.api.types.is_list_like()** has gained a keyword **allow_sets** which is **True** by default; if **False**, all instances of **set** will not be considered “list-like” anymore (GH23061)

• **Index.to_frame()** now supports overriding column name(s) (GH22580).

• **Categorical.from_codes()** now can take a **dtype** parameter as an alternative to passing categories and ordered (GH24398).

• New attribute **__git_version__** will return git commit sha of current build (GH21295).

• Compatibility with Matplotlib 3.0 (GH22790).

• Added **Interval.overlaps(), arrays.IntervalArray.overlaps(), and IntervalIndex.overlaps()** for determining overlaps between interval-like objects (GH21998)

• **read_fwf()** now accepts keyword **infer_nrows** (GH15138).

• **to_parquet()** now supports writing a **DataFrame** as a directory of parquet files partitioned by a subset of the columns when engine = 'pyarrow' (GH23283)
pandas: powerful Python data analysis toolkit, Release 1.1.1

- `Timestamp.tz_localize()`, `DatetimeIndex.tz_localize()`, and `Series.tz_localize()` have gained the nonexistent argument for alternative handling of nonexistent times. See *Nonexistent times when localizing* (GH8917, GH24466)

- `Index.difference()`, `Index.intersection()`, `Index.union()`, and `Index.symmetric_difference()` now have an optional `sort` parameter to control whether the results should be sorted if possible (GH17839, GH24471)

- `read_excel()` now accepts `usecols` as a list of column names or callable (GH18273)

- `MultiIndex.to_flat_index()` has been added to flatten multiple levels into a single-level `Index` object.

- `DataFrame.to_stata()` and `pandas.io.stata.StataWriter117` can write mixed string columns to Stata strel format (GH23633)

- `DataFrame.between_time()` and `DataFrame.at_time()` have gained the `axis` parameter (GH8839)

- `DataFrame.to_records()` now accepts `index_dtypes` and `column_dtypes` parameters to allow different data types in stored column and index records (GH18146)

- `IntervalIndex` has gained the `is_overlapping` attribute to indicate if the `IntervalIndex` contains any overlapping intervals (GH23309)

- `pandas.DataFrame.to_sql()` has gained the `method` argument to control SQL insertion clause. See the *insertion method* section in the documentation. (GH8953)

- `DataFrame.corrwith()` now supports Spearman’s rank correlation, Kendall’s tau as well as callable correlation methods. (GH21925)

- `DataFrame.to_json()`, `DataFrame.to_csv()`, `DataFrame.to_pickle()`, and other export methods now support tilde(–) in path argument. (GH23473)

**Backwards incompatible API changes**

Pandas 0.24.0 includes a number of API breaking changes.

**Increased minimum versions for dependencies**

We have updated our minimum supported versions of dependencies (GH21242, GH18742, GH23774, GH24767). If installed, we now require:

<table>
<thead>
<tr>
<th>Package</th>
<th>Minimum Version</th>
<th>Required</th>
</tr>
</thead>
<tbody>
<tr>
<td>numpy</td>
<td>1.12.0</td>
<td>X</td>
</tr>
<tr>
<td>bottleneck</td>
<td>1.2.0</td>
<td></td>
</tr>
<tr>
<td>fastparquet</td>
<td>0.2.1</td>
<td></td>
</tr>
<tr>
<td>matplotlib</td>
<td>2.0.0</td>
<td></td>
</tr>
<tr>
<td>numexpr</td>
<td>2.6.1</td>
<td></td>
</tr>
<tr>
<td>pandas-gbq</td>
<td>0.8.0</td>
<td></td>
</tr>
<tr>
<td>pyarrow</td>
<td>0.9.0</td>
<td></td>
</tr>
<tr>
<td>pytables</td>
<td>3.4.2</td>
<td></td>
</tr>
<tr>
<td>scipy</td>
<td>0.18.1</td>
<td></td>
</tr>
<tr>
<td>xlrd</td>
<td>1.0.0</td>
<td></td>
</tr>
<tr>
<td>pytest (dev)</td>
<td>3.6</td>
<td></td>
</tr>
</tbody>
</table>
Additionally we no longer depend on feather-format for feather based storage and replaced it with references to pyarrow (GH21639 and GH23053).

**os.linesep is used for line_terminator of DataFrame.to_csv**

`DataFrame.to_csv()` now uses `os.linesep()` rather than '
' for the default line terminator (GH20353). This change only affects when running on Windows, where '
' was used for line terminator even when '
' was passed in `line_terminator`.

**Previous behavior** on Windows:

```
In [1]: data = pd.DataFrame({"string_with_lf": ["a\nbc"],
                  ...:                  "string_with_crlf": ["a\r\nbc"]})
In [2]: # When passing file PATH to to_csv,
      ...: # line_terminator does not work, and csv is saved with '
'.
      ...: # Also, this converts all '
's in the data to '
'.
      ...: data.to_csv("test.csv", index=False, line_terminator='\n')
In [3]: with open("test.csv", mode='rb') as f:
      ...:     print(f.read())
Out[3]: b'string_with_lf,string_with_crlf\n"a\rbc","a\r\nbc"

In [4]: # When passing file OBJECT with newline option to
      ...: # to_csv, line_terminator works.
      ...: with open("test2.csv", mode='w', newline='\n') as f:
      ...:     data.to_csv(f, index=False, line_terminator='\n')
In [5]: with open("test2.csv", mode='rb') as f:
      ...:     print(f.read())
Out[5]: b'string_with_lf,string_with_crlf\n"a\nbc","a\r\nbc"
```

**New behavior** on Windows:

Passing `line_terminator` explicitly, set the line terminator to that character.

```
In [1]: data = pd.DataFrame({"string_with_lf": ["a\nbc"],
                  ...:                  "string_with_crlf": ["a\r\nbc"]})
In [2]: data.to_csv("test.csv", index=False, line_terminator='\n')
In [3]: with open("test.csv", mode='rb') as f:
      ...:     print(f.read())
Out[3]: b'string_with_lf,string_with_crlf\n"a\nbc","a\r\nbc"

In [4]: data.to_csv("test.csv", index=False)
In [5]: with open("test2.csv", mode='rb') as f:
      ...:     print(f.read())
Out[5]: b'string_with_lf,string_with_crlf\n"a\nbc","a\r\nbc"
```

On Windows, the value of `os.linesep` is '
', so if `line_terminator` is not set, '
' is used for line terminator.
For file objects, specifying \texttt{newline} is not sufficient to set the line terminator. You must pass in the \texttt{line_terminator} explicitly, even in this case.

\begin{Verbatim}
In [1]: data = pd.DataFrame({"string_with_lf": ["a\nbc"],
...:   "string_with_crlf": ["a\r\nbc"]})

In [2]: with open("test2.csv", mode='w', newline='
') as f:
...:   data.to_csv(f, index=False)

In [3]: with open("test2.csv", mode='rb') as f:
...:   print(f.read())

Out[3]: b'string_with_lf,string_with_crlf\n"a\nbc","a\r\nbc"'
\end{Verbatim}

### Proper handling of \texttt{np.NaN} in a string data-typed column with the Python engine

There was bug in \texttt{read_excel()} and \texttt{read_csv()} with the Python engine, where missing values turned to 'nan' with \texttt{dtype=str} and \texttt{na_filter=True}. Now, these missing values are converted to the string missing indicator, \texttt{np.nan} (GH20377)

\textit{Previous behavior:}

\begin{Verbatim}
In [5]: data = 'a,b,c\n1,3
4,5,6'
In [6]: df = pd.read_csv(StringIO(data), engine='python', dtype=str, na_filter=True)
In [7]: df.loc[0, 'b']
Out[7]: 'nan'
\end{Verbatim}

\textit{New behavior:}

\begin{Verbatim}
In [53]: data = 'a,b,c\n1,3\n4,5,6'
In [54]: df = pd.read_csv(StringIO(data), engine='python', dtype=str, na_filter=True)
In [55]: df.loc[0, 'b']
Out[55]: nan
\end{Verbatim}

Notice how we now instead output \texttt{np.nan} itself instead of a stringified form of it.

### Parsing datetime strings with timezone offsets

Previously, parsing datetime strings with UTC offsets with \texttt{to_datetime()} or \texttt{DatetimeIndex} would automatically convert the datetime to UTC without timezone localization. This is inconsistent from parsing the same datetime string with \texttt{Timestamp} which would preserve the UTC offset in the \texttt{tz} attribute. Now, \texttt{to_datetime()} preserves the UTC offset in the \texttt{tz} attribute when all the datetime strings have the same UTC offset (GH17697, GH11736, GH22457)

\textit{Previous behavior:}

\begin{Verbatim}
In [2]: pd.to_datetime("2015-11-18 15:30:00+05:30")
Out[2]: Timestamp('2015-11-18 10:00:00')

In [3]: pd.Timestamp("2015-11-18 15:30:00+05:30")
Out[3]: Timestamp('2015-11-18 15:30:00+0530', tz='pytz.FixedOffset(330)')

# Different UTC offsets would automatically convert the datetimes to UTC (without a
UTC timezone)
\end{Verbatim}
In [4]: `pd.to_datetime(["2015-11-18 15:30:00+05:30", "2015-11-18 16:30:00+06:30"])`
Out[4]: DatetimeIndex(['2015-11-18 10:00:00', '2015-11-18 10:00:00'], dtype='datetime64[ns]', freq=None)

**New behavior:**

In [56]: `pd.to_datetime("2015-11-18 15:30:00+05:30")`
Out[56]: Timestamp('2015-11-18 15:30:00+0530', tz='pytz.FixedOffset(330)')

In [57]: `pd.Timestamp("2015-11-18 15:30:00+05:30")`
Out[57]: Timestamp('2015-11-18 15:30:00+0530', tz='pytz.FixedOffset(330)')

Parsing datetime strings with the same UTC offset will preserve the UTC offset in the tz

In [58]: `pd.to_datetime(["2015-11-18 15:30:00+05:30", ...
                          "2015-11-18 16:30:00+06:30"] * 2)`
Out[58]: DatetimeIndex(['2015-11-18 15:30:00+05:30', '2015-11-18 15:30:00+05:30'], dtype='datetime64[ns, pytz.FixedOffset(330)]', freq=None)

Parsing datetime strings with different UTC offsets will now create an Index of datetime.datetime objects with different UTC offsets

In [59]: `idx = pd.to_datetime(["2015-11-18 15:30:00+05:30", ...
                          "2015-11-18 16:30:00+06:30"])`
In [60]: `idx`
Out[60]: Index([2015-11-18 15:30:00+05:30, 2015-11-18 16:30:00+06:30], dtype='object')

In [61]: `idx[0]`
Out[61]: datetime.datetime(2015, 11, 18, 15, 30, tzinfo=tzoffset(None, 19800))

In [62]: `idx[1]`
Out[62]: datetime.datetime(2015, 11, 18, 16, 30, tzinfo=tzoffset(None, 23400))

Passing utc=True will mimic the previous behavior but will correctly indicate that the dates have been converted to UTC

In [63]: `pd.to_datetime(["2015-11-18 15:30:00+05:30", ...
                          "2015-11-18 16:30:00+06:30"], utc=True)`
Out[63]: DatetimeIndex(['2015-11-18 10:00:00+00:00', '2015-11-18 10:00:00+00:00'], dtype='datetime64[ns, UTC]', freq=None)

Parsing mixed-timezones with `read_csv()`

`read_csv()` no longer silently converts mixed-timezone columns to UTC (GH24987).

Previous behavior

```python
>>> import io
>>> content = """\n... a
... 2000-01-01T00:00:00+05:00
... 2000-01-01T00:00:00+06:00"
"""
>>> df = pd.read_csv(io.StringIO(content), parse_dates=['a'])
```

(continues on next page)
New behavior

```python
In [64]: import io
In [65]: content = ""
    ....: a
    ....: 2000-01-01T00:00:00+05:00
    ....: 2000-01-01T00:00:00+06:00"
    ....:
In [66]: df = pd.read_csv(io.StringIO(content), parse_dates=['a'])
In [67]: df.a
Out[67]:
0  2000-01-01 00:00:00+05:00
1  2000-01-01 00:00:00+06:00
Name: a, Length: 2, dtype: object
```

As can be seen, the `dtype` is object; each value in the column is a string. To convert the strings to an array of datetimes, the `date_parser` argument

```python
In [68]: df = pd.read_csv(io.StringIO(content), parse_dates=['a'],
    ....: date_parser=lambda col: pd.to_datetime(col, utc=True))
In [69]: df.a
Out[69]:
0  1999-12-31 19:00:00+00:00
1  1999-12-31 18:00:00+00:00
Name: a, Length: 2, dtype: datetime64[ns, UTC]
```

See Parsing datetime strings with timezone offsets for more.

### Time values in `pd.Series.dt.end_time` and `Period.to_timestamp()`

The time values in `Period` and `PeriodIndex` objects are now set to ‘23:59:59.999999999’ when calling `Series.dt.end_time`, `Period.end_time`, `PeriodIndex.end_time`, `Period.to_timestamp()` with `how='end'`, or `PeriodIndex.to_timestamp()` with `how='end'` (GH17157)

**Previous behavior:**

```python
In [2]: p = pd.Period('2017-01-01', 'D')
In [3]: pi = pd.PeriodIndex([p])
In [4]: pd.Series(pi).dt.end_time[0]
Out[4]: Timestamp(2017-01-01 00:00:00)
In [5]: p.end_time
```

**New behavior:**
Calling `Series.dt.end_time` will now result in a time of ‘23:59:59.999999999’ as is the case with `Period.end_time`, for example

```python
In [70]: p = pd.Period('2017-01-01', 'D)
In [71]: pi = pd.PeriodIndex([p])
Out[72]: Timestamp('2017-01-01 23:59:59.999999999')
In [73]: p.end_time
Out[73]: Timestamp('2017-01-01 23:59:59.999999999')
```

**Series.unique for timezone-aware data**

The return type of `Series.unique()` for datetime with timezone values has changed from an `numpy.ndarray` of `Timestamp` objects to a `arrays.DatetimeArray` (GH24024).

```python
In [74]: ser = pd.Series([pd.Timestamp('2000', tz='UTC'),
....:     pd.Timestamp('2000', tz='UTC'))
....:     pd.Timestamp('2000', tz='UTC'))
```

**Previous behavior:**

```python
In [3]: ser.unique()  
Out[3]: array([Timestamp('2000-01-01 00:00:00+0000', tz='UTC')], dtype=object)
```

**New behavior:**

```python
In [75]: ser.unique()  
Out[75]: <DatetimeArray>['2000-01-01 00:00:00+00:00']  
Length: 1, dtype: datetime64[ns, UTC]
```

**SparseArray data structure refactor**

SparseArray, the array backing `SparseSeries` and the columns in a `SparseDataFrame`, is now an extension array (GH21978, GH19056, GH22835). To conform to this interface and for consistency with the rest of pandas, some API breaking changes were made:

- SparseArray is no longer a subclass of `numpy.ndarray`. To convert a SparseArray to a NumPy array, use `numpy.asarray()`.
- SparseArray.dtype and SparseSeries.dtype are now instances of `SparseDtype`, rather than `np.dtype`. Access the underlying dtype with `SparseDtype.subtype`.
- `numpy.asarray(sparse_array)` now returns a dense array with all the values, not just the non-fill-value values (GH14167)
- SparseArray.take now matches the API of `pandas.api.extensions.ExtensionArray.take()` (GH19506):
  - The default value of `allow_fill` has changed from `False` to `True`.
  - The `out` and `mode` parameters are now longer accepted (previously, this raised if they were specified).
– Passing a scalar for indices is no longer allowed.

• The result of `concat()` with a mix of sparse and dense Series is a Series with sparse values, rather than a SparseSeries.

• `SparseDataFrame.combine` and `DataFrame.combine_first` no longer supports combining a sparse column with a dense column while preserving the sparse subtype. The result will be an object-dtype SparseArray.

• Setting `SparseArray.fill_value` to a fill value with a different dtype is now allowed.

• `DataFrame[column]` is now a Series with sparse values, rather than a SparseSeries, when slicing a single column with sparse values (GH23559).

• The result of `Series.where()` is now a Series with sparse values, like with other extension arrays (GH24077)

Some new warnings are issued for operations that require or are likely to materialize a large dense array:

• A `errors.PerformanceWarning` is issued when using fillna with a method, as a dense array is constructed to create the filled array. Filling with a value is the efficient way to fill a sparse array.

• A `errors.PerformanceWarning` is now issued when concatenating sparse Series with differing fill values. The fill value from the first sparse array continues to be used.

In addition to these API breaking changes, many Performance Improvements and Bug Fixes have been made.

Finally, a `Series.sparse` accessor was added to provide sparse-specific methods like `Series.sparse.from_coo()`.

```
In [76]: s = pd.Series([0, 0, 1, 1, 1], dtype='Sparse[int]')
In [77]: s.sparse.density
Out[77]: 0.6
```

get_dummies() always returns a DataFrame

Previously, when `sparse=True` was passed to `get_dummies()`, the return value could be either a `DataFrame` or a `SparseDataFrame`, depending on whether all or a just a subset of the columns were dummy-encoded. Now, a `DataFrame` is always returned (GH24284).

**Previous behavior**

The first `get_dummies()` returns a `DataFrame` because the column A is not dummy encoded. When just ["B", "C"] are passed to `get_dummies`, then all the columns are dummy-encoded, and a `SparseDataFrame` was returned.

```
In [2]: df = pd.DataFrame({'A': [1, 2], 'B': ['a', 'b'], 'C': ['a', 'a']})
In [3]: type(pd.get_dummies(df, sparse=True))
Out[3]: pandas.core.frame.DataFrame
In [4]: type(pd.get_dummies(df[ ['B', 'C']], sparse=True))
Out[4]: pandas.core.sparse.frame.SparseDataFrame
```

**New behavior**

Now, the return type is consistently a `DataFrame`. 

In [78]: type(pd.get_dummies(df, sparse=True))
Out[78]: pandas.core.frame.DataFrame

In [79]: type(pd.get_dummies(df[['B', 'C']], sparse=True))
Out[79]: pandas.core.frame.DataFrame

Note: There's no difference in memory usage between a SparseDataFrame and a DataFrame with sparse values. The memory usage will be the same as in the previous version of pandas.

**Raise ValueError in DataFrame.to_dict(orient='index')**

Bug in DataFrame.to_dict() raises ValueError when used with orient='index' and a non-unique index instead of losing data (GH22801)

In [80]: df = pd.DataFrame({'a': [1, 2], 'b': [0.5, 0.75]}, index=['A', 'A'])

In [81]: df
Out[81]:
<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1</td>
<td>0.5</td>
</tr>
<tr>
<td>A</td>
<td>2</td>
<td>0.75</td>
</tr>
</tbody>
</table>

[2 rows x 2 columns]

In [82]: df.to_dict(orient='index')

---------------------------------------------------------------------------
ValueError Traceback (most recent call last)
<ipython-input-82-f5309a7c6adb> in <module>
----> 1 df.to_dict(orient='index')

/pandas-release/pandas/pandas/core/frame.py in to_dict(self, orient, into)
    1541    elif orient == "index":
    1542        if not self.index.is_unique:
-> 1543            raise ValueError("DataFrame index must be unique for orient=
    ""index".")
    1544            return into_c(
    1545                {t[0], dict(zip(self.columns, t[1:]))})

ValueError: DataFrame index must be unique for orient='index'.

**Tick DateOffset normalize restrictions**

Creating a Tick object (Day, Hour, Minute, Second, Milli, Micro, Nano) with normalize=True is no longer supported. This prevents unexpected behavior where addition could fail to be monotone or associative. (GH21427)

Previous behavior:

In [2]: ts = pd.Timestamp('2018-06-11 18:01:14')

In [3]: ts
Out[3]: Timestamp('2018-06-11 18:01:14')

(continues on next page)
In [4]: tic = pd.offsets.Hour(n=2, normalize=True)

...:

In [5]: tic
Out[5]: <2 * Hours>

In [6]: ts + tic
Out[6]: Timestamp('2018-06-11 00:00:00')

In [7]: ts + tic + tic + tic == ts + (tic + tic + tic)
Out[7]: False

**New behavior:**

In [83]: ts = pd.Timestamp('2018-06-11 18:01:14')

In [84]: tic = pd.offsets.Hour(n=2)

In [85]: ts + tic + tic + tic == ts + (tic + tic + tic)
Out[85]: True

**Period subtraction**

Subtraction of a Period from another Period will give a DateOffset, instead of an integer (GH21314)

**Previous behavior:**

In [2]: june = pd.Period('June 2018')

In [3]: april = pd.Period('April 2018')

In [4]: june - april
Out [4]: 2

**New behavior:**

In [86]: june = pd.Period('June 2018')

In [87]: april = pd.Period('April 2018')

In [88]: june - april
Out[88]: <2 * MonthEnds>

Similarly, subtraction of a Period from a PeriodIndex will now return an Index of DateOffset objects instead of an Int64Index

**Previous behavior:**

In [2]: pi = pd.period_range('June 2018', freq='M', periods=3)

In [3]: pi - pi[0]
Out[3]: Int64Index([0, 1, 2], dtype='int64')

**New behavior:**
In [89]: pi = pd.period_range('June 2018', freq='M', periods=3)
In [90]: pi - pi[0]
Out[90]: Index([<0 * MonthEnds>, <MonthEnd>, <2 * MonthEnds>], dtype='object')

Addition/subtraction of NaN from DataFrame

Adding or subtracting NaN from a DataFrame column with timedelta64[ns] dtype will now raise a TypeError instead of returning all-NaT. This is for compatibility with TimedeltaIndex and Series behavior (GH22163)

In [91]: df = pd.DataFrame([pd.Timedelta(days=1)])
In [92]: df
Out[92]:
0 1 days
[1 rows x 1 columns]

Previous behavior:

In [4]: df = pd.DataFrame([pd.Timedelta(days=1)])
In [5]: df - np.nan
Out[5]:
0    NaT

New behavior:

In [2]: df - np.nan
...  
TypeError: unsupported operand type(s) for -: 'TimedeltaIndex' and 'float'

DataFrame comparison operations broadcasting changes

Previously, the broadcasting behavior of DataFrame comparison operations (==, !=,...) was inconsistent with the behavior of arithmetic operations (+, −,...). The behavior of the comparison operations has been changed to match the arithmetic operations in these cases. (GH22880)

The affected cases are:

• operating against a 2-dimensional np.ndarray with either 1 row or 1 column will now broadcast the same way a np.ndarray would (GH23000).

• a list or tuple with length matching the number of rows in the DataFrame will now raise ValueError instead of operating column-by-column (GH22880).

• a list or tuple with length matching the number of columns in the DataFrame will now operate row-by-row instead of raising ValueError (GH22880).

In [93]: arr = np.arange(6).reshape(3, 2)
In [94]: df = pd.DataFrame(arr)

In [95]: df
Out[95]:
   0  1
0  0  1
1  2  3
2  4  5

[3 rows x 2 columns]

**Previous behavior:**

In [5]: df == arr[[0], :]
    ...: # comparison previously broadcast where arithmetic would raise
Out[5]:
   0  1
0  True  True
1  False False
2  False False
In [6]: df + arr[[0], :]

...  
ValueError: Unable to coerce to DataFrame, shape must be (3, 2): given (1, 2)

In [7]: df == (1, 2)
    ...: # length matches number of columns;
    ...: # comparison previously raised where arithmetic would broadcast
    ...
    
ValueError: Invalid broadcasting comparison [(1, 2)] with block values
In [8]: df + (1, 2)
Out[8]:
   0  1
0  1  3
1  3  5
2  5  7

In [9]: df == (1, 2, 3)
    ...: # length matches number of rows
    ...: # comparison previously broadcast where arithmetic would raise
Out[9]:
   0  1
0  False True
1  True False
2  False False
In [10]: df + (1, 2, 3)

...  
ValueError: Unable to coerce to Series, length must be 2: given 3

**New behavior:**

# Comparison operations and arithmetic operations both broadcast.
In [96]: df == arr[[0], :]
Out[96]:
   0  1
0  True  True
1  False False
2  False False

(continues on next page)
In [97]: df + arr[[0], :]
Out[97]:
   0 1  
0  0 2  
1  2 4  
2  4 6  

[3 rows x 2 columns]

# Comparison operations and arithmetic operations both broadcast.
In [98]: df == (1, 2)
Out[98]:
   0 1  
0 False False  
1 False False  
2 False False  

[3 rows x 2 columns]

In [99]: df + (1, 2)
Out[99]:
   0 1  
0 1 3  
1 3 5  
2 5 7  

[3 rows x 2 columns]

# Comparison operations and arithmetic operations both raise ValueError.
In [6]: df == (1, 2, 3)
...  
ValueError: Unable to coerce to Series, length must be 2: given 3

In [7]: df + (1, 2, 3)
...  
ValueError: Unable to coerce to Series, length must be 2: given 3

**DataFrame arithmetic operations broadcasting changes**

*DataFrame* arithmetic operations when operating with 2-dimensional *np.ndarray* objects now broadcast in the same way as *np.ndarray* broadcast. (GH23000)

In [100]: arr = np.arange(6).reshape(3, 2)
In [101]: df = pd.DataFrame(arr)

In [102]: df
Out[102]:
   0 1  
0 0 1  
1 2 3  
(continues on next page)
**Previous behavior:**

```python
In [5]: df + arr[[0], :]  # 1 row, 2 columns
   ...: ValueError: Unable to coerce to DataFrame, shape must be (3, 2): given (1, 2)
In [6]: df + arr[:, [1]]  # 1 column, 3 rows
   ...: ValueError: Unable to coerce to DataFrame, shape must be (3, 2): given (3, 1)
```

**New behavior:**

```python
In [103]: df + arr[[0], :]  # 1 row, 2 columns
Out[103]:
     0  1
0  0  2
1  2  4
2  4  6
[3 rows x 2 columns]

In [104]: df + arr[:, [1]]  # 1 column, 3 rows
Out[104]:
     0  1
0  1  2
1  5  6
2  9 10
[3 rows x 2 columns]
```

**Series and Index data-dtype incompatibilities**

Series and Index constructors now raise when the data is incompatible with a passed `dtype=` *(GH15832)*

**Previous behavior:**

```python
In [4]: pd.Series([-1], dtype="uint64")
Out [4]:
0  18446744073709551615
dtype: uint64
```

**New behavior:**

```python
In [4]: pd.Series([-1], dtype="uint64")
Out [4]:
...:
OverflowError: Trying to coerce negative values to unsigned integers
Concatenation changes

Calling `pandas.concat()` on a `Categorical` of ints with NA values now causes them to be processed as objects when concatenating with anything other than another `Categorical` of ints (GH19214)

```python
In [105]: s = pd.Series([0, 1, np.nan])
In [106]: c = pd.Series([0, 1, np.nan], dtype="category")
```

**Previous behavior**

```python
In [3]: pd.concat([s, c])
Out[3]:
0  0.0  
1  1.0  
2  NaN  
0  0.0  
1  1.0  
2  NaN  
dtype: float64
```

**New behavior**

```python
In [107]: pd.concat([s, c])
Out[107]:
0  0.0  
1  1.0  
2  NaN  
0  0.0  
1  1.0  
2  NaN  
Length: 6, dtype: float64
```

Datetimelike API changes

- For `DatetimeIndex` and `TimedeltaIndex` with non-`None` freq attribute, addition or subtraction of integer-dtyped array or `Index` will return an object of the same class (GH19959)
- `DateOffset` objects are now immutable. Attempting to alter one of these will now raise `AttributeError` (GH21341)
- `PeriodIndex` subtraction of another `PeriodIndex` will now return an object-dtype `Index` of `DateOffset` objects instead of raising a `TypeError` (GH20049)
- `cut()` and `qcut()` now returns a `DatetimeIndex` or `TimedeltaIndex` bins when the input is datetime or timedelta dtype respectively and `retbins=True` (GH19891)
- `DatetimeIndex.to_period()` and `Timestamp.to_period()` will issue a warning when timezone information will be lost (GH21333)
- `PeriodIndex.tz_convert()` and `PeriodIndex.tz_localize()` have been removed (GH21781)
Other API changes

- A newly constructed empty DataFrame with integer as the dtype will now only be cast to float64 if index is specified (GH22858)
- Series.str.cat() will now raise if others is a set (GH23009)
- Passing scalar values to DatetimeIndex or TimedeltaIndex will now raise TypeError instead of ValueError (GH23539)
- max_rows and max_cols parameters removed from HTMLFormatter since truncation is handled by DataFrameFormatter (GH23818)
- read_csv() will now raise a ValueError if a column with missing values is declared as having dtype bool (GH20591)
- The column order of the resultant DataFrame from MultiIndex.to_frame() is now guaranteed to match the MultiIndex.names order. (GH22420)
- Incorrectly passing a DatetimeIndex to MultiIndex.from_tuples(), rather than a sequence of tuples, now raises a TypeError rather than a ValueError (GH24024)
- pd.offsets.generate_range() argument time_rule has been removed; use offset instead (GH24157)
- In 0.23.x, pandas would raise a ValueError on a merge of a numeric column (e.g. int dtyped column) and an object dtyped column (GH9780). We have re-enabled the ability to merge object and other dtypes; pandas will still raise on a merge between a numeric and an object dtyped column that is composed only of strings (GH21681)
- Accessing a level of a MultiIndex with a duplicate name (e.g. in get_level_values()) now raises a ValueError instead of a KeyError (GH21678).
- Invalid construction of IntervalDtype will now always raise a TypeError rather than a ValueError if the subtype is invalid (GH21185)
- Trying to reindex a DataFrame with a non unique MultiIndex now raises a ValueError instead of an Exception (GH21770)
- Index subtraction will attempt to operate element-wise instead of raising TypeError (GH19369)
- pandas.io.formats.style.Styler supports a number-format property when using to_excel() (GH22015)
- DataFrame.corr() and Series.corr() now raise a ValueError along with a helpful error message instead of a KeyError when supplied with an invalid method (GH22298)
- shift() will now always return a copy, instead of the previous behaviour of returning self when shifting by 0 (GH22397)
- DataFrame.set_index() now gives a better (and less frequent) KeyError, raises a ValueError for incorrect types, and will not fail on duplicate column names with drop=True. (GH22484)
- Slicing a single row of a DataFrame with multiple ExtensionArrays of the same type now preserves the dtype, rather than coercing to object (GH22784)
- DateOffset attribute _cacheable and method _should_cache have been removed (GH23118)
- Series.searchsorted(), when supplied a scalar value to search for, now returns a scalar instead of an array (GH23801).
- Categorical.searchsorted(), when supplied a scalar value to search for, now returns a scalar instead of an array (GH23466).
• `Categorical.searchsorted()` now raises a `KeyError` rather than a `ValueError`, if a searched for key is not found in its categories (GH23466).

• `Index.hasnans()` and `Series.hasnans()` now always return a python boolean. Previously, a python or a numpy boolean could be returned, depending on circumstances (GH23294).

• The order of the arguments of `DataFrame.to_html()` and `DataFrame.to_string()` is rearranged to be consistent with each other. (GH23614)

• `CategoricalIndex.reindex()` now raises a `ValueError` if the target index is non-unique and not equal to the current index. It previously only raised if the target index was not of a categorical dtype (GH23963).

• `Series.to_list()` and `Index.to_list()` are now aliases of `Series.tolist` respectively `Index.tolist` (GH8826)

• The result of `SparseSeries.unstack()` is now a `DataFrame` with sparse values, rather than a `SparseDataFrame` (GH24372).

• `DatetimeIndex` and `TimedeltaIndex` no longer ignore the dtype precision. Passing a non-nanosecond resolution dtype will raise a `ValueError` (GH24753)

### Extension type changes

#### Equality and hashability

Pandas now requires that extension dtypes be hashable (i.e. the respective `ExtensionDtype` objects; hashability is not a requirement for the values of the corresponding `ExtensionArray`). The base class implements a default `__eq__` and `__hash__`. If you have a parametrized dtype, you should update the `ExtensionDtype._metadata` tuple to match the signature of your `__init__` method. See `pandas.api.extensions.ExtensionDtype` for more (GH22476).

#### New and changed methods

• `dropna()` has been added (GH21185)

• `repeat()` has been added (GH24349)

• The `ExtensionArray` constructor, `__from_sequence` now take the keyword arg `copy=False` (GH21185)

• `pandas.api.extensions.ExtensionArray.shift()` added as part of the basic `ExtensionArray` interface (GH22387).

• `searchsorted()` has been added (GH24350)

• Support for reduction operations such as `sum`, `mean` via opt-in base class method override (GH22762)

• `ExtensionArray.isna()` is allowed to return an `ExtensionArray` (GH22325).

#### Dtype changes

• `ExtensionDtype` has gained the ability to instantiate from string dtypes, e.g. `decimal` would instantiate a registered `DecimalDtype`; furthermore the `ExtensionDtype` has gained the method `construct_array_type` (GH21185)

• Added `ExtensionDtype._is_numeric` for controlling whether an extension dtype is considered numeric (GH22290).

• Added `pandas.api.types.register_extension_dtype()` to register an extension type with pandas (GH22664)

• Updated the `.type` attribute for `PeriodDtype`, `DatetimeTZDtype`, and `IntervalDtype` to be instances of the dtype (`Period`, `Timestamp`, and `Interval` respectively) (GH22938)
Operator support

A `Series` based on an `ExtensionArray` now supports arithmetic and comparison operators (GH19577). There are two approaches for providing operator support for an `ExtensionArray`:

1. Define each of the operators on your `ExtensionArray` subclass.
2. Use an operator implementation from pandas that depends on operators that are already defined on the underlying elements (scalars) of the `ExtensionArray`.

See the `ExtensionArray Operator Support` documentation section for details on both ways of adding operator support.

Other changes

- A default repr for `pandas.api.extensions.ExtensionArray` is now provided (GH23601).
- `ExtensionArray._formatting_values()` is deprecated. Use `ExtensionArray._formatter` instead. (GH23601)
- An `ExtensionArray` with a boolean dtype now works correctly as a boolean indexer. `pandas.api.types.is_bool_dtype()` now properly considers them boolean (GH22326)

Bug fixes

- Bug in `Series.get()` for `Series` using `ExtensionArray` and integer index (GH21257)
- `shift()` now dispatches to `ExtensionArray.shift()` (GH22386)
- `Series.combine()` works correctly with `ExtensionArray` inside of `Series` (GH20825)
- `Series.combine()` with scalar argument now works for any function type (GH21248)
- `Series.astype()` and `DataFrame.astype()` now dispatch to `ExtensionArray.astype()` (GH21185).
- Slicing a single row of a `DataFrame` with multiple `ExtensionArrays` of the same type now preserves the dtype, rather than coercing to object (GH22784)
- Bug when concatenating multiple `Series` with different extension dtypes not casting to object dtype (GH22994)
- `Series` backed by an `ExtensionArray` now work with `util.hash_pandas_object()` (GH23066)
- `DataFrame.stack()` no longer converts to object dtype for DataFrames where each column has the same extension dtype. The output `Series` will have the same dtype as the columns (GH23077).
- `Series.unstack()` and `DataFrame.unstack()` no longer convert extension arrays to object-dtype ndarrays. Each column in the output `DataFrame` will now have the same dtype as the input (GH23077).
- Bug when grouping `Dataframe.groupby()` and aggregating on `ExtensionArray` it was not returning the actual `ExtensionArray` dtype (GH23227).
- Bug in `pandas.merge()` when merging on an extension array-backed column (GH23020).
Deprecations

- **MultiIndex.labels** has been deprecated and replaced by **MultiIndex.codes**. The functionality is unchanged. The new name better reflects the natures of these codes and makes the MultiIndex API more similar to the API for **CategoricalIndex** (GH13443). As a consequence, other uses of the name labels in MultiIndex have also been deprecated and replaced with codes:
  - You should initialize a MultiIndex instance using a parameter named codes rather than labels.
  - MultiIndex.set_labels has been deprecated in favor of MultiIndex.set_codes().
  - For method MultiIndex.copy(), the labels parameter has been deprecated and replaced by a codes parameter.

- **DataFrame.to_stata(), read_stata(), StataReader and StataWriter** have deprecated the encoding argument. The encoding of a Stata dta file is determined by the file type and cannot be changed (GH21244)

- **MultiIndex.to_hierarchical()** is deprecated and will be removed in a future version (GH21613)

- **Series.ptp()** is deprecated. Use numpy.ptp instead (GH21614)

- **Series.compress()** is deprecated. Use Series[condition] instead (GH18262)

- The signature of **Series.to_csv()** has been uniformed to that of **DataFrame.to_csv()**: the name of the first argument is now path_or_buf, the order of subsequent arguments has changed, the header argument now defaults to True. (GH19715)

- **Categorical.from_codes()** has deprecated providing float values for the codes argument. (GH21767)

- **pandas.read_table()** is deprecated. Instead, use read_csv() passing sep="\t" if necessary. This deprecation has been removed in 0.25.0. (GH21948)

- **Series.str.cat()** has deprecated using arbitrary list-likes within list-likes. A list-like container may still contain many Series, Index or 1-dimensional np.ndarray, or alternatively, only scalar values. (GH21950)

- **FrozenNDArray.searchsorted()** has deprecated the v parameter in favor of value (GH14645)

- **DatetimeIndex.shift()** and **PeriodIndex.shift()** now accept periods argument instead of n for consistency with Index.shift() and Series.shift(). Using n throws a deprecation warning (GH22458, GH22912)

- The fastpath keyword of the different Index constructors is deprecated (GH23110).

- **Timestamp.tz_localize(), DatetimeIndex.tz_localize(), and Series.tz_localize()** have deprecated the errors argument in favor of the nonexistent argument (GH8917)

- The class **FrozenNDArray** has been deprecated. When unpickling, FrozenNDArray will be unpickled to np.ndarray once this class is removed (GH9031)

- The methods **DataFrame.update()** and **Panel.update()** have deprecated the raise_conflict=False|True keyword in favor of errors='ignore'|'raise' (GH23585)

- The methods **Series.str.partition()** and **Series.str.rpartition()** have deprecated the pat keyword in favor of sep (GH22676)

- Deprecated the nthreads keyword of **pandas.read_feather()** in favor of use_threads to reflect the changes in pyarrow>=0.11.0. (GH23053)

- **pandas.read_excel()** has deprecated accepting usecols as an integer. Please pass in a list of ints from 0 to usecols inclusive instead (GH23527)
pandas: powerful Python data analysis toolkit, Release 1.1.1

- Constructing a `TimedeltaIndex` from data with `datetime64`-dtyped data is deprecated, will raise `TypeError` in a future version (GH23539)
- Constructing a `DatetimeIndex` from data with `timedelta64`-dtyped data is deprecated, will raise `TypeError` in a future version (GH23675)
- The `keep_tz=False` option (the default) of the `keep_tz` keyword of `DatetimeIndex.to_series()` is deprecated (GH17832).
- Timezone converting a tz-aware `datetime.datetime` or `Timestamp` with `Timestamp` and the `tz` argument is now deprecated. Instead, use `Timestamp.tz_convert()` (GH23579)
- `pandas.api.types.is_period()` is deprecated in favor of `pandas.api.types.is_period_dtype` (GH23917)
- `pandas.api.types.is_datetimetz()` is deprecated in favor of `pandas.api.types.is_datetime64tz` (GH23917)
- Creating a `TimedeltaIndex`, `DatetimeIndex`, or `PeriodIndex` by passing range arguments `start`, `end`, and `periods` is deprecated in favor of `timedelta_range()`, `date_range()`, or `period_range()` (GH23919)
- Passing a string alias like 'datetime64[ns, UTC]' as the unit parameter to `DatetimeTZDtype` is deprecated. Use `DatetimeTZDtype.construct_from_string` instead (GH23990).
- The `skipna` parameter of `infer_dtype()` will switch to `True` by default in a future version of pandas (GH17066, GH24050)
- In `Series.where()` with Categorical data, providing an `other` that is not present in the categories is deprecated. Convert the categorical to a different dtype or add the `other` to the categories first (GH24077).
- `Series.clip_lower()`, `Series.clip_upper()`, `DataFrame.clip_lower()` and `DataFrame.clip_upper()` are deprecated and will be removed in a future version. Use `Series.clip(lower=threshold)`, `Series.clip(upper=threshold)` and the equivalent `DataFrame` methods (GH24203)
- `Series.nonzero()` is deprecated and will be removed in a future version (GH18262)
- Passing an integer to `Series.fillna()` and `DataFrame.fillna()` with `timedelta64[ns]` dtypes is deprecated, will raise `TypeError` in a future version. Use `obj.fillna(pd.Timedelta(...))` instead (GH24694)
- `Series.cat.categorical`, `Series.cat.name` and `Series.cat.index` have been deprecated. Use the attributes on `Series.cat` or `Series` directly. (GH24751).
- Passing a dtypes without a precision like `np.dtype('datetime64')` or `timedelta64` to `Index`, `DatetimeIndex` and `TimedeltaIndex` is now deprecated. Use the nanosecond-precision dtypes instead (GH24753).

**Integer addition/subtraction with datetimes and timedeltas is deprecated**

In the past, users could—in some cases—add or subtract integers or integer-dtype arrays from `Timestamp`, `DatetimeIndex` and `TimedeltaIndex`.

This usage is now deprecated. Instead add or subtract integer multiples of the object’s `freq` attribute (GH21939, GH23878).

*Previous behavior:*
In [6]: ts + 2

In [7]: tdi = pd.timedelta_range('1D', periods=2)
In [8]: tdi - np.array([2, 1])
Out[8]: TimedeltaIndex(["-1 days", '1 days'], dtype='timedelta64[ns]', freq=None)

In [9]: dti = pd.date_range('2001-01-01', periods=2, freq='7D')
In [10]: dti + pd.Index([1, 2])
Out[10]: DatetimeIndex(['2001-01-08', '2001-01-22'], dtype='datetime64[ns]', freq=None)

New behavior:

In [109]: ts + 2 * ts.freq
In [110]: tdi = pd.timedelta_range('1D', periods=2)
In [111]: tdi - np.array([2 * tdi.freq, 1 * tdi.freq])
Out[111]: TimedeltaIndex(["-1 days", '1 days'], dtype='timedelta64[ns]', freq=None)
In [112]: dti = pd.date_range('2001-01-01', periods=2, freq='7D')
In [113]: dti + pd.Index([1 * dti.freq, 2 * dti.freq])
Out[113]: DatetimeIndex(['2001-01-08', '2001-01-22'], dtype='datetime64[ns]', freq=None)

Passing integer data and a timezone to DatetimeIndex

The behavior of DatetimeIndex when passed integer data and a timezone is changing in a future version of pandas. Previously, these were interpreted as wall times in the desired timezone. In the future, these will be interpreted as wall times in UTC, which are then converted to the desired timezone (GH24559).

The default behavior remains the same, but issues a warning:

In [3]: pd.DatetimeIndex([946684800000000000], tz="US/Central")
/bin/ipython:1: FutureWarning:
    Integer values will be interpreted differently in a future version of pandas. Previously, these were viewed as datetime64[ns] values representing the wall time in the specified timezone. In the future, these will be viewed as datetime64[ns] values representing the wall time in UTC. This is similar to a nanosecond-precision UNIX epoch. To accept the future behavior, use
    pd.to_datetime(integer_data, utc=True).tz_convert(tz)
    To keep the previous behavior, use
    pd.to_datetime(integer_data).tz_localize(tz)

Out[3]: DatetimeIndex(['2000-01-01 00:00:00-06:00'], dtype='datetime64[ns, US/Central]', freq=None)
As the warning message explains, opt in to the future behavior by specifying that the integer values are UTC, and then converting to the final timezone:

```
In [114]: pd.to_datetime([946684800000000000], utc=True).tz_convert('US/Central')
Out[114]: DatetimeIndex(['1999-12-31 18:00:00-06:00'], dtype='datetime64[ns, US/Central]', freq=None)
```

The old behavior can be retained by directly localizing to the final timezone:

```
In [115]: pd.to_datetime([946684800000000000]).tz_localize('US/Central')
Out[115]: DatetimeIndex(['2000-01-01 00:00:00-06:00'], dtype='datetime64[ns, US/Central]', freq=None)
```

### Converting timezone-aware Series and Index to NumPy arrays

The conversion from a `Series` or `Index` with timezone-aware datetime data will change to preserve timezones by default (GH23569).

NumPy doesn’t have a dedicated dtype for timezone-aware datetimes. In the past, converting a `Series` or `DatetimeIndex` with timezone-aware datetimes would convert to a NumPy array by

1. converting the tz-aware data to UTC
2. dropping the timezone-info
3. returning a `numpy.ndarray` with `datetime64[ns]` dtype

Future versions of pandas will preserve the timezone information by returning an object-dtype NumPy array where each value is a `Timestamp` with the correct timezone attached

```
In [116]: ser = pd.Series(pd.date_range('2000', periods=2, tz='CET'))
In [117]: ser
Out[117]:
0  2000-01-01 00:00:00+01:00
1  2000-01-02 00:00:00+01:00
Length: 2, dtype: datetime64[ns, CET]
```

The default behavior remains the same, but issues a warning

```
In [8]: np.asarray(ser)
/bin/ipython:1: FutureWarning: Converting timezone-aware DatetimeArray to timezone-naive ndarray with 'datetime64[ns]' dtype. In the future, this will return an ndarray with 'object' dtype where each element is a 'pandas.Timestamp' with the correct 'tz'.

To accept the future behavior, pass 'dtype=object'.
To keep the old behavior, pass 'dtype="datetime64[ns]"'.

#!/bin/python3
Out[8]:
array(['1999-12-31T23:00:00.000000000', '2000-01-01T23:00:00.000000000'], dtype='datetime64[ns]')
```

The previous or future behavior can be obtained, without any warnings, by specifying the `dtype`
Previous behavior

```python
In [118]: np.asarray(ser, dtype='datetime64[ns]')
Out[118]:
array([  '1999-12-31T23:00:00.000000000', '2000-01-01T23:00:00.000000000'],
      dtype='datetime64[ns]')
```

Future behavior

```python
# New behavior
In [119]: np.asarray(ser, dtype=object)
Out[119]:
array([Timestamp('2000-01-01 00:00:00+0100', tz='CET', freq='D'),
      Timestamp('2000-01-02 00:00:00+0100', tz='CET', freq='D')],
      dtype=object)
Or by using `Series.to_numpy()`
```

```python
In [120]: ser.to_numpy()
Out[120]:
array([Timestamp('2000-01-01 00:00:00+0100', tz='CET', freq='D'),
      Timestamp('2000-01-02 00:00:00+0100', tz='CET', freq='D')],
      dtype=object)
In [121]: ser.to_numpy(dtype="datetime64[ns]")
Out[121]:
array([  '1999-12-31T23:00:00.000000000', '2000-01-01T23:00:00.000000000'],
      dtype='datetime64[ns]')
```

All the above applies to a `DatetimeIndex` with tz-aware values as well.

Removal of prior version deprecations/changes

- The `LongPanel` and `WidePanel` classes have been removed (GH10892)
- `Series.repeat()` has renamed the `reps` argument to `repeats` (GH14645)
- Several private functions were removed from the (non-public) module `pandas.core.common` (GH22001)
- Removal of the previously deprecated module `pandas.core.datetools` (GH14105, GH14094)
- Strings passed into `DataFrame.groupby()` that refer to both column and index levels will raise a `ValueError` (GH14432)
- `Index.repeat()` and `MultiIndex.repeat()` have renamed the `n` argument to `repeats` (GH14645)
- The `Series` constructor and `.astype` method will now raise a `ValueError` if timestamp dtypes are passed in without a unit (e.g. `np.datetime64`) for the `dtype` parameter (GH15987)
- Removal of the previously deprecated `as_indexer` keyword completely from `str.match()` (GH22356, GH6581)
- The modules `pandas.types`, `pandas.computation`, and `pandas.util.decorators` have been removed (GH16157, GH16250)
- Removed the `pandas.formats.style` shim for `pandas.io.formats.style.Styler` (GH16059)
- `pandas.pnow`, `pandas.match`, `pandas.groupby`, `pd.get_store`, `pd.Expr`, and `pd.Term` have been removed (GH15538, GH15940)
• Categorical.searchsorted() and Series.searchsorted() have renamed the v argument to value (GH14645)
• pandas.parser, pandas.lib, and pandas.tslib have been removed (GH15537)
• Index.searchsorted() have renamed the key argument to value (GH14645)
• DataFrame.consolidate and Series.consolidate have been removed (GH15501)
• Removal of the previously deprecated module pandas.json (GH19944)
• The module pandas.tools has been removed (GH15358, GH16005)
• SparseArray.get_values() and SparseArray.to_dense() have dropped the fill parameter (GH14686)
• DataFrame.sortlevel and Series.sortlevel have been removed (GH15099)
• SparseSeries.to_dense() has dropped the sparse_only parameter (GH14686)
• DataFrame.astype() and Series.astype() have renamed the raise_on_error argument to errors (GH14967)
• is_sequence, is_any_int_dtype, and is_floating_dtype have been removed from pandas.api.types (GH16163, GH16189)

Performance improvements

• Slicing Series and DataFrames with an monotonically increasing CategoricalIndex is now very fast and has speed comparable to slicing with an Int64Index. The speed increase is both when indexing by label (using .loc) and position(.iloc) (GH20395) Slicing a monotonically increasing CategoricalIndex itself (i.e. ci[1000:2000]) shows similar speed improvements as above (GH21659)
• Improved performance of CategoricalIndex.equals() when comparing to another CategoricalIndex (GH24023)
• Improved performance of Series.describe() in case of numeric dtypes (GH21274)
• Improved performance of pandas.core.groupby.GroupBy.rank() when dealing with tied rankings (GH21237)
• Improved performance of DataFrame.set_index() with columns consisting of Period objects (GH21582, GH21606)
• Improved performance of Series.at() and Index.get_value() for Extension Arrays values (e.g. Categorical) (GH24204)
• Improved performance of membership checks in Categorical and CategoricalIndex (i.e. x in cat-style checks are much faster). CategoricalIndex.contains() is likewise much faster (GH21369, GH21508)
• Improved performance of HDFStore.groups() (and dependent functions like HDFStore.keys()). (i.e. x in store checks are much faster) (GH21372)
• Improved the performance of pandas.get_dummies() with sparse=True (GH21997)
• Improved performance of IndexEngine.get_indexer_non_unique() for sorted, non-unique indexes (GH9466)
• Improved performance of PeriodIndex.unique() (GH23083)
• Improved performance of concat() for Series objects (GH23404)
• Improved performance of `DatetimeIndex.normalize()` and `Timestamp.normalize()` for time-zone naive or UTC datetimes (GH23634)

• Improved performance of `DatetimeIndex.tz_localize()` and various `DatetimeIndex` attributes with dateutil UTC timezone (GH23772)

• Fixed a performance regression on Windows with Python 3.7 of `read_csv()` (GH23516)

• Improved performance of `Categorical` constructor for `Series` objects (GH23814)

• Improved performance of `where()` for Categorical data (GH24077)

• Improved performance of iterating over a `Series`. Using `DataFrame.itertuples()` now creates iterators without internally allocating lists of all elements (GH20783)

• Improved performance of `Period` constructor, additionally benefitting `PeriodArray` and `PeriodIndex` creation (GH24084, GH24118)

• Improved performance of `tz-aware DatetimeArray` binary operations (GH24491)

Bug fixes

Categorical

• Bug in `Categorical.from_codes()` where NaN values in codes were silently converted to 0 (GH21767). In the future this will raise a `ValueError`. Also changes the behavior of `.from_codes([1.1, 2.0])`.

• Bug in `Categorical.sort_values()` where NaN values were always positioned in front regardless of `na_position` value. (GH22556).

• Bug when indexing with a boolean-valued `Categorical`. Now a boolean-valued `Categorical` is treated as a boolean mask (GH22665)

• Constructing a `CategoricalIndex` with empty values and boolean categories was raising a `ValueError` after a change to dtype coercion (GH22702).

• Bug in `Categorical.take()` with a user-provided fill_value not encoding the fill_value, which could result in a `ValueError`, incorrect results, or a segmentation fault (GH23296).

• In `Series.unstack()`, specifying a fill_value not present in the categories now raises a `TypeError` rather than ignoring the fill_value (GH23284)

• Bug when resampling `DataFrame.resample()` and aggregating on categorical data, the categorical dtype was getting lost. (GH23227)

• Bug in many methods of the `.str-accessor`, which always failed on calling the `CategoricalIndex.str` constructor (GH23555, GH23556)

• Bug in `Series.where()` losing the categorical dtype for categorical data (GH24077)

• Bug in `Categorical.apply()` where NaN values could be handled unpredictably. They now remain unchanged (GH24241)

• Bug in `Categorical` comparison methods incorrectly raising `ValueError` when operating against a `DataFrame` (GH24630)

• Bug in `Categorical.set_categories()` where setting fewer new categories with `rename=True` caused a segmentation fault (GH24675)
Datetimelike

- Fixed bug where two DateOffset objects with different normalize attributes could evaluate as equal (GH21404)
- Fixed bug where Timestamp.resolution() incorrectly returned 1-microsecond timedelta instead of 1-nanosecond timedelta (GH21336, GH21365)
- Bug in to_datetime() that did not consistently return an Index when box=True was specified (GH21864)
- Bug in DatetimeIndex comparisons where string comparisons incorrectly raises TypeError (GH22074)
- Bug in DatetimeIndex comparisons when comparing against timedelta64[ns] dtypes; in some cases TypeError was incorrectly raised, in others it incorrectly failed to raise (GH22074)
- Bug in DatetimeIndex comparisons when comparing against object-dtyped arrays (GH22074)
- Bug in DataFrame with datetime64[ns] dtype addition and subtraction with Timedelta-like objects (GH22005, GH22163)
- Bug in DataFrame with datetime64[ns] dtype addition and subtraction with DateOffset objects returning an object dtype instead of datetime64[ns] dtype (GH21610, GH22163)
- Bug in DataFrame with datetime64[ns] dtype comparing against NaT incorrectly (GH22242, GH22163)
- Bug in DataFrame with datetime64[ns] dtype subtracting Timestamp-like object incorrectly returned datetime64[ns] dtype instead of timedelta64[ns] dtype (GH8554, GH22163)
- Bug in DataFrame with datetime64[ns] dtype subtracting np.datetime64 object with non-nanosecond unit failing to convert to nanoseconds (GH18874, GH22163)
- Bug in DataFrame comparisons against Timestamp-like objects failing to raise TypeError for inequality checks with mismatched types (GH8932, GH22163)
- Bug in DataFrame with mixed dtypes including datetime64[ns] incorrectly raising TypeError on equality comparisons (GH13128, GH22163)
- Bug in DataFrame.values returning a DatetimeIndex for a single-column DataFrame with tz-aware datetime values. Now a 2-D numpy.ndarray of Timestamp objects is returned (GH24024)
- Bug in DataFrame.eq() comparison against NaT incorrectly returning True or NaN (GH15697, GH22163)
- Bug in DatetimeIndex subtraction that incorrectly failed to raise OverflowError (GH22492, GH22508)
- Bug in DatetimeIndex incorrectly allowing indexing with Timedelta object (GH20464)
- Bug in DatetimeIndex where frequency was being set if original frequency was None (GH22150)
- Bug in rounding methods of DatetimeIndex (round(), ceil(), floor()) and Timestamp (round(), ceil(), floor()) could give rise to loss of precision (GH22591)
- Bug in to_datetime() with an Index argument that would drop the name from the result (GH21697)
- Bug in PeriodIndex where adding or subtracting a timedelta or Tick object produced incorrect results (GH22988)
- Bug in the Series repr with period-dtype data missing a space before the data (GH23601)
- Bug in date_range() when decrementing a start date to a past end date by a negative frequency (GH23270)
- Bug in Series.min() which would return NaN instead of NaT when called on a series of NaT (GH23282)
- Bug in Series.combine_first() not properly aligning categoricals, so that missing values in self where not filled by valid values from other (GH24147)
- Bug in `DataFrame.combine()` with datetimelike values raising a TypeError (GH23079)
- Bug in `date_range()` with frequency of `Day` or higher where dates sufficiently far in the future could wrap around to the past instead of raising `OutOfBoundsDatetime` (GH14187)
- Bug in `period_range()` ignoring the frequency of `start` and `end` when those are provided as `Period` objects (GH20535).
- Bug in `PeriodIndex` with attribute `freq.n` greater than 1 where adding a `DateOffset` object would return incorrect results (GH23215)
- Bug in `Series` that interpreted string indices as lists of characters when setting datetimelike values (GH23451)
- Bug in `DataFrame` when creating a new column from an ndarray of `Timestamp` objects with timezones creating an object-dtype column, rather than datetime with timezone (GH23932)
- Bug in `Timestamp` constructor which would drop the frequency of an input `Timestamp` (GH22311)
- Bug in `DatetimeIndex` where constructing a `DatetimeIndex` from a `Categorical` or `CategoricalIndex` would incorrectly drop timezone information (GH18664)
- Bug in `DatetimeIndex` and `TimedeltaIndex` where indexing with `Ellipsis` would incorrectly lose the index’s `freq` attribute (GH21282)
- Clarified error message produced when passing an incorrect `freq` argument to `DatetimeIndex` with `NaT` as the first entry in the passed data (GH11587)
- Bug in `to_datetime()` where `box` and `utc` arguments were ignored when passing a `DataFrame` or `dict` of unit mappings (GH23760)
- Bug in `Series.dt` where the cache would not update properly after an in-place operation (GH24408)
- Bug in `PeriodIndex` where comparisons against an array-like object with length 1 failed to raise `ValueError` (GH23078)
- Bug in `DatetimeIndex.astype()`, `PeriodIndex.astype()` and `TimedeltaIndex.astype()` ignoring the sign of the `dtype` for unsigned integer dtypes (GH24405).
- Fixed bug in `Series.max()` with `datetime64[ns]`-dtype failing to return `NaT` when nulls are present and `skipna=False` is passed (GH24265)
- Bug in `to_datetime()` where arrays of datet ime objects containing both timezone-aware and timezone-naive datetimes would fail to raise `ValueError` (GH24569)
- Bug in `to_datetime()` with invalid datetime format doesn’t coerce input to `NaT` even if `errors='coerce'` (GH24763)
Timedelta

- Bug in `DataFrame` with `timedelta64[ns]` dtype division by `Timedelta`-like scalar incorrectly returning `timedelta64[ns]` dtype instead of `float64` dtype (GH20088, GH22163)
- Bug in adding a `Index` object dtype to a `Series` object dtype incorrectly raising `TypeError` (GH22390)
- Bug in multiplying a `Series` object dtype against a `timedelta` object (GH22390)
- Bug in `Series` object dtype when adding or subtracting an array or `Series` with `timedelta64[ns]` dtype (GH22390)
- Bug in `Index` object dtype when multiplying or dividing an array or `Series` with `timedelta64[ns]` dtype (GH22390)
- Bug in `TimedeltaIndex` incorrectly allowing indexing with `Timestamp` object (GH20464)
- Fixed bug where subtracting `Timedelta` from an object-dtyped array would raise `TypeError` (GH21980)
- Fixed bug in adding a `DataFrame` object with all-`timedelta64[ns]` dtypes to a `DataFrame` object with all-integer dtypes returning incorrect results instead of raising `TypeError` (GH22696)
- Bug in `TimedeltaIndex` where adding a timezone-aware datetime scalar incorrectly returned a timezone-naive `DatetimeIndex` (GH23215)
- Bug in `TimedeltaIndex` where adding `np.timedelta64('NaT')` incorrectly returned an all-`NaT` `DatetimeIndex` instead of an all-`NaT` `TimedeltaIndex` (GH23215)
- Bug in `Timedelta` and `to_timedelta()` have inconsistencies in supported unit string (GH21762)
- Bug in `TimedeltaIndex` division where dividing by another `TimedeltaIndex` raised `TypeError` instead of returning a `Float64Index` (GH23849, GH22631)
- Bug in `TimedeltaIndex` comparison operations where comparing against non-Timedelta-like objects would raise `TypeError` instead of returning all-False for `__eq__` and all-True for `__ne__` (GH24056)
- Bug in `Timedelta` comparisons when comparing with a `Tick` object incorrectly raising `TypeError` (GH24710)

Timezones

- Bug in `Index.shift()` where an `AssertionError` would raise when shifting across DST (GH8616)
- Bug in `Timestamp` constructor where passing an invalid timezone offset designator (Z) would not raise a `ValueError` (GH8910)
- Bug in `Timestamp.replace()` where replacing at a DST boundary would retain an incorrect offset (GH7825)
- Bug in `Series.replace()` with `datetime64[ns, tz]` data when replacing `NaT` (GH11792)
- Bug in `Timestamp` when passing different string date formats with a timezone offset would produce different timezone offsets (GH12064)
- Bug when comparing a tz-naive `Timestamp` to a tz-aware `DatetimeIndex` which would coerce the `DatetimeIndex` to tz-naive (GH12601)
- Bug in `Series.truncate()` with a tz-aware `DatetimeIndex` which would cause a core dump (GH9243)
- Bug in `Series` constructor which would coerce tz-aware and tz-naive `Timestamp` to tz-aware (GH13051)
- Bug in `Index` object dtype that did not localize integer data correctly (GH20964)
• Bug in `DatetimeIndex` where constructing with an integer and tz would not localize correctly (GH12619)

• Fixed bug where `DataFrame.describe()` and `Series.describe()` on tz-aware datetimes did not show first and last result (GH21328)

• Bug in `DatetimeIndex` comparisons failing to raise `TypeError` when comparing timezone-aware `DatetimeIndex` against `np.datetime64` (GH22074)

• Bug in `DataFrame` assignment with a timezone-aware scalar (GH19843)

• Bug in `DataFrame.asof()` that raised a `TypeError` when attempting to compare tz-naive and tz-aware timestamps (GH21846)

• Bug when constructing a `DatetimeIndex` with `Timestamp` constructed with the `replace` method across DST (GH18785)

• Bug when setting a new value with `DataFrame.loc()` with a `DatetimeIndex` with a DST transition (GH18308, GH20724)

• Bug in `Index.unique()` that did not re-localize tz-aware dates correctly (GH21737)

• Bug when indexing a `Series` with a DST transition (GH21846)

• Bug in `DataFrame.resample()` and `Series.resample()` where an `AmbiguousTimeError` or `NonExistentTimeError` would raise if a timezone aware timeseries ended on a DST transition (GH19375, GH10117)

• Bug in `DataFrame.drop()` and `Series.drop()` when specifying a tz-aware `Timestamp` key to drop from a `DatetimeIndex` with a DST transition (GH21761)

• Bug in `DatetimeIndex` constructor where `NaT` and `dateutil.tz.tzlocal` would raise an `OutOfBoundsDatetimeError` (GH23807)

• Bug in `DatetimeIndex.tz_localize()` and `Timestamp.tz_localize()` with `dateutil.tz.tzlocal` near a DST transition that would return an incorrectly localized datetime (GH23807)

• Bug in `Timestamp` constructor where a `dateutil.tz.tzutc` timezone passed with a `datetime` argument would be converted to a `pytz.UTC` timezone (GH23807)

• Bug in `to_datetime()` where utc=True was not respected when specifying a unit and errors='ignore' (GH23758)

• Bug in `to_datetime()` where utc=True was not respected when passing a `Timestamp` (GH24415)

• Bug in `DataFrame.any()` returns wrong value when axis=1 and the data is of datetimelike type (GH23070)

• Bug in `DatetimeIndex.to_period()` where a timezone aware index was converted to UTC first before creating `PeriodIndex` (GH22905)

• Bug in `DataFrame.tz_localize()`, `DataFrame.tz_convert()`, `Series.tz_localize()` , and `Series.tz_convert()` where copy=False would mutate the original argument in place (GH6326)

• Bug in `DataFrame.max()` and `DataFrame.min()` with axis=1 where a `Series` with NaN would be returned when all columns contained the same timezone (GH10390)
Offsets

- Bug in FY5253 where date offsets could incorrectly raise an AssertionError in arithmetic operations (GH14774)
- Bug in `DateOffset` where keyword arguments `week` and `milliseconds` were accepted and ignored. Passing these will now raise ValueError (GH19398)
- Bug in adding `DateOffset` with `DataFrame` or `PeriodIndex` incorrectly raising TypeError (GH23215)
- Bug in comparing `DateOffset` objects with non-DateOffset objects, particularly strings, raising ValueError instead of returning False for equality checks and True for not-equal checks (GH23524)

Numeric

- Bug in `Series __rmatmul__` doesn’t support matrix vector multiplication (GH21530)
- Bug in `factorize()` fails with read-only array (GH12813)
- Fixed bug in `unique()` handled signed zeros inconsistently: for some inputs 0.0 and -0.0 were treated as equal and for some inputs as different. Now they are treated as equal for all inputs (GH21866)
- Bug in `DataFrame.agg()`, `DataFrame.transform()` and `DataFrame.apply()` where, when supplied with a list of functions and `axis=1` (e.g. `df.apply(['sum', 'mean'], axis=1)`), a TypeError was wrongly raised. For all three methods such calculation are now done correctly. (GH16679).
- Bug in `Series` comparison against datetime-like scalars and arrays (GH22074)
- Bug in `DataFrame` multiplication between boolean dtype and integer returning object dtype instead of integer dtype (GH22047, GH22163)
- Bug in `DataFrame.apply()` where, when supplied with a string argument and additional positional or keyword arguments (e.g. `df.apply('sum', min_count=1)`) a TypeError was wrongly raised (GH22376)
- Bug in `DataFrame.astype()` to extension dtype may raise AttributeError (GH22578)
- Bug in `DataFrame` with timedelta64[ns] dtype arithmetic operations with ndarray with integer dtype incorrectly treating the ndarray as timedelta64[ns] dtype (GH23114)
- Bug in `Series.pow()` with object dtype NaN for 1 ** NA instead of 1 (GH22922).
- `Series.agg()` can now handle nans in methods like `numpy.nansum()` (GH19629)
- Bug in `Series.rank()` and `DataFrame.rank()` when `pct=True` and more than 2^34 rows are present. Full support for `keepdims` has not been implemented (GH24356).
Conversion

- Bug in `DataFrame.combine_first()` in which column types were unexpectedly converted to float (GH20699)
- Bug in `DataFrame.clip()` in which column types are not preserved and casted to float (GH24162)
- Bug in `DataFrame.clip()` when order of columns of dataframes doesn’t match, result observed is wrong in numeric values (GH20911)
- Bug in `DataFrame.astype()` where converting to an extension dtype when duplicate column names are present causes a RecursionError (GH24704)

Strings

- Bug in `Index.str.partition()` was not nan-safe (GH23558).
- Bug in `Index.str.split()` was not nan-safe (GH23677).
- Bug `Series.str.contains()` not respecting the na argument for a Categorical dtype Series (GH22158)
- Bug in `Index.str.cat()` when the result contained only NaN (GH24044)

Interval

- Bug in the `IntervalIndex` constructor where the closed parameter did not always override the inferred closed (GH19370)
- Bug in the `IntervalIndex` repr where a trailing comma was missing after the list of intervals (GH20611)
- Bug in `Interval` where scalar arithmetic operations did not retain the closed value (GH22313)
- Bug in `IntervalIndex` where indexing with datetime-like values raised a KeyError (GH20636)
- Bug in `IntervalTree` where data containing NaN triggered a warning and resulted in incorrect indexing queries with `IntervalIndex` (GH23352)

Indexing

- Bug in `DataFrame.ne()` fails if columns contain column name “dtype” (GH22383)
- The traceback from a KeyError when asking `.loc` for a single missing label is now shorter and more clear (GH21557)
- `PeriodIndex` now emits a KeyError when a malformed string is looked up, which is consistent with the behavior of `DatetimeIndex` (GH22803)
- When `.ix` is asked for a missing integer label in a `MultiIndex` with a first level of integer type, it now raises a KeyError, consistently with the case of a flat `Int64Index`, rather than falling back to positional indexing (GH21593)
- Bug in `Index.reindex()` when reindexing a tz-naive and tz-aware `DatetimeIndex` (GH8306)
- Bug in `Series.reindex()` when reindexing an empty series with a `datetime64[ns, tz]` dtype (GH20869)
- Bug in `DataFrame` when setting values with `.loc` and a timezone aware `DatetimeIndex` (GH11365)
pandas: powerful Python data analysis toolkit, Release 1.1.1

- **DataFrame.__getitem__** now accepts dictionaries and dictionary keys as list-likes of labels, consistently with **Series.__getitem__** (GH21294)
- Fixed **DataFrame[np.nan]** when columns are non-unique (GH21428)
- Bug when indexing **DatetimeIndex** with nanosecond resolution dates and timezones (GH11679)
- Bug where indexing with a Numpy array containing negative values would mutate the indexer (GH21867)
- Bug where mixed indexes wouldn’t allow integers for **.at** (GH19860)
- **Float64Index.get_loc** now raises **KeyError** when boolean key passed. (GH19087)
- Bug in **DataFrame.loc()** when indexing with an **IntervalIndex** (GH19977)
- **Index** no longer mangles None, NaN and NaT, i.e. they are treated as three different keys. However, for numeric Index all three are still coerced to a NaN (GH2332)
- Bug in **scalar in Index** if scalar is a float while the Index is of integer dtype (GH22085)
- Bug in **MultiIndex.set_levels()** when levels value is not subscriptable (GH23237)
- Bug where setting a timedelta column by Index causes it to be casted to double, and therefore lose precision (GH23511)
- Bug in **Index.union()** and **Index.intersection()** where name of the Index of the result was not computed correctly for certain cases (GH9943, GH9862)
- Bug in **Index slicing with boolean Index** may raise **TypeError** (GH22533)
- Bug in **PeriodArray.__setitem__** when accepting slice and list-like value (GH23978)
- Bug in **DatetimeIndex, TimedeltaIndex** where indexing with **Ellipsis** would lose their freq attribute (GH21282)
- Bug in **iat** where using it to assign an incompatible value would create a new column (GH23236)

**Missing**

- Bug in **DataFrame.fillna()** where a **ValueError** would raise when one column contained a **datetime64[ns, tz] dtype** (GH15522)
- Bug in **Series.hasnans()** that could be incorrectly cached and return incorrect answers if null elements are introduced after an initial call (GH19700)
- **Series.isin()** now treats all NaN-floats as equal also for np.object-dtype. This behavior is consistent with the behavior for float64 (GH22119)
- **unique()** no longer mangles NaN-floats and the NaT-object for np.object-dtype, i.e. NaT is no longer coerced to a NaN-value and is treated as a different entity. (GH22295)
- **DataFrame** and **Series** now properly handle numpy masked arrays with hardened masks. Previously, constructing a DataFrame or Series from a masked array with a hard mask would create a pandas object containing the underlying value, rather than the expected NaN. (GH24574)
- Bug in **DataFrame** constructor where **dtype** argument was not honored when handling numpy masked record arrays. (GH24874)
**MultiIndex**

- Bug in `io.formats.style.Styler.applymap()` where `subset=` with `MultiIndex` slice would reduce to `Series` (GH19861)
- Removed compatibility for `MultiIndex` pickles prior to version 0.8.0; compatibility with `MultiIndex` pickles from version 0.13 forward is maintained (GH21654)
- `MultiIndex.get_loc_level()` (and as a consequence, `.loc` on a `Series` or `DataFrame` with a `MultiIndex` index) will now raise a `KeyError`, rather than returning an empty slice, if asked a label which is present in the levels but is unused (GH22221)
- `MultiIndex` has gained the `MultiIndex.from_frame()`, it allows constructing a `MultiIndex` object from a `DataFrame` (GH22420)
- Fix `TypeError` in Python 3 when creating `MultiIndex` in which some levels have mixed types, e.g. when some labels are tuples (GH15457)

**I/O**

- Bug in `read_csv()` in which a column specified with `CategoricalDtype` of boolean categories was not being correctly coerced from string values to booleans (GH20498)
- Bug in `read_csv()` in which unicode column names were not being properly recognized with Python 2.x (GH13253)
- Bug in `DataFrame.to_sql()` when writing timezone aware data (`datetime64[ns, tz]` dtype) would raise a `TypeError` (GH9086)
- Bug in `DataFrame.to_sql()` where a naive `DatetimeIndex` would be written as `TIMESTAMP WITH TIMEZONE` type in supported databases, e.g. PostgreSQL (GH23510)
- Bug in `read_excel()` when `parse_cols` is specified with an empty dataset (GH9208)
- `read_html()` no longer ignores all-whitespace `<tr>` within `<thead>` when considering the `skiprows` and `header` arguments. Previously, users had to decrease their `header` and `skiprows` values on such tables to work around the issue. (GH21641)
- `read_excel()` will correctly show the deprecation warning for previously deprecated `sheetname` (GH17994)
- `read_csv()` and `read_table()` will throw `UnicodeError` and not coredump on badly encoded strings (GH22748)
- `read_csv()` will correctly parse timezone-aware datetimes (GH22256)
- Bug in `read_csv()` in which memory management was prematurely optimized for the C engine when the data was being read in chunks (GH23509)
- Bug in `read_csv()` in unnamed columns were being improperly identified when extracting a multi-index (GH23687)
- `read_sas()` will parse numbers in `sas7bdat`-files that have width less than 8 bytes correctly. (GH21616)
- `read_sas()` will correctly parse `sas7bdat` files with many columns (GH22628)
- `read_sas()` will correctly parse `sas7bdat` files with data page types having also bit 7 set (so page type is 128 + 256 = 384) (GH16615)
- Bug in `read_sas()` in which an incorrect error was raised on an invalid file format. (GH24548)
- Bug in `detect_client_encoding()` where potential IOError goes unhandled when importing in a mod_wsgi process due to restricted access to stdout. (GH21552)
- Bug in `DataFrame.to_html()` with `index=False` misses truncation indicators (...) on truncated DataFrame (GH15019, GH22783)
- Bug in `DataFrame.to_html()` with `index=False` when both columns and row index are MultiIndex (GH22579)
- Bug in `DataFrame.to_html()` with `index_names=False` displaying index name (GH22747)
- Bug in `DataFrame.to_html()` with `header=False` not displaying row index names (GH23788)
- Bug in `DataFrame.to_html()` with `sparsify=False` that caused it to raise TypeError (GH22887)
- Bug in `DataFrame.to_string()` that broke column alignment when `index=False` and width of first column’s values is greater than the width of first column’s header (GH16839, GH13032)
- Bug in `DataFrame.to_string()` that caused representations of `DataFrame` to not take up the whole window (GH22984)
- Bug in `DataFrame.to_csv()` where a single level MultiIndex incorrectly wrote a tuple. Now just the value of the index is written (GH19589).
- HDFStore will raise ValueError when the format kwarg is passed to the constructor (GH13291)
- Bug in `HDFStore.append()` when appending a DataFrame with an empty string column and `min_itemsize < 8` (GH12242)
- Bug in `read_csv()` in which memory leaks occurred in the C engine when parsing NaN values due to insufficient cleanup on completion or error (GH21353)
- Bug in `read_csv()` in which incorrect error messages were being raised when skipfooter was passed in along with nrows, iterator, or chunksize (GH23711)
- Bug in `read_csv()` in which MultiIndex index names were being improperly handled in the cases when they were not provided (GH23484)
- Bug in `read_csv()` in which unnecessary warnings were being raised when the dialect’s values conflicted with the default arguments (GH23761)
- Bug in `read_html()` in which the error message was not displaying the valid flavors when an invalid one was provided (GH23549)
- Bug in `read_excel()` in which extraneous header names were extracted, even though none were specified (GH11733)
- Bug in `read_excel()` in which column names were not being properly converted to string sometimes in Python 2.x (GH23874)
- Bug in `read_excel()` in which `index_col=None` was not being respected and parsing index columns anyway (GH18792, GH20480)
- Bug in `read_excel()` in which `usecols` was not being validated for proper column names when passed in as a string (GH20480)
- Bug in `DataFrame.to_dict()` when the resulting dict contains non-Python scalars in the case of numeric data (GH23753)
- `DataFrame.to_string()`, `DataFrame.to_html()`, `DataFrame.to_latex()` will correctly format output when a string is passed as the `float_format` argument (GH21625, GH22270)
- Bug in `read_csv()` that caused it to raise OverflowError when trying to use ‘inf’ as `na_value` with integer index column (GH17128)
- Bug in `read_csv()` that caused the C engine on Python 3.6+ on Windows to improperly read CSV filenames with accented or special characters (GH15086)
- Bug in `read_fwf()` in which the compression type of a file was not being properly inferred (GH22199)
- Bug in `pandas.io.json.json_normalize()` that caused it to raise `TypeError` when two consecutive elements of `record_path` are dicts (GH22706)
- Bug in `DataFrame.to_stata()`, `pandas.io.stata.StataWriter` and `pandas.io.stata.StataWriter117` where a exception would leave a partially written and invalid dta file (GH23573)
- Bug in `DataFrame.to_stata()` and `pandas.io.stata.StataWriter117` that produced invalid files when using `strLs` with non-ASCII characters (GH23573)
- Bug in `HDFStore` that caused it to raise `ValueError` when reading a Dataframe in Python 3 from fixed format written in Python 2 (GH24510)
- Bug in `DataFrame.to_string()` and more generally in the floating `repr` formatter. Zeros were not trimmed if `inf` was present in a columns while it was the case with NA values. Zeros are now trimmed as in the presence of NA (GH24861).
- Bug in the `repr` when truncating the number of columns and having a wide last column (GH24849).

**Plotting**

- Bug in `DataFrame.plot.scatter()` and `DataFrame.plot.hexbin()` caused x-axis label and tick-labels to disappear when colorbar was on in IPython inline backend (GH10611, GH10678, and GH20455)
- Bug in plotting a Series with datetimes using `matplotlib.axes.Axes.scatter()` (GH22039)
- Bug in `DataFrame.plot.bar()` caused bars to use multiple colors instead of a single one (GH20585)
- Bug in validating color parameter caused extra color to be appended to the given color array. This happened to multiple plotting functions using `matplotlib`. (GH20726)

**Groupby/resample/rolling**

- Bug in `pandas.core.window.Rolling.min()` and `pandas.core.window.Rolling.max()` with `closed='left'`, a datetime-like index and only one entry in the series leading to segfault (GH24718)
- Bug in `pandas.core.groupby.GroupBy.first()` and `pandas.core.groupby.GroupBy.last()` with `as_index=False` leading to the loss of timezone information (GH15884)
- Bug in `DataFrame.resample()` when downsampling across a DST boundary (GH8531)
- Bug in date anchoring for `DataFrame.resample()` with offset `Day` when n > 1 (GH24127)
- Bug where `ValueError` is wrongly raised when calling `count()` method of a `SeriesGroupBy` when the grouping variable only contains NaNs and numpy version < 1.13 (GH21956).
- Multiple bugs in `pandas.core.window.Rolling.min()` with `closed='left'` and a datetime-like index leading to incorrect results and also segfault. (GH21704)
- Bug in `pandas.core.resample.Resampler.apply()` when passing positional arguments to applied func (GH14615).
- Bug in `Series.resample()` when passing `numpy.timedelta64` to `offset` kwarg (GH7687).
- Bug in `pandas.core.resample.Resampler.asfreq()` when frequency of `TimedeltaIndex` is a subperiod of a new frequency (GH13022).
• Bug in pandas.core.groupby.SeriesGroupBy.mean() when values were integral but could not fit inside of int64, overflowing instead. (GH22487)

• pandas.core.groupby.RollingGroupby.agg() and pandas.core.groupby.ExpandingGroupby.agg() now support multiple aggregation functions as parameters (GH15072)

• Bug in DataFrame.resample() and Series.resample() when resampling by a weekly offset ('W') across a DST transition (GH9119, GH21459)

• Bug in DataFrame.expanding() in which the axis argument was not being respected during aggregations (GH23372)

• Bug in pandas.core.groupby.GroupBy.transform() which caused missing values when the input function can accept a DataFrame but renames it (GH23455).

• Bug in pandas.core.groupby.GroupBy.nth() where column order was not always preserved (GH20760)

• Bug in pandas.core.groupby.GroupBy.rank() with method='dense' and pct=True when a group has only one member would raise a ZeroDivisionError (GH23666).

• Calling pandas.core.groupby.GroupBy.rank() with empty groups and pct=True was raising a ZeroDivisionError (GH22519)

• Bug in DataFrame.resample() when resampling NaT in TimeDeltaIndex (GH13223).

• Bug in DataFrame.groupby() did not respect the observed argument when selecting a column and instead always used observed=False (GH23970)

• Bug in pandas.core.groupby.SeriesGroupBy.pct_change() or pandas.core.groupby.DataFrameGroupBy.pct_change() would previously work across groups when calculating the percent change, where it now correctly works per group (GH21200, GH21235).

• Bug preventing hash table creation with very large number (2^32) of rows (GH22805)

• Bug in groupby when grouping on categorical causes ValueError and incorrect grouping if observed=True and nan is present in categorical column (GH24740, GH21151).

**Reshaping**

• Bug in pandas.concat() when joining resampled DataFrames with timezone aware index (GH13783)

• Bug in pandas.concat() when joining only Series the names argument of concat is no longer ignored (GH23490)

• Bug in Series.combine_first() with datetime64[ns, tz] dtype which would return tz-naive result (GH21469)

• Bug in Series.where() and DataFrame.where() with datetime64[ns, tz] dtype (GH21546)

• Bug in DataFrame.where() with an empty DataFrame and empty cond having non-bool dtype (GH21947)

• Bug in Series.mask() and DataFrame.mask() with list conditionals (GH21891)

• Bug in DataFrame.replace() raises RecursionError when converting OutOfBounds datetime64[ns, tz] (GH20380)

• pandas.core.groupby.GroupBy.rank() now raises a ValueError when an invalid value is passed for argument na_option (GH22124)

• Bug in get_dummies() with Unicode attributes in Python 2 (GH22084)

• Bug in DataFrame.replace() raises RecursionError when replacing empty lists (GH22083)
• Bug in `Series.replace()` and `DataFrame.replace()` when dict is used as the `to_replace` value and one key in the dict is another key’s value, the results were inconsistent between using integer key and using string key (GH20656)

• Bug in `DataFrame.drop_duplicates()` for empty DataFrame which incorrectly raises an error (GH20516)

• Bug in `pandas.wide_to_long()` when a string is passed to the stubnames argument and a column name is a substring of that stubname (GH22468)

• Bug in `merge()` when merging `datetime64[ns, tz]` data that contained a DST transition (GH18885)

• Bug in `merge_asof()` when merging on float values within defined tolerance (GH22981)

• Bug in `pandas.concat()` when concatenating a multicolumn DataFrame with tz-aware data against a DataFrame with a different number of columns (GH22796)

• Bug in `merge_asof()` where confusing error message raised when attempting to merge with missing values (GH23189)

• Bug in `DataFrame.nsmallest()` and `DataFrame.nlargest()` for dataframes that have a `MultiIndex` for columns (GH23033).

• Bug in `pandas.melt()` when passing column names that are not present in `DataFrame` (GH23575)

• Bug in `DataFrame.append()` with a `Series` with a dateutil timezone would raise a `TypeError` (GH23682)

• Bug in `Series` construction when passing no data and `dtype=str` (GH22477)

• Bug in `cut()` with bins as an overlapping `IntervalIndex` where multiple bins were returned per item instead of raising a `ValueError` (GH23980)

• Bug in `pandas.concat()` when joining `Series` datetimetz with `Series` category would lose timezone (GH23816)

• Bug in `DataFrame.join()` when joining on partial `MultiIndex` would drop names (GH20452).

• `DataFrame.nlargest()` and `DataFrame.nsmallest()` now returns the correct n values when keep != ‘all’ also when tied on the first columns (GH22752)

• Constructing a DataFrame with an index argument that wasn’t already an instance of `Index` was broken (GH22227).

• Bug in `DataFrame` prevented list subclasses to be used to construction (GH21226)

• Bug in `DataFrame.unstack()` and `DataFrame.pivot_table()` returning a misleading error message when the resulting DataFrame has more elements than `int32` can handle. Now, the error message is improved, pointing towards the actual problem (GH20601)

• Bug in `DataFrame.unstack()` where a `ValueError` was raised when unstacking timezone aware values (GH18338)

• Bug in `DataFrame.stack()` where timezone aware values were converted to timezone naive values (GH19420)

• Bug in `merge_asof()` where a `TypeError` was raised when `by_col` were timezone aware values (GH21184)

• Bug showing an incorrect shape when throwing error during `DataFrame` construction. (GH20742)
Sparse

- Updating a boolean, datetime, or timedelta column to be Sparse now works (GH22367)
- Bug in `Series.to_sparse()` with Series already holding sparse data not constructing properly (GH22389)
- Providing a `sparse_index` to the `SparseArray` constructor no longer defaults the `na-value` to `np.nan` for all dtypes. The correct `na_value` for `data.dtype` is now used.
- Bug in `SparseArray.nbytes` under-reporting its memory usage by not including the size of its sparse index.
- Improved performance of `Series.shift()` for non-NA `fill_value`, as values are no longer converted to a dense array.
- Bug in `DataFrame.groupby` not including `fill_value` in the groups for non-NA `fill_value` when grouping by a sparse column (GH5078)
- Bug in unary inversion operator (~) on a `SparseSeries` with boolean values. The performance of this has also been improved (GH22835)
- Bug in `SparseArray.unique()` not returning the unique values (GH19595)
- Bug in `SparseArray.nonzero()` and `SparseDataFrame.dropna()` returning shifted/incorrect results (GH21172)
- Bug in `DataFrame.apply()` where dtypes would lose sparseness (GH23744)
- Bug in `concat()` when concatenating a list of `Series` with all-sparse values changing the `fill_value` and converting to a dense Series (GH24371)

Style

- `background_gradient()` now takes a `text_color_threshold` parameter to automatically lighten the text color based on the luminance of the background color. This improves readability with dark background colors without the need to limit the background colormap range. (GH21258)
- `background_gradient()` now also supports tablewise application (in addition to rowwise and columnwise) with `axis=None` (GH15204)
- `bar()` now also supports tablewise application (in addition to rowwise and columnwise) with `axis=None` and setting clipping range with `vmin` and `vmax` (GH21548 and GH21526). NaN values are also handled properly.

Build changes

- Building pandas for development now requires `cython` >= 0.28.2 (GH21688)
- Testing pandas now requires `hypothesis`>=3.58. You can find the `Hypothesis` docs here, and a pandas-specific introduction in the contributing guide. (GH22280)
- Building pandas on macOS now targets minimum macOS 10.9 if run on macOS 10.9 or above (GH23424)
Other

- Bug where C variables were declared with external linkage causing import errors if certain other C libraries were imported before Pandas. (GH24113)

Contributors

A total of 337 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- AJ Dyka +
- AJ Pryor, Ph.D +
- Aaron Critchley
- Adam Hooper
- Adam J. Stewart
- Adam Kim
- Adam Klimont +
- Addison Lynch +
- Alan Hogue +
- Alex Radu +
- Alex Rychyk
- Alex Strick van Linschoten +
- Alex Volkov +
- Alexander Buchkovsky
- Alexander Hess +
- Alexander Ponomaroff +
- Allison Browne +
- Aly Sivji
- Andrew
- Andrew Gross +
- Andrew Spott +
- Andy +
- Aniket uttam +
- Anjali2019 +
- Anjana S +
- Antti Kähölä +
- Anudeep Tubati +
- Arjun Sharma +
- Armin Varshokar
pandas: powerful Python data analysis toolkit, Release 1.1.1

- Artem Bogachev
- ArtinSarraf +
- Barry Fitzgerald +
- Bart Aelterman +
- Ben James +
- Ben Nelson +
- Benjamin Grove +
- Benjamin Rowell +
- Benoit Paquet +
- Boris Lau +
- Brett Naul
- Brian Choi +
- C.A.M. Gerlach +
- Carl Johan +
- Chalmer Lowe
- Chang She
- Charles David +
- Cheuk Ting Ho
- Chris
- Chris Roberts +
- Christopher Whelan
- Chu Qing Hao +
- Da Cheezy Mobsta +
- Damini Satya
- Daniel Himmelstein
- Daniel Saxton +
- Darcy Meyer +
- DataOmbudsman
- David Arcos
- David Krych
- Dean Langsam +
- Diego Argueta +
- Diego Torres +
- Dobatymo +
- Doug Latornell +
- Dr. Irv
• Dylan Dmitri Gray +
• Eric Boxer +
• Eric Chea
• Erik +
• Erik Nilsson +
• Fabian Haase +
• Fabian Retkowski
• Fabien Aulaire +
• Fakabbir Amin +
• Fei Phoon +
• Fernando Margueirat +
• Florian Müller +
• Fábio Rosado +
• Gabe Fernando
• Gabriel Reid +
• Giftlin Rajaiah
• Gioia Ballin +
• Gjelt
• Gosuke Shibahara +
• Graham Inggs
• Guillaume Gay
• Guillaume Lemaitre +
• Hannah Ferchland
• Haochen Wu
• Hubert +
• HubertKl +
• HyunTruth +
• Iain Barr
• Ignacio Vergara Kausel +
• Irv Lustig +
• IsvenC +
• Jacopo Rota
• Jakob Jarmar +
• James Bourbeau +
• James Myatt +
• James Winegar +
• Jan Rudolph
• Jared Groves +
• Jason Kiley +
• Javad Noorbakhsh +
• Jay Offerdahl +
• Jeff Reback
• Jeongmin Yu +
• Jeremy Schendel
• Jerod Estapa +
• Jesper Dramsch +
• Jim Jeon +
• Joe Jevnik
• Joel Nothman
• Joel Ostblom +
• Jordi Contestí
• Jorge López Fueyo +
• Joris Van den Bossche
• Jose Quinones +
• Jose Rivera-Rubio +
• Josh
• Jun +
• Justin Zheng +
• Kaiqi Dong +
• Kalyan Gokhale
• Kang Yoosam +
• Karl Dunkle Werner +
• Karmanya Aggarwal +
• Kevin Markham +
• Kevin Sheppard
• Kimi Li +
• Koustav Samaddar +
• Krishna +
• Kristian Holsheimer +
• Ksenia Gueletina +
• Kyle Prestel +
• LJ +
• LeakedMemory +
• Li Jin +
• Licht Takeuchi
• Luca Donini +
• Luciano Viola +
• Mak Sze Chun +
• Marc Garcia
• Marius Potgieter +
• Mark Sikora +
• Markus Meier +
• Marlene Silva Marchena +
• Martin Babka +
• MatanCohe +
• Mateusz Woś +
• Mathew Topper +
• Matt Boggess +
• Matt Cooper +
• Matt Williams +
• Matthew Gilbert
• Matthew Roeschke
• Max Kanter
• Michael Odintsov
• Michael Silverstein +
• Michael-J-Ward +
• Mickaël Schoentgen +
• Miguel Sánchez de León Peque +
• Ming Li
• Mitar
• Mitch Negus
• Monson Shao +
• Moonsoo Kim +
• Mortada Mehyar
• Myles Braithwaite
• Nehil Jain +
• Nicholas Musolino +
• Nicolas Dickreuter +
• Nikhil Kumar Mengani +
• Nikoleta Glynatsi +
• Ondrej Kokes
• Pablo Ambrosio +
• Pamela Wu +
• Parfait G +
• Patrick Park +
• Paul
• Paul Ganssle
• Paul Reidy
• Paul van Mulbregt +
• Phillip Cloud
• Pietro Battiston
• Piyush Aggarwal +
• Prabakaran Kumaresshan +
• Pulkit Maloo
• Pyry Kovanen
• Rajib Mitra +
• Redonnet Louis +
• Rhys Parry +
• Rick +
• Robin
• Roei.r +
• RomainSa +
• Roman Imankulov +
• Roman Yurchak +
• Ruijing Li +
• Ryan +
• Ryan Nazareth +
• Rüdiger Busche +
• SEUNG HOON, SHIN +
• Sandrine Pataut +
• Sangwoong Yoon
• Santosh Kumar +
• Saurav Chakravorty +
• Scott McAllister +
• Sean Chan +
• Shadi Akiki +
• Shengpu Tang +
• Shirish Kadam +
• Simon Hawkins +
• Simon Riddell +
• Simone Basso
• Sinhrks
• Soyoun(Rose) Kim +
• Srinivas Reddy Thatiparthya ( ) +
• Stefaan Lippens +
• Stefano Cianciulli
• Stefano Miccoli +
• Stephen Childs
• Stephen Pascoe
• Steve Baker +
• Steve Cook +
• Steve Dower +
• Stéphane Taljaard +
• Sumin Byeon +
• Sören +
• Tamas Nagy +
• Tanya Jain +
• Tarbo Fukazawa
• Thein Oo +
• Thiago Cordeiro da Fonseca +
• Thierry Moisan
• Thiviyan Thanapalasingam +
• Thomas Lentali +
• Tim D. Smith +
• Tim Swast
• Tom Augspurger
• Tomasz Kluczkowski +
• Tony Tao +
• Triple0 +
• Troels Nielsen +
pandas: powerful Python data analysis toolkit, Release 1.1.1

- Tuhin Mahmud +
- Tyler Reddy +
- Uddeshya Singh
- Uwe L. Korn +
- Vadym Barda +
- Varad Gunjal +
- Victor Maryama +
- Victor Villas
- Vincent La
- Vitória Helena +
- Vu Le
- Vyom Jain +
- Weiwen Gu +
- Wenhuan
- Wes Turner
- Wil Tan +
- William Ayd
- Yeojin Kim +
- Yitzhak Andrade +
- Yuecheng Wu +
- Yuliya Dovzhenko +
- Yury Bayda +
- Zac Hatfield-Dodds +
- aberres +
- aeltanawy +
- ailchau +
- alimcmaster1
- alphaCTzo7G +
- amphy +
- araraonline +
- azure-pipelines[bot] +
- benarthur91 +
- bk521234 +
- cgangwar11 +
- chris-b1
- cxl923cc +
5.5 Version 0.23

5.5.1 What’s new in 0.23.4 (August 3, 2018)

This is a minor bug-fix release in the 0.23.x series and includes some small regression fixes and bug fixes. We recommend that all users upgrade to this version.

Warning: Starting January 1, 2019, pandas feature releases will support Python 3 only. See Dropping Python 2.7 for more.

What’s new in v0.23.4

- Fixed regressions
- Bug fixes
- Contributors
Fixed regressions

- Python 3.7 with Windows gave all missing values for rolling variance calculations (GH21813)

Bug fixes

Groupby/resample/rolling

- Bug where calling DataFrameGroupBy.agg() with a list of functions including ohlc as the non-initial element would raise a ValueError (GH21716)
- Bug in roll_quantile caused a memory leak when calling .rolling(...).quantile(q) with q in (0,1) (GH21965)

Missing

- Bug in Series.clip() and DataFrame.clip() cannot accept list-like threshold containing NaN (GH19992)

Contributors

A total of 6 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Jeff Reback
- MeeseeksMachine +
- Tom Augspurger
- chris-b1
- h-vetinari
- meeseeksdev[bot]

5.5.2 What’s new in 0.23.3 (July 7, 2018)

This release fixes a build issue with the sdist for Python 3.7 (GH21785) There are no other changes.

Contributors

A total of 2 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Tom Augspurger
- meeseeksdev[bot] +
5.5.3 What’s new in 0.23.2 (July 5, 2018)

This is a minor bug-fix release in the 0.23.x series and includes some small regression fixes and bug fixes. We recommend that all users upgrade to this version.

Note: Pandas 0.23.2 is first pandas release that’s compatible with Python 3.7 (GH20552)

Warning: Starting January 1, 2019, pandas feature releases will support Python 3 only. See Dropping Python 2.7 for more.

What’s new in v0.23.2

- Logical reductions over entire DataFrame
- Fixed regressions
- Build changes
- Bug fixes
- Contributors

Logical reductions over entire DataFrame

DataFrame.all() and DataFrame.any() now accept axis=None to reduce over all axes to a scalar (GH19976)

```
In [1]: df = pd.DataFrame({"A": [1, 2], "B": [True, False]})
In [2]: df.all(axis=None)
Out[2]: False
```

This also provides compatibility with NumPy 1.15, which now dispatches to DataFrame.all. With NumPy 1.15 and pandas 0.23.1 or earlier, numpy.all() will no longer reduce over every axis:

```
>>> # NumPy 1.15, pandas 0.23.1
>>> np.any(pd.DataFrame({"A": [False], "B": [False]}))
A     False
B     False
dtype: bool
```

With pandas 0.23.2, that will correctly return False, as it did with NumPy < 1.15.

```
In [3]: np.any(pd.DataFrame({"A": [False], "B": [False]}))
Out[3]: False
```
Fixed regressions

- Fixed regression in `to_csv()` when handling file-like object incorrectly (GH21471)
- Re-allowed duplicate level names of a MultiIndex. Accessing a level that has a duplicate name by name still raises an error (GH19029).
- Bug in both `DataFrame.first_valid_index()` and `Series.first_valid_index()` raised for a row index having duplicate values (GH21441)
- Fixed printing of DataFrames with hierarchical columns with long names (GH21180)
- Fixed regression in `reindex()` and `groupby()` with a MultiIndex or multiple keys that contains categorical datetime-like values (GH21390).
- Fixed regression in unary negative operations with object dtype (GH21380)
- Bug in `Timestamp.ceil()` and `Timestamp.floor()` when timestamp is a multiple of the rounding frequency (GH21262)
- Fixed regression in `to_clipboard()` that defaulted to copying dataframes with space delimited instead of tab delimited (GH21104)

Build changes

- The source and binary distributions no longer include test data files, resulting in smaller download sizes. Tests relying on these data files will be skipped when using `pandas.test()`.(GH19320)

Bug fixes

Conversion

- Bug in constructing `Index` with an iterator or generator (GH21470)
- Bug in `Series.nlargest()` for signed and unsigned integer dtypes when the minimum value is present (GH21426)

Indexing

- Bug in `Index.get_indexer_non_unique()` with categorical key (GH21448)
- Bug in comparison operations for `MultiIndex` where error was raised on equality / inequality comparison involving a MultiIndex with `nlevels == 1` (GH21149)
- Bug in `DataFrame.drop()` behaviour is not consistent for unique and non-unique indexes (GH21494)
- Bug in `DataFrame.duplicated()` with a large number of columns causing a ‘maximum recursion depth exceeded’ (GH21524).

I/O

- Bug in `read_csv()` that caused it to incorrectly raise an error when `nrows=0, low_memory=True, and index_col` was not None (GH21141)
- Bug in `json_normalize()` when formatting the `record_prefix` with integer columns (GH21536)

Categorical

- Bug in rendering `Series` with `Categorical` dtype in rare conditions under Python 2.7 (GH21002)

Timezones

5.5. Version 0.23
• Bug in `Timestamp` and `DatetimeIndex` where passing a `Timestamp` localized after a DST transition would return a datetime before the DST transition (GH20854)

• Bug in comparing `DataFrame` with tz-aware `DatetimeIndex` columns with a DST transition that raised a `KeyError` (GH19970)

• Bug in `DatetimeIndex.shift()` where an `AssertionError` would raise when shifting across DST (GH8616)

• Bug in `Timestamp` constructor where passing an invalid timezone offset designator (Z) would not raise a `ValueError` (GH8910)

• Bug in `Timestamp.replace()` where replacing at a DST boundary would retain an incorrect offset (GH7825)

• Bug in `DatetimeIndex.reindex()` when reindexing a tz-naive and tz-aware `DatetimeIndex` (GH8306)

• Bug in `DatetimeIndex.resample()` when downspacing across a DST boundary (GH8531)

**Timedelta**

• Bug in `Timedelta` where non-zero timedeltas shorter than 1 microsecond were considered False (GH21484)

**Contributors**

A total of 17 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

• David Krych
• Jacopo Rota +
• Jeff Reback
• Jeremy Schendel
• Joris Van den Bossche
• Kalyan Gokhale
• Matthew Roeschke
• Michael Odintsov +
• Ming Li
• Pietro Battistoni
• Tom Augspurger
• Uddeshya Singh
• Vu Le +
• alimcmaster1 +
• david-liu-brattle-1 +
• gfyong
• jbrockmendel
5.5.4 What’s new in 0.23.1 (June 12, 2018)

This is a minor bug-fix release in the 0.23.x series and includes some small regression fixes and bug fixes. We recommend that all users upgrade to this version.

Warning: Starting January 1, 2019, pandas feature releases will support Python 3 only. See Dropping Python 2.7 for more.

What’s new in v0.23.1

• Fixed regressions
• Performance improvements
• Bug fixes
• Contributors

Fixed regressions

Comparing Series with datetime.date

We’ve reverted a 0.23.0 change to comparing a Series holding datetimes and a datetime.date object (GH21152). In pandas 0.22 and earlier, comparing a Series holding datetimes and datetime.date objects would coerce the datetime.date to a datetime before comparing. This was inconsistent with Python, NumPy, and DatetimeIndex, which never consider a datetime and datetime.date equal.

In 0.23.0, we unified operations between DatetimeIndex and Series, and in the process changed comparisons between a Series of datetimes and datetime.date without warning.

We’ve temporarily restored the 0.22.0 behavior, so datetimes and dates may again compare equal, but restore the 0.23.0 behavior in a future release.

To summarize, here’s the behavior in 0.22.0, 0.23.0, 0.23.1:

```python
# 0.22.0... Silently coerce the datetime.date
>>> import datetime
>>> pd.Series(pd.date_range('2017', periods=2)) == datetime.date(2017, 1, 1)
0   True
1  False
dtype: bool

# 0.23.0... Do not coerce the datetime.date
>>> pd.Series(pd.date_range('2017', periods=2)) == datetime.date(2017, 1, 1)
0   False
1   False
dtype: bool

# 0.23.1... Coerce the datetime.date with a warning
>>> pd.Series(pd.date_range('2017', periods=2)) == datetime.date(2017, 1, 1)
/bin/python:1: FutureWarning: Comparing Series of datetimes with 'datetime.date'.
Currently, the 'datetime.date' is coerced to a datetime. In the future pandas will not coerce, and the values not compare equal to the 'datetime.date'.
To retain the current behavior, convert the 'datetime.date' to a
```

(continues on next page)
In addition, ordering comparisons will raise a `TypeError` in the future.

**Other fixes**

- Reverted the ability of `to_sql()` to perform multivalue inserts as this caused regression in certain cases (GH21103). In the future this will be made configurable.
- Fixed regression in the `DatetimeIndex.date` and `DatetimeIndex.time` attributes in case of timezone-aware data: `DatetimeIndex.time` returned a tz-aware time instead of tz-naive (GH21267) and `DatetimeIndex.date` returned incorrect date when the input date has a non-UTC timezone (GH21230).
- Fixed regression in `pandas.io.json.json_normalize()` when called with `None` values in nested levels in JSON, and to not drop keys with value as `None` (GH21158, GH21356).
- Bug in `to_csv()` causes encoding error when compression and encoding are specified (GH21241, GH21118)
- Bug preventing pandas from being importable with -OO optimization (GH21071)
- Bug in `Categorical.fillna()` incorrectly raising a `TypeError` when `value` the individual categories are iterable and `value` is an iterable (GH21097, GH19788)
- Fixed regression in constructors coercing NA values like `None` to strings when passing `dtype=str` (GH21083)
- Regression in `pivot_table()` where an ordered `Categorical` with missing values for the pivot's index would give a mis-aligned result (GH21133)
- Fixed regression in merging on boolean index/columns (GH21119).

**Performance improvements**

- Improved performance of `CategoricalIndex.is_monotonic_increasing()`, `CategoricalIndex.is_monotonic_decreasing()` and `CategoricalIndex.is_monotonic()` (GH21025)
- Improved performance of `CategoricalIndex.is_unique()` (GH21107)

**Bug fixes**

**Groupby/resample/rolling**

- Bug in `DataFrame.agg()` where applying multiple aggregation functions to a `DataFrame` with duplicated column names would cause a stack overflow (GH21063)
- Bug in `pandas.core.groupby.GroupBy.ffill()` and `pandas.core.groupby.GroupBy.bfill()` where the fill within a grouping would not always be applied as intended due to the implementations’ use of a non-stable sort (GH21207)
- Bug in `pandas.core.groupby.GroupBy.rank()` where results did not scale to 100% when specifying method='dense' and pct=True
- Bug in `pandas.DataFrame.rolling()` and `pandas.Series.rolling()` which incorrectly accepted a 0 window size rather than raising (GH21286)
Data-type specific

- Bug in Series.str.replace() where the method throws TypeError on Python 3.5.2 (GH21078)
- Bug in Timedelta where passing a float with a unit would prematurely round the float precision (GH14156)
- Bug in pandas.testing.assert_index_equal() which raised AssertionError incorrectly, when comparing two CategoricalIndex objects with param check_categorical=False (GH19776)

Sparse

- Bug in SparseArray.shape which previously only returned the shape SparseArray.sp_values (GH21126)

Indexing

- Bug in Series.reset_index() where appropriate error was not raised with an invalid level name (GH20925)
- Bug in interval_range() when start/periods or end/periods are specified with float start or end (GH21161)
- Bug in MultiIndex.set_names() where error raised for a MultiIndex with nlevels == 1 (GH21149)
- Bug in IntervalIndex constructors where creating an IntervalIndex from categorical data was not fully supported (GH21243, GH21253)
- Bug in MultiIndex.sort_index() which was not guaranteed to sort correctly with level=1; this was also causing data misalignment in particular DataFrame.stack() operations (GH20994, GH20945, GH21052)

Plotting

- New keywords (sharex, sharey) to turn on/off sharing of x/y-axis by subplots generated with pandas.DataFrame().groupby().boxplot() (GH20968)

I/O

- Bug in IO methods specifying compression='zip' which produced uncompressed zip archives (GH17778, GH21144)
- Bug in DataFrame.to_stata() which prevented exporting DataFrames to buffers and most file-like objects (GH21041)
- Bug in read_stata() and StataReader which did not correctly decode utf-8 strings on Python 3 from Stata 14 files (dta version 118) (GH21244)
- Bug in IO JSON read_json() reading empty JSON schema with orient='table' back to DataFrame caused an error (GH21287)

Reshaping

- Bug in concat() where error was raised in concatenating Series with numpy scalar and tuple names (GH21015)
- Bug in concat() warning message providing the wrong guidance for future behavior (GH21101)

Other

- Tab completion on Index in IPython no longer outputs deprecation warnings (GH21125)
- Bug preventing pandas being used on Windows without C++ redistributable installed (GH21106)
Contributors

A total of 30 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Adam J. Stewart
- Adam Kim +
- Aly Sivji
- Chalmer Lowe +
- Damini Satya +
- Dr. Irv
- Gabe Fernando +
- Giftlin Rajaiah
- Jeff Reback
- Jeremy Schendel +
- Joris Van den Bossche
- Kalyan Gokhale +
- Kevin Sheppard
- Matthew Roeschke
- Max Kanter +
- Ming Li
- Pyry Kovanen +
- Stefano Cianciulli
- Tom Augspurger
- Uddeshya Singh +
- Wenhuan
- William Ayd
- chris-b1
- gfyounq
- h-vetinari
- nprad +
- ssikdar1 +
- tmnhat2001
- topper-123
- zertrin +
5.5.5 What’s new in 0.23.0 (May 15, 2018)

This is a major release from 0.22.0 and includes a number of API changes, deprecations, new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- Round-trippable JSON format with ‘table’ orient.
- Instantiation from dicts respects order for Python 3.6+.
- Dependent column arguments for assign.
- Merging / sorting on a combination of columns and index levels.
- Extending pandas with custom types.
- Excluding unobserved categories from groupby.
- Changes to make output shape of DataFrame.apply consistent.

Check the API Changes and deprecations before updating.

Warning: Starting January 1, 2019, pandas feature releases will support Python 3 only. See Dropping Python 2.7 for more.

What’s new in v0.23.0

- New features
  - JSON read/write round-trippable with orient='table'
  - .assign() accepts dependent arguments
  - Merging on a combination of columns and index levels
  - Sorting by a combination of columns and index levels
  - Extending pandas with custom types (experimental)
  - New observed keyword for excluding unobserved categories in groupby
  - Rolling/Expanding.apply() accepts raw=False to pass a Series to the function
  - DataFrame.interpolate has gained the limit_area kwarg
  - get_dummies now supports dtype argument
  - Timedelta mod method
  - .rank() handles inf values when NaN are present
  - Series.str.cat has gained the join kwarg
  - DataFrame.astype performs column-wise conversion to Categorical
  - Other enhancements

- Backwards incompatible API changes
  - Dependencies have increased minimum versions
  - Instantiation from dicts preserves dict insertion order for python 3.6+
– Deprecate Panel
– pandas.core.common removals
– Changes to make output of DataFrame.apply consistent
– Concatenation will no longer sort
– Build changes
– Index division by zero fills correctly
– Extraction of matching patterns from strings
– Default value for the ordered parameter of CategoricalDtype
– Better pretty-printing of DataFrames in a terminal
– Datetimelike API changes
– Other API changes

• Deprecations
• Removal of prior version deprecations/changes
• Performance improvements
• Documentation changes
• Bug fixes
  – Categorical
  – Datetimelike
  – Timedelta
  – Timezones
  – Offsets
  – Numeric
  – Strings
  – Indexing
  – MultiIndex
  – I/O
  – Plotting
  – Groupby/resample/rolling
  – Sparse
  – Reshaping
  – Other

• Contributors
New features

**JSON read/write round-trippable with orient='table'**

A DataFrame can now be written to and subsequently read back via JSON while preserving metadata through usage of the `orient='table'` argument (see GH18912 and GH9146). Previously, none of the available `orient` values guaranteed the preservation of dtypes and index names, amongst other metadata.

```python
In [1]: df = pd.DataFrame({
    'foo': [1, 2, 3, 4],
    'bar': ['a', 'b', 'c', 'd'],
    'baz': pd.date_range('2018-01-01', freq='d', periods=4),
    'qux': pd.Categorical(['a', 'b', 'c', 'c'])},
    index=pd.Index(range(4), name='idx'))

In [2]: df
Out[2]:
     foo  bar     baz     qux
  idx
   0  1    a 2018-01-01    a
   1  2    b 2018-01-02    b
   2  3    c 2018-01-03    c
   3  4    d 2018-01-04    c

[4 rows x 4 columns]

In [3]: df.dtypes
Out[3]:
foo     int64
bar    object
baz  datetime64[ns]
qux   category
Length: 4, dtype: object

In [4]: df.to_json('test.json', orient='table')

In [5]: new_df = pd.read_json('test.json', orient='table')

In [6]: new_df
Out[6]:
     foo  bar     baz     qux
  idx
   0  1    a 2018-01-01    a
   1  2    b 2018-01-02    b
   2  3    c 2018-01-03    c
   3  4    d 2018-01-04    c

[4 rows x 4 columns]

In [7]: new_df.dtypes
Out[7]:
foo     int64
bar    object
baz  datetime64[ns]
qux   category
Length: 4, dtype: object
```

Please note that the string `index` is not supported with the round trip format, as it is used by default in `write_json`
to indicate a missing index name.

```python
In [8]: df.index.name = 'index'
In [9]: df.to_json('test.json', orient='table')
In [10]: new_df = pd.read_json('test.json', orient='table')
In [11]: new_df
Out[11]:
    foo  bar   baz   qux
 0   1     a 2018-01-01   a
 1   2     b 2018-01-02   b
 2   3     c 2018-01-03   c
 3   4     d 2018-01-04   c
[4 rows x 4 columns]
In [12]: new_df.dtypes
Out[12]:
foo    int64
bar   object
baz  datetime64[ns]
qux     category
Length: 4, dtype: object
```

**.assign() accepts dependent arguments**

The `DataFrame.assign()` now accepts dependent keyword arguments for python version later than 3.6 (see also PEP 468). Later keyword arguments may now refer to earlier ones if the argument is a callable. See the documentation [here](GH14207).

```python
In [13]: df = pd.DataFrame({'A': [1, 2, 3]})
In [14]: df
Out[14]:
  A
0  1
1  2
2  3
[3 rows x 1 columns]
In [15]: df.assign(B=df.A, C=lambda x: x['A'] + x['B'])
Out[15]:
  A  B  C
0  1  1  2
1  2  2  4
2  3  3  6
[3 rows x 3 columns]
```

**Warning:** This may subtly change the behavior of your code when you’re using `.assign()` to update an existing column. Previously, callables referring to other variables being updated would get the “old” values.
Previous behavior:
In [2]: df = pd.DataFrame({"A": [1, 2, 3]})

In [3]: df.assign(A=\lambda df: df.A + 1, C=\lambda df: df.A * -1)
Out[3]:
   A  C
0  2 -1
1  3 -2
2  4 -3

New behavior:
In [16]: df.assign(A=df.A + 1, C=\lambda df: df.A * -1)
Out[16]:
   A  C
0  2 -2
1  3 -3
2  4 -4

[3 rows x 2 columns]

Merging on a combination of columns and index levels

Strings passed to DataFrame.merge() as the on, left_on, and right_on parameters may now refer to either column names or index level names. This enables merging DataFrame instances on a combination of index levels and columns without resetting indexes. See the Merge on columns and levels documentation section. (GH14355)

In [17]: left_index = pd.Index(['K0', 'K0', 'K1', 'K2'], name='key1')

In [18]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
                      'B': ['B0', 'B1', 'B2', 'B3'],
                      'key2': ['K0', 'K1', 'K0', 'K1'],
                      index=left_index)

In [19]: right_index = pd.Index(['K0', 'K1', 'K2', 'K2'], name='key1')

In [20]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
                         'D': ['D0', 'D1', 'D2', 'D3'],
                         'key2': ['K0', 'K0', 'K0', 'K1'],
                         index=right_index)

In [21]: left.merge(right, on=['key1', 'key2'])
Out[21]:
   A  B  key2  C  D
key1
K0  A0  B0  K0  C0  D0
K1  A2  B2  K0  C1  D1
K2  A3  B3  K1  C3  D3
[3 rows x 5 columns]
Sorting by a combination of columns and index levels

Strings passed to `DataFrame.sort_values()` as the `by` parameter may now refer to either column names or index level names. This enables sorting `DataFrame` instances by a combination of index levels and columns without resetting indexes. See the *Sorting by Indexes and Values* documentation section. (GH14353)

```python
# Build MultiIndex
In [22]: idx = pd.MultiIndex.from_tuples([('a', 1), ('a', 2), ('a', 2),
                                     ....: ('b', 2), ('b', 1), ('b', 1)])

In [23]: idx.names = ['first', 'second']

# Build DataFrame
In [24]: df_multi = pd.DataFrame({'A': np.arange(6, 0, -1)},
                             index=idx)

In [25]: df_multi
Out[25]:
   A
first second
a   1   6
    2   5
    2   4
b   2   3
    1   2
    1   1

[6 rows x 1 columns]

# Sort by 'second' (index) and 'A' (column)
In [26]: df_multi.sort_values(by=['second', 'A'])
Out[26]:
   A
first second
b   1   1
    1   2
a   1   6
b   2   3
a   2   4
    2   5

[6 rows x 1 columns]
```

Extending pandas with custom types (experimental)

Pandas now supports storing array-like objects that aren’t necessarily 1-D NumPy arrays as columns in a DataFrame or values in a Series. This allows third-party libraries to implement extensions to NumPy’s types, similar to how pandas implemented categoricals, datetimes with timezones, periods, and intervals.

As a demonstration, we’ll use cyberpandas, which provides an `IPArray` type for storing ip addresses.

```python
In [1]: from cyberpandas import IPArray
In [2]: values = IPArray({
```
IPArray isn’t a normal 1-D NumPy array, but because it’s a pandas ExtensionArray, it can be stored properly inside pandas’ containers.

```
In [3]: ser = pd.Series(values)
In [4]: ser
Out[4]:
0 0.0.0.0
1 192.168.1.1
2 2001:db8:85a3::8a2e:370:7334
dtype: ip
```

Notice that the dtype is ip. The missing value semantics of the underlying array are respected:

```
In [5]: ser.isna()
Out[5]:
0   True
1  False
2  False
dtype: bool
```

For more, see the extension types documentation. If you build an extension array, publicize it on our ecosystem page.

**New observed keyword for excluding unobserved categories in groupby**

Grouping by a categorical includes the unobserved categories in the output. When grouping by multiple categorical columns, this means you get the cartesian product of all the categories, including combinations where there are no observations, which can result in a large number of groups. We have added a keyword `observed` to control this behavior, it defaults to `observed=False` for backward-compatibility. (GH14942, GH8138, GH15217, GH17594, GH8669, GH20583, GH20902)

```
In [27]: cat1 = pd.Categorical(["a", "a", "b", "b"],
    categories=["a", "b", "z"], ordered=True)
    ....:
In [28]: cat2 = pd.Categorical(["c", "d", "c", "d"],
    categories=["c", "d", "y"], ordered=True)
    ....:
In [29]: df = pd.DataFrame({"A": cat1, "B": cat2, "values": [1, 2, 3, 4]})
In [30]: df['C'] = ['foo', 'bar'] * 2
In [31]: df
Out[31]:
A  B  values  C
0 a  c    1  foo
1 a  d    2  bar
```

(continues on next page)
To show all values, the previous behavior:

```python
In [32]: df.groupby(['A', 'B', 'C'], observed=False).count()
Out[32]:
   values
   A  B  C
a  c  bar  NaN
   foo  1.0
   d  bar  1.0
   foo  NaN
b  c  foo  NaN
   d  bar  NaN
   foo  NaN
... ... ...
z  c  foo  NaN
   d  bar  NaN
   foo  NaN
   NaN
[18 rows x 1 columns]
```

To show only observed values:

```python
In [33]: df.groupby(['A', 'B', 'C'], observed=True).count()
Out[33]:
   values
   A  B  C
a  c  foo  1
   d  bar  1
b  c  foo  1
   d  bar  1
[4 rows x 1 columns]
```

For pivoting operations, this behavior is already controlled by the `dropna` keyword:

```python
In [34]: cat1 = pd.Categorical(['a', 'a', 'b', 'b'], categories=['a', 'b', 'z'], ordered=True)
In [35]: cat2 = pd.Categorical(['c', 'd', 'c', 'd'], categories=['c', 'd', 'y'], ordered=True)
In [36]: df = pd.DataFrame({'A': cat1, 'B': cat2, 'values': [1, 2, 3, 4]})
In [37]: df
Out[37]:
   A  B  values
0  a  c   1
1  a  d   2
2  b  c   3
3  b  d   4
```

(continues on next page)
[4 rows x 3 columns]

```
In [38]: pd.pivot_table(df, values='values', index=['A', 'B'],
                  ....: dropna=True)
Out[38]:
   values
  A  B
a  c  1
  d  2
b  c  3
  d  4
[4 rows x 1 columns]
```

```
In [39]: pd.pivot_table(df, values='values', index=['A', 'B'],
                  ....: dropna=False)
Out[39]:
   values
  A  B
a  c  1.0
  d  2.0
b  c  3.0
  d  4.0
y  NaN  
z  c  NaN
  d  NaN
  y  NaN
[9 rows x 1 columns]
```

**Rolling/Expanding.apply() accepts raw=False to pass a Series to the function**

Series.rolling().apply(), DataFrame.rolling().apply(), Series.expanding().apply(), and DataFrame.expanding().apply() have gained a raw=None parameter. This is similar to DataFrame.apply(). This parameter, if True allows one to send a np.ndarray to the applied function. If False a Series will be passed. The default is None, which preserves backward compatibility, so this will default to True, sending an np.ndarray. In a future version the default will be changed to False, sending a Series. (GH5071, GH20584)

```
In [40]: s = pd.Series(np.arange(5), np.arange(5) + 1)

In [41]: s
Out[41]:
  0  1
  1  2
  2  3
  3  4
  4  5
Length: 5, dtype: int64
```

Pass a Series:
In [42]: s.rolling(2, min_periods=1).apply(lambda x: x.iloc[-1], raw=False)
Out[42]:
   0   0.0
   1   1.0
   2   2.0
   3   3.0
   4   4.0
Length: 5, dtype: float64

Mimic the original behavior of passing a ndarray:

In [43]: s.rolling(2, min_periods=1).apply(lambda x: x[-1], raw=True)
Out[43]:
   0   0.0
   1   1.0
   2   2.0
   3   3.0
   4   4.0
Length: 5, dtype: float64

**DataFrame.interpolate has gained the limit_area kwarg**

*DataFrame.interpolate()* has gained a *limit_area* parameter to allow further control of which NaNs are replaced. Use *limit_area='inside'* to fill only NaNs surrounded by valid values or use *limit_area='outside'* to fill only NaNs outside the existing valid values while preserving those inside. (GH16284) See the full documentation here.

In [44]: ser = pd.Series([np.nan, np.nan, 5, np.nan, np.nan,
     ....: np.nan, 13, np.nan, np.nan])

In [45]: ser
Out[45]:
   0   NaN
   1   NaN
   2   5.0
   3   NaN
   4   NaN
   5   NaN
   6   13.0
   7   NaN
   8   NaN
Length: 9, dtype: float64

Fill one consecutive inside value in both directions

In [46]: ser.interpolate(limit_direction='both', limit_area='inside', limit=1)
Out[46]:
   0   NaN
   1   NaN
   2   5.0
   3   7.0
   4   NaN
   5   11.0
   6   13.0
(continues on next page)
Fill all consecutive outside values backward

In [47]: ser.interpolate(limit_direction='backward', limit_area='outside')
Out[47]:
0   5.0  
1   5.0  
2   5.0  
3   NaN  
4   NaN  
5   NaN  
6  13.0  
7   NaN  
8   NaN  
Length: 9, dtype: float64

Fill all consecutive outside values in both directions

In [48]: ser.interpolate(limit_direction='both', limit_area='outside')
Out[48]:
0   5.0  
1   5.0  
2   5.0  
3   NaN  
4   NaN  
5   NaN  
6  13.0  
7  13.0  
8  13.0  
Length: 9, dtype: float64

get_dummies now supports dtype argument

The `get_dummies()` now accepts a `dtype` argument, which specifies a dtype for the new columns. The default remains `uint8`. (GH18330)

In [49]: df = pd.DataFrame({'a': [1, 2], 'b': [3, 4], 'c': [5, 6]})
In [50]: pd.get_dummies(df, columns=['c']).dtypes
Out[50]:
a  int64
b  int64
c_5 uint8
c_6 uint8
Length: 4, dtype: object
In [51]: pd.get_dummies(df, columns=['c'], dtype=bool).dtypes
Out[51]:
a  int64
b  int64
c_5 bool
Length: 4, dtype: object

(continues on next page)
Timedelta mod method

mod(%) and divmod operations are now defined on Timedelta objects when operating with either timedelta-like or with numeric arguments. See the documentation here. (GH19365)

In [52]: td = pd.Timedelta(hours=37)
In [53]: td % pd.Timedelta(minutes=45)
Out[53]: Timedelta('0 days 00:15:00')

.rank() handles inf values when NaN are present

In previous versions, .rank() would assign inf elements NaN as their ranks. Now ranks are calculated properly. (GH6945)

In [54]: s = pd.Series([-np.inf, 0, 1, np.nan, np.inf])
In [55]: s
Out[55]:
0   -inf
1    0.0
2    1.0
3    NaN
4     inf
Length: 5, dtype: float64

Previous behavior:

In [11]: s.rank()
Out[11]:
0    1.0
1    2.0
2    3.0
3    NaN
4    NaN
dtype: float64

Current behavior:

In [56]: s.rank()
Out[56]:
0    1.0
1    2.0
2    3.0
3    NaN
4    4.0
Length: 5, dtype: float64

Furthermore, previously if you rank inf or -inf values together with NaN values, the calculation won’t distinguish NaN from infinity when using ‘top’ or ‘bottom’ argument.
In [57]: s = pd.Series([np.nan, np.nan, -np.inf, -np.inf])

In [58]: s
Out[58]:
0    NaN
1    NaN
2   -inf
3   -inf
Length: 4, dtype: float64

Previous behavior:

In [15]: s.rank(na_option='top')
Out[15]:
0   2.5
1   2.5
2   2.5
3   2.5
dtype: float64

Current behavior:

In [59]: s.rank(na_option='top')
Out[59]:
0   1.5
1   1.5
2   3.5
3   3.5
Length: 4, dtype: float64

These bugs were squashed:

- Bug in `DataFrame.rank()` and `Series.rank()` when method='dense' and pct=True in which percentile ranks were not being used with the number of distinct observations (GH15630)
- Bug in `Series.rank()` and `DataFrame.rank()` when ascending='False' failed to return correct ranks for infinity if NaN were present (GH19538)
- Bug in `DataFrameGroupBy.rank()` where ranks were incorrect when both infinity and NaN were present (GH20561)

`Series.str.cat` has gained the `join` kwarg

Previously, `Series.str.cat()` did not – in contrast to most of pandas – align `Series` on their index before concatenation (see GH18657). The method has now gained a keyword `join` to control the manner of alignment, see examples below and [here](#).

In v.0.23 `join` will default to None (meaning no alignment), but this default will change to 'left' in a future version of pandas.

In [60]: s = pd.Series(['a', 'b', 'c', 'd'])

In [61]: t = pd.Series(['b', 'd', 'e', 'c'], index=[1, 3, 4, 2])

In [62]: s.str.cat(t)
Out[62]:
0    NaN
(continues on next page)
Furthermore, `Series.str.cat()` now works for `CategoricalIndex` as well (previously raised a `ValueError`; see GH20842).

### DataFrame.astype performs column-wise conversion to Categorical

`DataFrame.astype()` can now perform column-wise conversion to `Categorical` by supplying the string 'category' or a `CategoricalDtype`. Previously, attempting this would raise a `NotImplementedError`. See the `Object creation` section of the documentation for more details and examples. (GH12860, GH18099)

Supplying the string 'category' performs column-wise conversion, with only labels appearing in a given column set as categories:

```python
In [64]: df = pd.DataFrame({'A': list('abca'), 'B': list('bccd'))
In [65]: df = df.astype('category')
In [66]: df['A'].dtype
Out[66]: CategoricalDtype(categories=['a', 'b', 'c'], ordered=False)
In [67]: df['B'].dtype
Out[67]: CategoricalDtype(categories=['b', 'c', 'd'], ordered=False)
```

Supplying a `CategoricalDtype` will make the categories in each column consistent with the supplied dtype:

```python
In [68]: from pandas.api.types import CategoricalDtype
In [69]: df = pd.DataFrame({'A': list('abca'), 'B': list('bccd'))
In [70]: cdt = CategoricalDtype(categories=list('abcd'), ordered=True)
In [71]: df = df.astype(cdt)
In [72]: df['A'].dtype
Out[72]: CategoricalDtype(categories=['a', 'b', 'c', 'd'], ordered=True)
In [73]: df['B'].dtype
Out[73]: CategoricalDtype(categories=['a', 'b', 'c', 'd'], ordered=True)
```
Other enhancements

- Unary + now permitted for Series and DataFrame as numeric operator (GH16073)
- Better support for `to_excel()` output with the xlsxwriter engine. (GH16149)
- `pandas.tseries.frequencies.to_offset()` now accepts leading ‘+’ signs e.g. ‘+1h’. (GH18171)
- `MultiIndex.unique()` now supports the level= argument, to get unique values from a specific index level (GH18796)
- `pandas.io.formats.style.Styler` now has method `hide_index()` to determine whether the index will be rendered in output (GH14194)
- `pandas.io.formats.style.Styler` now has method `hide_columns()` to determine whether columns will be hidden in output (GH14194)
- Improved wording of `ValueError` raised in `to_datetime()` when unit= is passed with a non-convertible value (GH14350)
- `Series.fillna()` now accepts a Series or a dict as a value for a categorical dtype (GH17033)
- `pandas.read_clipboard()` updated to use qtpy, falling back to PyQt5 and then PyQt4, adding compatibility with Python3 and multiple python-qt bindings (GH17722)
- Improved wording of `ValueError` raised in `read_csv()` when the usecols argument cannot match all columns. (GH17301)
- `DataFrame.corrwith()` now silently drops non-numeric columns when passed a Series. Before, an exception was raised (GH18570).
- `IntervalIndex` now supports time zone aware `Interval` objects (GH18537, GH18538)
- `Series()` / `DataFrame()` tab completion also returns identifiers in the first level of a `MultiIndex()`. (GH16326)
- `read_excel()` has gained the `nrows` parameter (GH16645)
- `DataFrame.append()` can now in more cases preserve the type of the calling dataframe’s columns (e.g. if both are CategoricalIndex) (GH18359)
- `DataFrame.to_json()` and `Series.to_json()` now accept an index argument which allows the user to exclude the index from the JSON output (GH17394)
- `IntervalIndex.to_tuples()` has gained the `na_tuple` parameter to control whether NA is returned as a tuple of NA, or NA itself (GH18756)
- `Categorical.rename_categories`, `CategoricalIndex.rename_categories` and `Series.cat.rename_categories` can now take a callable as their argument (GH18862)
- `Interval` and `IntervalIndex` have gained a `length` attribute (GH18789)
- `Resampler` objects now have a functioning `pipe` method. Previously, calls to `pipe` were diverted to the mean method (GH17905).
- `is_scalar()` now returns True for DateOffset objects (GH18943).
- `DataFrame.pivot()` now accepts a list for the values= kwarg (GH17160).
- Added `pandas.api.extensions.register_dataframe_accessor()`, `pandas.api.extensions.register_series_accessor()`, and `pandas.api.extensions.register_index_accessor()`, accessor for libraries downstream of pandas to register custom accessors like `.cat` on pandas objects. See `Registering Custom Accessors` for more (GH14781).
• IntervalIndex.astype now supports conversions between subtypes when passed an IntervalDtype (GH19197)

• IntervalIndex and its associated constructor methods (from_arrays, from_breaks, from_tuples) have gained a dtype parameter (GH19262)

• Added pandas.core.groupby.SeriesGroupBy.is_monotonic_increasing() and pandas.core.groupby.SeriesGroupBy.is_monotonic_decreasing() (GH17015)

• For subclassed DataFrames, DataFrame.apply() will now preserve the Series subclass (if defined) when passing the data to the applied function (GH19822)

• DataFrame.from_dict() now accepts a columns argument that can be used to specify the column names when orient='index' is used (GH18529)

• Added option display.html.use_mathjax so MathJax can be disabled when rendering tables in Jupyter notebooks (GH19856, GH19824)

• DataFrame.replace() now supports the method parameter, which can be used to specify the replacement method when to_replace is a scalar, list or tuple and value is None (GH19632)

• Timestamp.month_name(), DatetimeIndex.month_name(), and Series.dt.month_name() are now available (GH12805)

• Timestamp.day_name() and DatetimeIndex.day_name() are now available to return day names with a specified locale (GH12806)

• DataFrame.to_sql() now performs a multi-value insert if the underlying connection supports itk rather than inserting row by row. SQLAlchemy dialects supporting multi-value inserts include: mysql, postgresql, sqlite and any dialect with supports_multivalues_insert. (GH14315, GH8953)

• read_html() now accepts a displayed_only keyword argument to controls whether or not hidden elements are parsed (True by default) (GH20027)

• read_html() now reads all <tbody> elements in a <table>, not just the first. (GH20690)

• quantile() and quantile() now accept the interpolation keyword, linear by default (GH20497)

• zip compression is supported via compression=zip in DataFrame.to_pickle(), Series.to_pickle(), DataFrame.to_csv(), Series.to_csv(), DataFrame.to_json(), Series.to_json(). (GH17778)

• WeekOfMonth constructor now supports n=0 (GH20517).

• DataFrame and Series now support matrix multiplication (@) operator (GH10259) for Python>=3.5

• Updated DataFrame.to_gbq() and pandas.read_gbq() signature and documentation to reflect changes from the Pandas-GBQ library version 0.4.0. Adds intersphinx mapping to Pandas-GBQ library. (GH20564)

• Added new writer for exporting Stata dta files in version 117, StataWriter117. This format supports exporting strings with lengths up to 2,000,000 characters (GH16450)

• to_hdf() and read_hdf() now accept an errors keyword argument to control encoding error handling (GH20835)

• cut() has gained the duplicates='raise' | 'drop' option to control whether to raise on duplicated edges (GH20947)

• date_range(), timedelta_range(), and interval_range() now return a linearly spaced index if start, stop, and periods are specified, but freq is not. (GH20808, GH20983, GH20976)
Backwards incompatible API changes

Dependencies have increased minimum versions

We have updated our minimum supported versions of dependencies (GH15184). If installed, we now require:

<table>
<thead>
<tr>
<th>Package</th>
<th>Minimum Version</th>
<th>Required</th>
<th>Issue</th>
</tr>
</thead>
<tbody>
<tr>
<td>python-dateutil</td>
<td>2.5.0</td>
<td>X</td>
<td>GH15184</td>
</tr>
<tr>
<td>openpyxl</td>
<td>2.4.0</td>
<td></td>
<td>GH15184</td>
</tr>
<tr>
<td>beautifulsoup4</td>
<td>4.2.1</td>
<td></td>
<td>GH20082</td>
</tr>
<tr>
<td>setuptools</td>
<td>24.2.0</td>
<td></td>
<td>GH20698</td>
</tr>
</tbody>
</table>

Instantiation from dicts preserves dict insertion order for python 3.6+

Until Python 3.6, dicts in Python had no formally defined ordering. For Python version 3.6 and later, dicts are ordered by insertion order, see PEP 468. Pandas will use the dict’s insertion order, when creating a `Series` or `DataFrame` from a dict and you’re using Python version 3.6 or higher. (GH19884)

Previous behavior (and current behavior if on Python < 3.6):

```
in [16]: pd.Series({'Income': 2000,
........:   'Expenses': -1500,
........:   'Taxes': -200,
........:   'Net result': 300})
```

```
Out[16]:
Expenses -1500
Income 2000
Net result 300
Taxes -200
dtype: int64
```

Note the Series above is ordered alphabetically by the index values.

New behavior (for Python >= 3.6):

```
in [74]: pd.Series({'Income': 2000,
........:   'Expenses': -1500,
........:   'Taxes': -200,
........:   'Net result': 300})
```

```
Out[74]:
Income 2000
Expenses -1500
Taxes -200
Net result 300
Length: 4, dtype: int64
```

Notice that the Series is now ordered by insertion order. This new behavior is used for all relevant pandas types (`Series`, `DataFrame`, `SparseSeries` and `SparseDataFrame`).

If you wish to retain the old behavior while using Python >= 3.6, you can use `.sort_index()`:

```
in [75]: pd.Series({'Income': 2000,
........:   'Expenses': -1500,
........:   'Taxes': -200,
```

(continues on next page)
.....:        'Net result': 300}).sort_index()
.....:
Out[75]:
Expenses  -1500
Income     2000
Net result  300
Taxes      -200
Length: 4, dtype: int64

Deprecate Panel

Panel was deprecated in the 0.20.x release, showing as a DeprecationWarning. Using Panel will now show a FutureWarning. The recommended way to represent 3-D data are with a MultiIndex on a DataFrame via the to_frame() or with the xarray package. Pandas provides a to_xarray() method to automate this conversion (GH13563, GH18324).

In [75]: import pandas._testing as tm

In [76]: p = tm.makePanel()

In [77]: p
Out[77]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 3 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D

Convert to a MultiIndex DataFrame

In [78]: p.to_frame()
Out[78]:
   major   minor
2000-01-03 A  0.469112  0.721555  0.404705
         B -1.135632  0.271860 -1.039268
         C  0.119209  0.276232 -1.344312
         D -2.104569  0.113648 -0.109050
2000-01-04 A -0.282863 -0.706771  0.577046
         B  1.212112 -0.424972 -0.370647
         C -1.044236 -1.087401  0.844885
         D -0.494929 -1.478427  1.643563
2000-01-05 A -1.509059 -1.039575 -1.715002
         B -0.173215  0.567020 -1.157892
         C -0.861849 -0.673690  1.075770
         D  1.071804  0.524988 -1.469388
[12 rows x 3 columns]

Convert to an xarray DataArray

In [79]: p.to_xarray()
Out[79]:
<xarray.DataArray (items: 3, major_axis: 3, minor_axis: 4)>

(continues on next page)
array([[ 0.469112, -1.135632, 0.119209, -2.104569],
       [-0.282863,  1.212112, -1.044236, -0.494929],
       [-1.509059, -0.173215, -0.861849,  1.071804]],
      [[ 0.721555,  0.271860, 0.276232, 0.113648],
       [-0.282863,  1.212112, -1.044236, -0.494929],
       [-1.509059, -0.173215, -0.861849,  1.071804]],
      [[ 0.469112, -1.135632, 0.119209, -2.104569],
       [-0.282863,  1.212112, -1.044236, -0.494929],
       [-1.509059, -0.173215, -0.861849,  1.071804]])

Coordinates:
  * items (items) object 'ItemA' 'ItemB' 'ItemC'
  * major_axis (major_axis) datetime64[ns] 2000-01-03 2000-01-04 2000-01-05
  * minor_axis (minor_axis) object 'A' 'B' 'C' 'D'

pandas.core.common removals

The following error & warning messages are removed from pandas.core.common (GH13634, GH19769):

- PerformanceWarning
- UnsupportedFunctionCall
- UnsortedIndexError
- AbstractMethodError

These are available from import from pandas.errors (since 0.19.0).

Changes to make output of DataFrame.apply consistent

DataFrame.apply() was inconsistent when applying an arbitrary user-defined-function that returned a list-like with axis=1. Several bugs and inconsistencies are resolved. If the applied function returns a Series, then pandas will return a DataFrame; otherwise a Series will be returned, this includes the case where a list-like (e.g. tuple or list is returned) (GH16353, GH17437, GH17970, GH17348, GH17892, GH18573, GH17602, GH18775, GH18901, GH18919).

In [76]: df = pd.DataFrame(np.tile(np.arange(3), 6).reshape(6, -1) + 1,
                          columns=['A', 'B', 'C'])

In [77]: df
Out[77]:
          A  B  C
0   1   2   3
1   2   2   3
2   3   2   3
3   4   2   3
4   5   2   3

[6 rows x 3 columns]

Previous behavior: if the returned shape happened to match the length of original columns, this would return a DataFrame. If the return shape did not match, a Series with lists was returned.
In [3]: df.apply(lambda x: [1, 2, 3], axis=1)
Out[3]:
   A  B  C
0  1  2  3
1  1  2  3
2  1  2  3
3  1  2  3
4  1  2  3
5  1  2  3

In [4]: df.apply(lambda x: [1, 2], axis=1)
Out[4]:
   0  1  2  3
0  [1, 2]
1  [1, 2]
2  [1, 2]
3  [1, 2]
4  [1, 2]
5  [1, 2]

dtype: object

New behavior: When the applied function returns a list-like, this will now always return a Series.

In [78]: df.apply(lambda x: [1, 2, 3], axis=1)
Out[78]:
   0  1  2  3
0  [1, 2]
1  [1, 2]
2  [1, 2]
3  [1, 2]
4  [1, 2]
5  [1, 2]

Length: 6, dtype: object

In [79]: df.apply(lambda x: [1, 2], axis=1)
Out[79]:
   0  1  2  3
0  [1, 2]
1  [1, 2]
2  [1, 2]
3  [1, 2]
4  [1, 2]
5  [1, 2]

Length: 6, dtype: object

To have expanded columns, you can use result_type='expand'

In [80]: df.apply(lambda x: [1, 2, 3], axis=1, result_type='expand')
Out[80]:
   0  1  2
0  1  2  3
1  1  2  3
2  1  2  3
3  1  2  3
4  1  2  3
5  1  2  3

[6 rows x 3 columns]

To broadcast the result across the original columns (the old behaviour for list-likes of the correct length), you can use result_type='broadcast'. The shape must match the original columns.
In [81]: df.apply(lambda x: [1, 2, 3], axis=1, result_type='broadcast')
Out[81]:
    A  B  C
0  1  2  3
1  1  2  3
2  1  2  3
3  1  2  3
4  1  2  3
5  1  2  3
[6 rows x 3 columns]

Returning a Series allows one to control the exact return structure and column names:

In [82]: df.apply(lambda x: pd.Series([1, 2, 3], index=['D', 'E', 'F']), axis=1)
Out[82]:
    D  E  F
0  1  2  3
1  1  2  3
2  1  2  3
3  1  2  3
4  1  2  3
5  1  2  3
[6 rows x 3 columns]

Concatenation will no longer sort

In a future version of pandas pandas.concat() will no longer sort the non-concatenation axis when it is not already aligned. The current behavior is the same as the previous (sorting), but now a warning is issued when sort is not specified and the non-concatenation axis is not aligned (GH4588).

In [83]: df1 = pd.DataFrame({"a": [1, 2], "b": [1, 2]}, columns=['b', 'a'])
In [84]: df2 = pd.DataFrame({"a": [4, 5]})
In [85]: pd.concat([df1, df2])
Out[85]:
    b  a
  0  1.0 1
  1  2.0 2
  NaN 4
  NaN 5
[4 rows x 2 columns]

To keep the previous behavior (sorting) and silence the warning, pass sort=True

In [86]: pd.concat([df1, df2], sort=True)
Out[86]:
    a  b
  0  1  1.0
  1  2  2.0
  0  4  NaN
  1  5  NaN

(continues on next page)
To accept the future behavior (no sorting), pass `sort=False`

Note that this change also applies to `DataFrame.append()`, which has also received a `sort` keyword for controlling this behavior.

### Build changes

- Building pandas for development now requires `cython >= 0.24` (GH18613)
- Building from source now explicitly requires `setuptools` in `setup.py` (GH18113)
- Updated conda recipe to be in compliance with conda-build 3.0+ (GH18002)

### Index division by zero fills correctly

Division operations on `Index` and subclasses will now fill division of positive numbers by zero with `np.inf`, division of negative numbers by zero with `-np.inf` and `0 / 0` with `np.nan`. This matches existing `Series` behavior. (GH19322, GH19347)

**Previous behavior:**

| In [6]: index = pd.Int64Index([-1, 0, 1]) |
| In [7]: index / 0 |
| Out[7]: Int64Index([0, 0, 0], dtype='int64') |

# Previous behavior yielded different results depending on the type of zero in the divisor
| In [8]: index / 0.0 |
| Out[8]: Float64Index([-inf, nan, inf], dtype='float64') |

| In [9]: index = pd.UInt64Index([0, 1]) |
| In [10]: index / np.array([0, 0], dtype=np.uint64) |
| Out[10]: UInt64Index([0, 0], dtype='uint64') |

| In [11]: pd.RangeIndex(1, 5) / 0 |
| ZeroDivisionError: integer division or modulo by zero |

**Current behavior:**

| In [87]: index = pd.Int64Index([-1, 0, 1]) |
| In [88]: index / 0 |
| Out[88]: Float64Index([-inf, nan, inf], dtype='float64') |

# The result of division by zero should not depend on whether the zero is int or float
| In [89]: index / 0.0 |
| Out[89]: Float64Index([-inf, nan, inf], dtype='float64') |
In [90]: index = pd.UInt64Index([0, 1])

In [91]: index / np.array([0, 0], dtype=np.uint64)
Out[91]: Float64Index([nan, inf], dtype='float64')

In [92]: pd.RangeIndex(1, 5) / 0
Out[92]: Float64Index([inf, inf, inf, inf], dtype='float64')

Extraction of matching patterns from strings

By default, extracting matching patterns from strings with `str.extract()` used to return a `Series` if a single group was being extracted (a `DataFrame` if more than one group was extracted). As of Pandas 0.23.0 `str.extract()` always returns a `DataFrame`, unless `expand` is set to `False`. Finally, `None` was an accepted value for the `expand` parameter (which was equivalent to `False`), but now raises a `ValueError` (GH11386).

Previous behavior:

In [1]: s = pd.Series(['number 10', '12 eggs'])

In [2]: extracted = s.str.extract(r'.*(\d\d).*')

In [3]: extracted
Out [3]:
   0  10
   1  12
   dtype: object

In [4]: type(extracted)
Out [4]:
pandas.core.series.Series

New behavior:

In [93]: s = pd.Series(['number 10', '12 eggs'])

In [94]: extracted = s.str.extract(r'.*(\d\d).*')

In [95]: extracted
Out[95]:
   0
   0  10
   1  12
   [2 rows x 1 columns]

In [96]: type(extracted)
Out[96]: pandas.core.frame.DataFrame

To restore previous behavior, simply set `expand` to `False`:

In [97]: s = pd.Series(['number 10', '12 eggs'])

In [98]: extracted = s.str.extract(r'.*(\d\d).*', expand=False)
In [99]: extracted
Out[99]:
0   10
1   12
Length: 2, dtype: object

In [100]: type(extracted)
Out[100]: pandas.core.series.Series

Default value for the ordered parameter of CategoricalDtype

The default value of the ordered parameter for CategoricalDtype has changed from False to None to allow updating of categories without impacting ordered. Behavior should remain consistent for downstream objects, such as Categorical (GH18790)

In previous versions, the default value for the ordered parameter was False. This could potentially lead to the ordered parameter unintentionally being changed from True to False when users attempt to update categories if ordered is not explicitly specified, as it would silently default to False. The new behavior for ordered=None is to retain the existing value of ordered.

New behavior:

```python
In [2]: from pandas.api.types import CategoricalDtype
In [3]: cat = pd.Categorical(list('abcaba'), ordered=True, categories=list('cba'))
In [4]: cat
Out[4]:
[a, b, c, a, b, a]
Categories (3, object): [c < b < a]
In [5]: cdt = CategoricalDtype(categories=list('cbad'))
In [6]: cat.astype(cdt)
Out[6]:
[a, b, c, a, b, a]
Categories (4, object): [c < b < a < d]
```

Notice in the example above that the converted Categorical has retained ordered=True. Had the default value for ordered remained as False, the converted Categorical would have become unordered, despite ordered=False never being explicitly specified. To change the value of ordered, explicitly pass it to the new dtype, e.g. CategoricalDtype(categories=list('cbad'), ordered=False).

Note that the unintentional conversion of ordered discussed above did not arise in previous versions due to separate bugs that prevented astype from doing any type of category to category conversion (GH10696, GH18593). These bugs have been fixed in this release, and motivated changing the default value of ordered.
Better pretty-printing of DataFrames in a terminal

Previously, the default value for the maximum number of columns was `pd.options.display.max_columns=20`. This meant that relatively wide data frames would not fit within the terminal width, and pandas would introduce line breaks to display these 20 columns. This resulted in an output that was relatively difficult to read:

If Python runs in a terminal, the maximum number of columns is now determined automatically so that the printed data frame fits within the current terminal width (`pd.options.display.max_columns=0`) (GH17023). If Python runs as a Jupyter kernel (such as the Jupyter QtConsole or a Jupyter notebook, as well as in many IDEs), this value cannot be inferred automatically and is thus set to 20 as in previous versions. In a terminal, this results in a much nicer output:
Note that if you don’t like the new default, you can always set this option yourself. To revert to the old setting, you can run this line:

```
pd.options.display.max_columns = 20
```

**Datetimelike API changes**

- The default `Timedelta` constructor now accepts an ISO 8601 Duration string as an argument (GH19040)

- Subtracting `NaT` from a `Series` with `dtype='datetime64[ns]'` returns a `Series` with `dtype='timedelta64[ns]'` instead of `dtype='datetime64[ns]'` (GH18808)

- Addition or subtraction of `NaT` from `TimedeltaIndex` will return `TimedeltaIndex` instead of `DatetimeIndex` (GH19124)

- `TimedeltaIndex.shift()` and `TimedeltaIndex.shift()` will now raise `NullFrequencyError` (which subclasses `ValueError`, which was raised in older versions) when the index object frequency is `None` (GH19147)

- Addition and subtraction of `NaN` from a `Series` with `dtype='timedelta64[ns]'` will raise a `TypeError` instead of treating the `NaN` as `NaT` (GH19274)

- `NaT` division with `datetime.timedelta` will now return `NaN` instead of raising (GH17876)
- Operations between a `Series` with dtype `datetime64[ns]` and a `PeriodIndex` will correctly raise a `TypeError` (GH18850)
- Subtraction of `Series` with timezone-aware dtype `datetime64[ns]` with mis-matched timezones will raise a `TypeError` instead of `ValueError` (GH18817)
- `Timestamp` will no longer silently ignore unused or invalid `tz` or `tzinfo` keyword arguments (GH17690)
- `Timestamp` will no longer silently ignore invalid `freq` arguments (GH5168)
- `CacheableOffset` and `WeekDay` are no longer available in the `pandas.tseries.offsets` module (GH17830)
- `pandas.tseries.frequencies.get_freq_group()` and `pandas.tseries.frequencies.DAYS` are removed from the public API (GH18034)
- `Series.truncate()` and `DataFrame.truncate()` will raise a `ValueError` if the index is not sorted instead of an unhelpful `KeyError` (GH17935)
- `Series.first` and `DataFrame.first` will now raise a `TypeError` rather than `NotImplementedError` when the index is not a `DatetimeIndex` (GH20725).
- `Series.last` and `DataFrame.last` will now raise a `TypeError` rather than `NotImplementedError` when the index is not a `DatetimeIndex` (GH20725).
- Restricted `DateOffset` keyword arguments. Previously, `DateOffset` subclasses allowed arbitrary keyword arguments which could lead to unexpected behavior. Now, only valid arguments will be accepted. (GH17176, GH18226).
- `pandas.merge()` provides a more informative error message when trying to merge on timezone-aware and timezone-agnostic columns (GH15800)
- For `DatetimeIndex` and `TimedeltaIndex` with `freq=None`, addition or subtraction of integer-dtyped array or `Index` will raise a `NullFrequencyError` instead of `TypeError` (GH19895)
- `Timestamp` constructor now accepts a `nanosecond` keyword or positional argument (GH18898)
- `DatetimeIndex` will now raise an `AttributeError` when the `tz` attribute is set after instantiation (GH3746)
- `DatetimeIndex` with a `pytz` timezone will now return a consistent `pytz` timezone (GH18595)

**Other API changes**

- `Series.astype()` and `Index.astype()` with an incompatible dtype will now raise a `TypeError` rather than a `ValueError` (GH18231)
- Series construction with an object dtype-attribute datetime and `dtype=object` specified, will now return an `object`-dtyped `Series`, previously this would infer the datetime dtype (GH18231)
- A `Series` of dtype=category constructed from an empty dict will now have categories of dtype=object rather than dtype=float64, consistently with the case in which an empty list is passed (GH18515)
- All-NaN levels in a MultiIndex are now assigned `float` rather than `object` dtype, promoting consistency with `Index` (GH17929).
- Levels names of a MultiIndex (when not None) are now required to be unique: trying to create a MultiIndex with repeated names will raise a `ValueError` (GH18872)
- Both construction and renaming of `Index/MultiIndex` with non-hashable name/keys will now raise `TypeError` (GH20527)
• **Index.map()** can now accept Series and dictionary input objects (GH12756, GH18482, GH18509).

• **DataFrame.unstack()** will now default to filling with np.nan for object columns. (GH12815)

• **IntervalIndex** constructor will raise if the closed parameter conflicts with how the input data is inferred to be closed (GH18421)

• Inserting missing values into indexes will work for all types of indexes and automatically insert the correct type of missing value (NaN, NaT, etc.) regardless of the type passed in (GH18295)

• When created with duplicate labels, MultiIndex now raises a ValueError. (GH17464)

• **Series.fillna()** now raises a TypeError instead of a ValueError when passed a list, tuple or DataFrame as a value (GH18293)

• **pandas.DataFrame.merge()** no longer casts a float column to object when merging on int and float columns (GH16572)

• **pandas.merge()** now raises a ValueError when trying to merge on incompatible data types (GH9780)

• The default NA value for UInt64Index has changed from 0 to NaN, which impacts methods that mask with NA, such as UInt64Index.where() (GH18398)

• Refactored setup.py to use find_packages instead of explicitly listing out all subpackages (GH18535)

• Rearranged the order of keyword arguments in read_excel() to align with read_csv() (GH16672)

• *wide_to_long()* previously kept numeric-like suffixes as object dtype. Now they are cast to numeric if possible (GH17627)

• In read_excel(), the comment argument is now exposed as a named parameter (GH18735)

• Rearranged the order of keyword arguments in read_excel() to align with read_csv() (GH16672)

• The options html.border and mode.use_inf_as_null were deprecated in prior versions, these will now show FutureWarning rather than a DeprecationWarning (GH19003)

• **IntervalIndex** and IntervalDtype no longer support categorical, object, and string subtypes (GH19016)

• IntervalDtype now returns True when compared against 'interval' regardless of subtype, and IntervalDtype.name now returns 'interval' regardless of subtype (GH18980)

• KeyError now raises instead of ValueError in drop(), drop(), drop(), drop() when dropping a non-existent element in an axis with duplicates (GH19186)

• **Series.to_csv()** now accepts a compression argument that works in the same way as the compression argument in DataFrame.to_csv() (GH18958)

• Set operations (union, difference...) on IntervalIndex with incompatible index types will now raise a TypeError rather than a ValueError (GH19329)

• DateOffset objects render more simply, e.g. `<DateOffset: days=1>` instead of `<DateOffset: kwds={'days': 1}> (GH19403)

• Categorical.fillna now validates its value and method keyword arguments. It now raises when both or none are specified, matching the behavior of Series.fillna() (GH19682)

• pd.to_datetime('today') now returns a datetime, consistent with pd.Timestamp('today'); previously pd.to_datetime('today') returned a .normalized() datetime (GH19935)

• **Series.str.replace()** now takes an optional regex keyword which, when set to False, uses literal string replacement rather than regex replacement (GH16808)

• DatetimeIndex.strftime() and PeriodIndex.strftime() now return an Index instead of a numpy array to be consistent with similar accessors (GH20127)
• Constructing a Series from a list of length 1 no longer broadcasts this list when a longer index is specified (GH19714, GH20391).

• `DataFrame.to_dict()` with `orient='index'` no longer casts int columns to float for a DataFrame with only int and float columns (GH18580).

• A user-defined-function that is passed to `Series.rolling().aggregate()`, `DataFrame.rolling().aggregate()`, or its expanding cousins, will now always be passed a `Series`, rather than a `np.array`; `.apply()` only has the `raw` keyword, see here. This is consistent with the signatures of `.aggregate()` across pandas (GH20584).

• Rolling and Expanding types raise `NotImplementedError` upon iteration (GH11704).

Deprecations

• `Series.from_array` and `SparseSeries.from_array` are deprecated. Use the normal constructor `Series(.,)` and `SparseSeries(.,)` instead (GH18213).

• `DataFrame.as_matrix` is deprecated. Use `DataFrame.values` instead (GH18458).

• `Series.asobject`, `DatetimeIndex.asobject`, `PeriodIndex.asobject` and `TimeDeltaIndex.asobject` have been deprecated. Use `.astype(object)` instead (GH18572).

• Grouping by a tuple of keys now emits a `FutureWarning` and is deprecated. In the future, a tuple passed to 'by' will always refer to a single key that is the actual tuple, instead of treating the tuple as multiple keys. To retain the previous behavior, use a list instead of a tuple (GH18314).

• `Series.valid` is deprecated. Use `Series.dropna()` instead (GH18800).

• `read_excel()` has deprecated the `skip_footer` parameter. Use `skipfooter` instead (GH18836).

• `ExcelFile.parse()` has deprecated `sheetname` in favor of `sheet_name` for consistency with `read_excel()` (GH20920).

• The `is_copy` attribute is deprecated and will be removed in a future version (GH18801).

• `IntervalIndex.from_intervals` is deprecated in favor of the `IntervalIndex` constructor (GH19263).

• `DataFrame.from_items` is deprecated. Use `DataFrame.from_dict()` instead, or `DataFrame.from_dict(OrderedDict())` if you wish to preserve the key order (GH17320, GH17312).

• Indexing a `MultiIndex` or a `FloatIndex` with a list containing some missing keys will now show a `FutureWarning`, which is consistent with other types of indexes (GH17758).

• The `broadcast` parameter of `.apply()` is deprecated in favor of `result_type='broadcast'` (GH18577).

• The `reduce` parameter of `.apply()` is deprecated in favor of `result_type='reduce'` (GH18577).

• The `order` parameter of `factorize()` is deprecated and will be removed in a future release (GH19727).

• `Timestamp.weekday_name`, `DatetimeIndex.weekday_name`, and `Series.dt.weekday_name` are deprecated in favor of `Timestamp.day_name()`, `DatetimeIndex.day_name()`, and `Series.dt.day_name()` (GH12806).

• `pandas.tseries.plotting.tsplot` is deprecated. Use `Series.plot()` instead (GH18627).

• `Index.summary()` is deprecated and will be removed in a future version (GH18217).

• `NDFrame.get_fype_counts()` is deprecated and will be removed in a future version (GH18243).
The convert_datetime64 parameter in DataFrame.to_records() has been deprecated and will be removed in a future version. The NumPy bug motivating this parameter has been resolved. The default value for this parameter has also changed from True to None (GH18160).

Series.rolling().apply(), DataFrame.rolling().apply(), Series.expanding().apply(), and DataFrame.expanding().apply() have deprecated passing an np.array by default. One will need to pass the new raw parameter to be explicit about what is passed (GH20584).

The data, base, strides, flags and itemsize properties of the Series and Index classes have been deprecated and will be removed in a future version (GH20419).

DatetimeIndex.offset is deprecated. Use DatetimeIndex.freq instead (GH20716)

Floor division between an integer ndarray and a Timedelta is deprecated. Divide by Timedelta.value instead (GH19761)

Setting PeriodIndex.freq (which was not guaranteed to work correctly) is deprecated. Use PeriodIndex.asfreq() instead (GH20678)

Index.get_duplicates() is deprecated and will be removed in a future version (GH20239)

The previous default behavior of negative indices in Categorical.take is deprecated. In a future version it will change from meaning missing values to meaning positional indices from the right. The future behavior is consistent with Series.take() (GH20664).

Passing multiple axes to the axis parameter in DataFrame.dropna() has been deprecated and will be removed in a future version (GH20987)

Removal of prior version deprecations/changes

- Warnings against the obsolete usage Categorical(codes, categories), which were emitted for instance when the first two arguments to Categorical() had different dtypes, and recommended the use of Categorical.from_codes, have now been removed (GH8074)
- The levels and labels attributes of a MultiIndex can no longer be set directly (GH4039).
- pd.tseries.util.pivot_annual has been removed (deprecated since v0.19). Use pivot_table instead (GH18370)
- pd.tseries.util.isleapyear has been removed (deprecated since v0.19). Use .is_leap_year property in Datetime-likes instead (GH18370)
- pd.ordered_merge has been removed (deprecated since v0.19). Use pd.merge_ordered instead (GH18459)
- The SparseList class has been removed (GH14007)
- The pandas.io.wb and pandas.io.data stub modules have been removed (GH13735)
- Categorical.from_array has been removed (GH13854)
- The freq and how parameters have been removed from the rolling/expanding/ewm methods of DataFrame and Series (deprecated since v0.18). Instead, resample before calling the methods. (GH18601 & GH18668)
- DatetimeIndex.to_datetime, Timestamp.to_datetime, PeriodIndex.to_datetime, and Index.to_datetime have been removed (GH8254, GH14096, GH14113)
- read_csv() has dropped the skip_footer parameter (GH13386)
- read_csv() has dropped the as_recarray parameter (GH13373)
- read_csv() has dropped the buffer_lines parameter (GH13360)
pandas: powerful Python data analysis toolkit, Release 1.1.1

- `read_csv()` has dropped the `compact_ints` and `use_unsigned` parameters (GH13323)
- The `Timestamp` class has dropped the `offset` attribute in favor of `freq` (GH13593)
- The `Series`, `Categorical`, and `Index` classes have dropped the `reshape` method (GH13012)
- `pandas.tseries.frequencies.get_standard_freq` has been removed in favor of `pandas.tseries.frequencies.to_offset(freq).rule_code` (GH13874)
- The `freqstr` keyword has been removed from `pandas.tseries.frequencies.to_offset` in favor of `freq` (GH13874)
- The `Panel4D` and `PanelND` classes have been removed (GH13776)
- The `Panel` class has dropped the `to_long` and `toLong` methods (GH19077)
- The options `display.line_with` and `display.height` are removed in favor of `display.width` and `display.max_rows` respectively (GH4391, GH19107)
- The `labels` attribute of the `Categorical` class has been removed in favor of `Categorical.codes` (GH7768)
- The `flavor` parameter have been removed from `func:to_sql` method (GH13611)
- The modules `pandas.tools.hashing` and `pandas.util.hashing` have been removed (GH16223)
- The top-level functions `pd.rolling_*`, `pd.expanding_*` and `pd.ewm*` have been removed (Deprecated since v0.18). Instead, use the DataFrame/Series methods `rolling`, `expanding` and `ewm` (GH18723)
- Imports from `pandas.core.common` for functions such as `is_datetime64_dtype` are now removed. These are located in `pandas.api.types`. (GH13634, GH19769)
- The `infer_dst` keyword in `Series.tz_localize()`, `DatetimeIndex.tz_localize()` and `DatetimeIndex` have been removed. `infer_dst=True` is equivalent to `ambiguous='infer'`, and `infer_dst=False` to `ambiguous='raise'` (GH7963).
- When `.resample()` was changed from an eager to a lazy operation, like `.groupby()` in v0.18.0, we put in place compatibility (with a `FutureWarning`), so operations would continue to work. This is now fully removed, so a `Resampler` will no longer forward compat operations (GH20554)
- Remove long deprecated `axis=None` parameter from `.replace()` (GH20271)

**Performance improvements**

- Indexers on `Series` or `DataFrame` no longer create a reference cycle (GH17956)
- Added a keyword argument, `cache`, to `to_datetime()` that improved the performance of converting duplicate datetime arguments (GH11665)
- `DateOffset` arithmetic performance is improved (GH18218)
- Converting a `Series` of `Timedelta` objects to days, seconds, etc... sped up through vectorization of underlying methods (GH18092)
- Improved performance of `.map()` with a `Series/dict` input (GH15081)
- The overridden `Timedelta` properties of days, seconds and microseconds have been removed, leveraging their built-in Python versions instead (GH18242)
- `Series` construction will reduce the number of copies made of the input data in certain cases (GH17449)
- Improved performance of `Series.dt.date()` and `DatetimeIndex.date()` (GH18058)
- Improved performance of `Series.dt.time()` and `DatetimeIndex.time()` (GH18461)
• Improved performance of `IntervalIndex.symmetric_difference()` (GH18475)
• Improved performance of `DatetimeIndex` and `Series` arithmetic operations with Business-Month and Business-Quarter frequencies (GH18489)
• `Series() / DataFrame()` tab completion limits to 100 values, for better performance. (GH18587)
• Improved performance of `DataFrame.median()` with axis=1 when bottleneck is not installed (GH16468)
• Improved performance of `MultiIndex.get_loc()` for large indexes, at the cost of a reduction in performance for small ones (GH18519)
• Improved performance of `MultiIndex.remove_unused_levels()` when there are no unused levels, at the cost of a reduction in performance when there are (GH19289)
• Improved performance of `Index.get_loc()` for non-unique indexes (GH19478)
• Improved performance of pairwise `.rolling()` and `.expanding()` with `.cov()` and `.corr()` operations (GH17917)
• Improved performance of `pandas.core.groupby.GroupBy.rank()` (GH15779)
• Improved performance of variable `.rolling()` on `.min()` and `.max()` (GH19521)
• Improved performance of `pandas.core.groupby.GroupBy.ffill()` and `pandas.core.groupby.GroupBy.bfill()` (GH11296)
• Improved performance of `pandas.core.groupby.GroupBy.any()` and `pandas.core.groupby.GroupBy.all()` (GH15435)
• Improved performance of `pandas.core.groupby.GroupBy.pct_change()` (GH19165)
• Improved performance of `Series.isin()` in the case of categorical dtypes (GH20003)
• Improved performance of `getattr(Series, attr)` when the Series has certain index types. This manifested in slow printing of large Series with a `DatetimeIndex` (GH19764)
• Fixed a performance regression for `GroupBy.nth()` and `GroupBy.last()` with some object columns (GH19283)
• Improved performance of `pandas.core.arrays.Categorical.from_codes()` (GH18501)

Documentation changes

Thanks to all of the contributors who participated in the Pandas Documentation Sprint, which took place on March 10th. We had about 500 participants from over 30 locations across the world. You should notice that many of the API docstrings have greatly improved.

There were too many simultaneous contributions to include a release note for each improvement, but this GitHub search should give you an idea of how many docstrings were improved.

Special thanks to Marc Garcia for organizing the sprint. For more information, read the NumFOCUS blogpost recapping the sprint.

• Changed spelling of “numpy” to “NumPy”, and “python” to “Python”. (GH19017)
• Consistency when introducing code samples, using either colon or period. Rewrote some sentences for greater clarity, added more dynamic references to functions, methods and classes. (GH18941, GH18948, GH18973, GH19017)
• Added a reference to `DataFrame.assign()` in the concatenate section of the merging documentation (GH18665)
Bug fixes

Categorical

Warning: A class of bugs were introduced in pandas 0.21 with CategoricalDtype that affects the correctness of operations like merge, concat, and indexing when comparing multiple unordered Categorical arrays that have the same categories, but in a different order. We highly recommend upgrading or manually aligning your categories before doing these operations.

- Bug in Categorical.equals returning the wrong result when comparing two unordered Categorical arrays with the same categories, but in a different order (GH16603)
- Bug in pandas.api.types.union_categoricals() returning the wrong result when for unordered categoricals with the categories in a different order. This affected pandas.concat() with Categorical data (GH19096).
- Bug in pandas.merge() returning the wrong result when joining on an unordered Categorical that had the same categories but in a different order (GH19551)
- Bug in CategoricalIndex.get_indexer() returning the wrong result when target was an unordered Categorical that had the same categories as self but in a different order (GH19551)
- Bug in Index.astype() with a categorical dtype where the resultant index is not converted to a CategoricalIndex for all types of index (GH18630)
- Bug in Series.astype() and Categorical.astype() where an existing categorical data does not get updated (GH10696, GH18593)
- Bug in Series.str.split() with expand=True incorrectly raising an IndexError on empty strings (GH20002).
- Bug in Index constructor with dtype=CategoricalDtype(...) where categories and ordered are not maintained (GH19032)
- Bug in Series constructor with scalar and dtype=CategoricalDtype(...) where categories and ordered are not maintained (GH19565)
- Bug in Categorical.__iter__ not converting to Python types (GH19909)
- Bug in pandas.factorize() returning the unique codes for the uniques. This now returns a Categorical with the same dtype as the input (GH19721)
- Bug in pandas.factorize() including an item for missing values in the uniques return value (GH19721)
- Bug in Series.take() with categorical data interpreting -1 in indices as missing value markers, rather than the last element of the Series (GH20664)
Datetimelike

- Bug in `Series.__sub__()` subtracting a non-nanosecond `np.datetime64` object from a `Series` gave incorrect results (GH7996)
- Bug in `DatetimeIndex`, `TimedeltaIndex` addition and subtraction of zero-dimensional integer arrays gave incorrect results (GH19012)
- Bug in `DatetimeIndex` and `TimedeltaIndex` where adding or subtracting an array-like of `DateOffset` objects either raised (`np.array`, `pd.Index`) or broadcast incorrectly (`pd.Series`) (GH18849)
- Bug in `Series.__add__()` adding `Series` with dtype `timedelta64[ns]` to a timezone-aware `DatetimeIndex` incorrectly dropped timezone information (GH13905)
- Adding a `Period` object to a `datetime` or `Timestamp` object will now correctly raise a `TypeError` (GH17983)
- Bug in `Timestamp` where comparison with an array of `Timestamp` objects would result in a `RecursionError` (GH15183)
- Bug in `Series` floor-division where operating on a scalar `timedelta` raises an exception (GH18846)
- Bug in `DatetimeIndex` where the repr was not showing high-precision time values at the end of a day (e.g., 23:59:59.999999999) (GH19030)
- Bug in `.astype()` to non-ns `timedelta` units would hold the incorrect dtype (GH19176, GH19223, GH12425)
- Bug in subtracting `Series` from `NaT` incorrectly returning `NaT` (GH19158)
- Bug in `Series.truncate()` which raises `TypeError` with a monotonic `PeriodIndex` (GH17717)
- Bug in `pct_change()` using periods and `freq` returned different length outputs (GH7292)
- Bug in comparison of `DatetimeIndex` against `None` or `datetime.date` objects raising `TypeError` for `==` and `!=` comparisons instead of all-False and all-True, respectively (GH19301)
- Bug in `Timestamp` and `to_datetime()` where a string representing a barely out-of-bounds timestamp would be incorrectly rounded down instead of raising `OutOfBoundsDatetime` (GH19382)
- Bug in `Timestamp.floor()` `DatetimeIndex.floor()` where time stamps far in the future and past were not rounded correctly (GH19206)
- Bug in `to_datetime()` where passing an out-of-bounds datetime with `errors='coerce'` and `utc=True` would raise `OutOfBoundsDatetimetime` instead of parsing to `NaT` (GH19612)
- Bug in `DatetimeIndex` and `TimedeltaIndex` addition and subtraction where name of the returned object was not always set consistently. (GH19744)
- Bug in `DatetimeIndex` and `TimedeltaIndex` addition and subtraction where operations with numpy arrays raised `TypeError` (GH19847)
- Bug in `DatetimeIndex` and `TimedeltaIndex` where setting the `freq` attribute was not fully supported (GH20678)
Timedelta

- Bug in `Timedelta.__mul__()` where multiplying by NaT returned NaT instead of raising a `TypeError` (GH19819)
- Bug in `Series` with `dtype='timedelta64[ns]'` where addition or subtraction of `TimedeltaIndex` had results cast to `dtype='int64'` (GH17250)
- Bug in `Series` with `dtype='timedelta64[ns]'` where addition or subtraction of `TimedeltaIndex` could return a `Series` with an incorrect name (GH19043)
- Bug in `Timedelta.__floordiv__()` and `Timedelta.__rfloordiv__()` dividing by many incompatible numpy objects was incorrectly allowed (GH18846)
- Bug where dividing a scalar timedelta-like object with `TimedeltaIndex` performed the reciprocal operation (GH19125)
- Bug in `TimedeltaIndex` where division by a `Series` would return a `TimedeltaIndex` instead of a `Series` (GH19042)
- Bug in `Timedelta.__add__()`, `Timedelta.__sub__()` where adding or subtracting a np.timedelta64 object would return another np.timedelta64 instead of a `Timedelta` (GH19738)
- Bug in `Timedelta.__floordiv__()`, `Timedelta.__rfloordiv__()` where operating with a `Tick` object would raise a `TypeError` instead of returning a numeric value (GH19738)
- Bug in `Period.asfreq()` where periods near `datetime(1, 1, 1)` could be converted incorrectly (GH19643, GH19834)
- Bug in `Timedelta.total_seconds()` causing precision errors, for example `Timedelta('30S').total_seconds() == 30.000000000000004` (GH19458)
- Bug in `Timedelta.__rmod__()` where operating with a `numpy.timedelta64` returned a `timedelta64` object instead of a `Timedelta` (GH19820)
- Multiplication of `TimedeltaIndex` by `TimedeltaIndex` will now raise `TypeError` instead of raising `ValueError` in cases of length mis-match (GH19333)
- Bug in indexing a `TimedeltaIndex` with a np.timedelta64 object which was raising a `TypeError` (GH20393)

Timezones

- Bug in creating a `Series` from an array that contains both tz-naive and tz-aware values will result in a `Series` whose `dtype` is tz-aware instead of object (GH16406)
- Bug in comparison of timezone-aware `DatetimeIndex` against NaT incorrectly raising `TypeError` (GH19276)
- Bug in `DatetimeIndex.astype()` when converting between timezone aware datatypes, and converting from timezone aware to naive (GH18951)
- Bug in comparing `DatetimeIndex`, which failed to raise `TypeError` when attempting to compare timezone-aware and timezone-naive datetimelike objects (GH18162)
- Bug in localization of a naive, datetime string in a `Series` constructor with a `datetime64[ns, tz]` `dtype` (GH174151)
- `Timestamp.replace()` will now handle Daylight Savings transitions gracefully (GH18319)
- Bug in tz-aware `DatetimeIndex` where addition/subtraction with a `TimedeltaIndex` or array with `dtype='timedelta64[ns]'` was incorrect (GH17558)
• Bug in `DatetimeIndex.insert()` where inserting `NaT` into a timezone-aware index incorrectly raised (GH16357)

• Bug in `DataFrame` constructor, where tz-aware Datetimeindex and a given column name will result in an empty DataFrame (GH19157)

• Bug in `Timestamp.tz_localize()` where localizing a timestamp near the minimum or maximum valid values could overflow and return a timestamp with an incorrect nanosecond value (GH12677)

• Bug when iterating over `DatetimeIndex` that was localized with fixed timezone offset that rounded nanosecond precision to microseconds (GH19603)

• Bug in `DataFrame.diff()` that raised an `IndexError` with tz-aware values (GH18578)

• Bug in `melt()` that converted tz-aware dtypes to tz-naive (GH15785)

• Bug in `DataFrame.count()` that raised an `ValueError`, if `DataFrame.dropna()` was called for a single column with timezone-aware values. (GH13407)

Offsets

• Bug in WeekOfMonth and Week where addition and subtraction did not roll correctly (GH18510, GH18672, GH18864)

• Bug in WeekOfMonth and LastWeekOfMonth where default keyword arguments for constructor raised `ValueError` (GH19142)

• Bug in `FY5253Quarter`, LastWeekOfMonth where rollback and rollforward behavior was inconsistent with addition and subtraction behavior (GH18854)

• Bug in `FY5253` where datetime addition and subtraction incremented incorrectly for dates on the year-end but not normalized to midnight (GH18854)

• Bug in `FY5253` where date offsets could incorrectly raise an `AssertionError` in arithmetic operations (GH14774)

Numeric

• Bug in `Series` constructor with an int or float list where specifying `dtype=str`, `dtype='str'` or `dtype='U'` failed to convert the data elements to strings (GH16605)

• Bug in `Index` multiplication and division methods where operating with a `Series` would return an `Index` object instead of a `Series` object (GH19042)

• Bug in the `DataFrame` constructor in which data containing very large positive or very large negative numbers was causing `OverflowError` (GH18584)

• Bug in `Index` constructor with `dtype='uint64'` where int-like floats were not coerced to `UInt64Index` (GH18400)

• Bug in `DataFrame` flex arithmetic (e.g. `df.add(other, fill_value=foo)`) with a `fill_value` other than `None` failed to raise `NotImplementedError` in corner cases where either the frame or other has length zero (GH19522)

• Multiplication and division of numeric-dtyped `Index` objects with timedelta-like scalars returns `TimedeltaIndex` instead of raising `TypeError` (GH19333)

• Bug where `NaN` was returned instead of `0` by `Series.pct_change()` and `DataFrame.pct_change()` when `fill_method` is not `None` (GH19873)
Strings

- Bug in `Series.str.get()` with a dictionary in the values and the index not in the keys, raising `KeyError` (GH20671)

Indexing

- Bug in `Index` construction from list of mixed type tuples (GH18505)
- Bug in `Index.drop()` when passing a list of both tuples and non-tuples (GH18304)
- Bug in `DataFrame.drop()`, `Panel.drop()`, `Series.drop()`, `Index.drop()` where no `KeyError` is raised when dropping a non-existent element from an axis that contains duplicates (GH19186)
- Bug in indexing a datetimelike `Index` that raised `ValueError` instead of `IndexError` (GH18386)
- `Index.to_series()` now accepts `index` and `name` kwargs (GH18699)
- `DatetimeIndex.to_series()` now accepts `index` and `name` kwargs (GH18699)
- Bug in indexing non-scalar value from `Series` having non-unique `Index` will return value flattened (GH17610)
- Bug in indexing with iterator containing only missing keys, which raised no error (GH20748)
- Fixed inconsistency in `.ix` between list and scalar keys when the index has integer dtype and does not include the desired keys (GH20753)
- Bug in `__setitem__` when indexing a `DataFrame` with a 2-d boolean ndarray (GH18582)
- Bug in `str.extractall` when there were no matches empty `Index` was returned instead of appropriate `MultiIndex` (GH19034)
- Bug in `IntervalIndex` where empty and purely NA data was constructed inconsistently depending on the construction method (GH18421)
- Bug in `IntervalIndex.symmetric_difference()` where the symmetric difference with a non-`IntervalIndex` did not raise (GH18475)
- Bug in `IntervalIndex` where set operations that returned an empty `IntervalIndex` had the wrong dtype (GH19101)
- Bug in `DataFrame.drop_duplicates()` where no `KeyError` is raised when passing in columns that don’t exist on the `DataFrame` (GH19726)
- Bug in `Index` subclasses constructors that ignore unexpected keyword arguments (GH19348)
- Bug in `Index.difference()` when taking difference of an `Index` with itself (GH20040)
- Bug in `DataFrame.first_valid_index()` and `DataFrame.last_valid_index()` in presence of entire rows of NaNs in the middle of values (GH20499).
- Bug in `IntervalIndex` where some indexing operations were not supported for overlapping or non-monotonic `uint64` data (GH20636)
- Bug in `Series.is_unique` where extraneous output in stderr is shown if Series contains objects with `__ne__` defined (GH20661)
- Bug in `.loc` assignment with a single-element list-like incorrectly assigns as a list (GH19474)
- Bug in partial string indexing on a `Series/DataFrame` with a monotonic decreasing `DatetimeIndex` (GH19362)
- Bug in performing in-place operations on a `DataFrame` with a duplicate `Index` (GH17105)
pandas: powerful Python data analysis toolkit, Release 1.1.1

• Bug in `IntervalIndex.get_loc()` and `IntervalIndex.get_indexer()` when used with an `IntervalIndex` containing a single interval (GH17284, GH20921)
• Bug in `.loc` with a uint64 indexer (GH20722)

MultiIndex

• Bug in `MultiIndex.__contains__()` where non-tuple keys would return `True` even if they had been dropped (GH19027)
• Bug in `MultiIndex.set_labels()` which would cause casting (and potentially clipping) of the new labels if the level argument is not 0 or a list like `[0, 1, ...]` (GH19057)
• Bug in `MultiIndex.get_level_values()` which would return an invalid index on level of ints with missing values (GH17924)
• Bug in `MultiIndex.unique()` when called on empty `MultiIndex` (GH20568)
• Bug in `MultiIndex.unique()` which would not preserve level names (GH20570)
• Bug in `MultiIndex.remove_unused_levels()` which would fill nan values (GH18417)
• Bug in `MultiIndex.from_tuples()` which would fail to take zipped tuples in python3 (GH18434)
• Bug in `MultiIndex.get_loc()` which would fail to automatically cast values between float and int (GH18818, GH15994)
• Bug in `MultiIndex.get_loc()` which would cast boolean to integer labels (GH19086)
• Bug in `MultiIndex.get_loc()` which would fail to locate keys containing `NaN` (GH18485)
• Bug in `MultiIndex.get_loc()` in large `MultiIndex`, would fail when levels had different dtypes (GH18520)
• Bug in indexing where nested indexers having only numpy arrays are handled incorrectly (GH19686)

I/O

• `read_html()` now rewinds seekable IO objects after parse failure, before attempting to parse with a new parser. If a parser errors and the object is non-seekable, an informative error is raised suggesting the use of a different parser (GH17975)
• `DataFrame.to_html()` now has an option to add an id to the leading `<table>` tag (GH8496)
• Bug in `read_msgpack()` with a non existent file is passed in Python 2 (GH15296)
• Bug in `read_csv()` where a MultiIndex with duplicate columns was not being mangled appropriately (GH18062)
• Bug in `read_csv()` where missing values were not being handled properly when `keep_default_na=False` with dictionary `na_values` (GH19227)
• Bug in `read_csv()` causing heap corruption on 32-bit, big-endian architectures (GH20785)
• Bug in `read_csv()` where a file with 0 variables gave an `AttributeError` incorrectly. Now it gives an `EmptyDataError` (GH18184)
• Bug in `DataFrame.to_latex()` where pairs of braces meant to serve as invisible placeholders were escaped (GH18667)
• Bug in `DataFrame.to_latex()` where a NaN in a MultiIndex would cause an `IndexError` or incorrect output (GH14249)
• Bug in `DataFrame.to_latex()` where a non-string index-level name would result in an AttributeError (GH19981)

• Bug in `DataFrame.to_latex()` where the combination of an index name and the `index_names=False` option would result in incorrect output (GH18326)

• Bug in `DataFrame.to_latex()` where a MultiIndex with an empty string as its name would result in incorrect output (GH18669)

• Bug in `DataFrame.to_latex()` where missing space characters caused wrong escaping and produced non-valid latex in some cases (GH20859)

• Bug in `read_json()` where large numeric values were causing an OverflowError (GH18842)

• Bug in `DataFrame.to_parquet()` where an exception was raised if the write destination is S3 (GH19134)

  • `Interval` now supported in `DataFrame.to_excel()` for all Excel file types (GH19242)

  • `Timedelta` now supported in `DataFrame.to_excel()` for all Excel file types (GH19242, GH9155, GH19900)

• Bug in `pandas.io.stata.StataReader.value_labels()` raising an AttributeError when called on very old files. Now returns an empty dict (GH19417)

• Bug in `read_pickle()` when unpickling objects with `TimedeltaIndex` or `Float64Index` created with pandas prior to version 0.20 (GH19939)

• Bug in `pandas.io.json.json_normalize()` where sub-records are not properly normalized if any sub-records values are NoneType (GH20030)

• Bug in `usecols` parameter in `read_csv()` where error is not raised correctly when passing a string. (GH20529)

• Bug in `HDFStore.keys()` when reading a file with a soft link causes exception (GH20523)

• Bug in `HDFStore.select_column()` where a key which is not a valid store raised an AttributeError instead of a KeyError (GH17912)

**Plotting**

• Better error message when attempting to plot but matplotlib is not installed (GH19810).

• `DataFrame.plot()` now raises a `ValueError` when the x or y argument is improperly formed (GH18671)

• Bug in `DataFrame.plot()` when x and y arguments given as positions caused incorrect referenced columns for line, bar and area plots (GH20056)

• Bug in formatting tick labels with `datetime.time()` and fractional seconds (GH18478).

• `Series.plot.kde()` has exposed the args `ind` and `bw_method` in the docstring (GH18461). The argument `ind` may now also be an integer (number of sample points).

• `DataFrame.plot()` now supports multiple columns to the y argument (GH19699)
Groupby/resample/rolling

- Bug when grouping by a single column and aggregating with a class like list or tuple (GH18079)
- Fixed regression in DataFrame.groupby() which would not emit an error when called with a tuple key not in the index (GH18798)
- Bug in DataFrame.resample() which silently ignored unsupported (or mistyped) options for label, closed and convention (GH19303)
- Bug in DataFrame.groupby() where tuples were interpreted as lists of keys rather than as keys (GH17979, GH18249)
- Bug in DataFrame.groupby() where aggregation by first/last/min/max was causing timestamps to lose precision (GH19526)
- Bug in DataFrame.transform() where particular aggregation functions were being incorrectly cast to match the dtype(s) of the grouped data (GH1900)
- Bug in DataFrame.groupby() passing the on= kwarg, and subsequently using .apply() (GH17813)
- Bug in DataFrame.resample().aggregate not raising a KeyError when aggregating a non-existent column (GH16766, GH19566)
- Bug in DataFrameGroupBy.cumsum() and DataFrameGroupBy.cumprod() when skipna was passed (GH19806)
- Bug in DataFrame.resample() that dropped timezone information (GH13238)
- Bug in DataFrame.groupby() where transformations using np.all and np.any were raising a ValueError (GH20653)
- Bug in DataFrame.resample() where ffill, bfill, pad, backfill, fillna, interpolate, and asfreq were ignoring loffset. (GH20744)
- Bug in DataFrame.groupby() when applying a function that has mixed data types and the user supplied function can fail on the grouping column (GH20949)
- Bug in DataFrameGroupBy.rolling().apply() where operations performed against the associated DataFrameGroupBy object could impact the inclusion of the grouped item(s) in the result (GH14013)

Sparse

- Bug in which creating a SparseDataFrame from a dense Series or an unsupported type raised an uncontrolled exception (GH19374)
- Bug in SparseDataFrame.to_csv causing exception (GH19384)
- Bug in SparseSeries.memory_usage which caused segfault by accessing non sparse elements (GH19368)
- Bug in constructing a SparseArray: if data is a scalar and index is defined it will coerce to float64 regardless of scalar’s dtype. (GH19163)
Reshaping

- Bug in `DataFrame.merge()` where referencing a `CategoricalIndex` by name, where the `by` kwarg would `KeyError` (GH20777)
- Bug in `DataFrame.stack()` which fails trying to sort mixed type levels under Python 3 (GH18310)
- Bug in `DataFrame.unstack()` which casts int to float if `columns` is a `MultiIndex` with unused levels (GH17845)
- Bug in `DataFrame.unstack()` which raises an error if `index` is a `MultiIndex` with unused labels on the unstacked level (GH18562)
- Fixed construction of a `Series` from a `dict` containing NaN as key (GH18480)
- Fixed construction of a `DataFrame` from a `dict` containing NaN as key (GH18455)
- Disabled construction of a `Series` where len(index) > len(data) = 1, which previously would broadcast the data item, and now raises a `ValueError` (GH18819)
- Suppressed error in the construction of a `DataFrame` from a `dict` containing scalar values when the corresponding keys are not included in the passed index (GH18600)
- Fixed (changed from `object` to `float64`) dtype of `DataFrame` initialized with axes, no data, and `dtype=int` (GH19646)
- Bug in `Series.rank()` where Series containing NaT modifies the Series inplace (GH18521)
- Bug in `cut()` which fails when using readonly arrays (GH18773)
- Bug in `DataFrame.pivot_table()` which fails when the `aggfunc` arg is of type string. The behavior is now consistent with other methods like `agg` and `apply` (GH18713)
- Bug in `DataFrame.merge()` in which merging using `Index` objects as vectors raised an Exception (GH19427)
- Bug in `DataFrame.stack()`, `DataFrame.unstack()`, `Series.unstack()` which were not returning subclasses (GH15563)
- Bug in timezone comparisons, manifesting as a conversion of the index to UTC in `.concat()` (GH18523)
- Bug in `concat()` when concatenating sparse and dense series it returns only a `SparseDataFrame`. Should be a `DataFrame`. (GH18914, GH18686, and GH16874)
- Improved error message for `DataFrame.merge()` when there is no common merge key (GH19427)
- Bug in `DataFrame.merge()` which does an outer instead of a left join when being called with multiple `DataFrame` and some have non-unique indices (GH19624)
- `Series.rename()` now accepts `axis` as a kwarg (GH18589)
- Bug in `rename()` where an Index of same-length tuples was converted to a `MultiIndex` (GH19497)
- Comparisons between `Series` and `Index` would return a `Series` with an incorrect name, ignoring the Index’s name attribute (GH19582)
- Bug in `qcut()` where datetime and timedelta data with NaT present raised a `ValueError` (GH19768)
- Bug in `DataFrame.iterrows()`, which would infers strings not compliant to `ISO8601` to datetimes (GH19671)
- Bug in `Series` constructor with `Categorical` where a `ValueError` is not raised when an index of different length is given (GH19342)
- Bug in `DataFrame.astype()` where column metadata is lost when converting to categorical or a dictionary of dtypes (GH19920)
• Bug in `cut()` and `qcut()` where timezone information was dropped (GH19872)
• Bug in `Series` constructor with a `dtype=str`, previously raised in some cases (GH19853)
• Bug in `get_dummies()`, and `select_dtypes()`, where duplicate column names caused incorrect behavior (GH20848)
• Bug in `isna()`, which cannot handle ambiguous typed lists (GH20675)
• Bug in `concat()` which raises an error when concatenating TZ-aware dataframes and all-NaT dataframes (GH12396)
• Bug in `concat()` which raises an error when concatenating empty TZ-aware series (GH18447)

Other

• Improved error message when attempting to use a Python keyword as an identifier in a `numexpr` backed query (GH18221)
• Bug in accessing a `pandas.get_option()`, which raised `KeyError` rather than `OptionError` when looking up a non-existent option key in some cases (GH19789)
• Bug in `testing.assert_series_equal()` and `testing.assert_frame_equal()` for Series or DataFrames with differing unicode data (GH20503)

Contributors

A total of 328 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

• Aaron Critchley
• AbdealiJK +
• Adam Hooper +
• Albert Villanova del Moral
• Alejandro Giacometti +
• Alejandro Hohmann +
• Alex Rychyk
• Alexander Buchkovsky
• Alexander Lenail +
• Alexander Michael Schade
• Aly Sivji +
• Andreas Költringer +
• Andrew
• Andrew Bui +
• András Novoszáth +
• Andy Craze +
• Andy R. Terrel
• Anh Le +
• Anil Kumar Pallekonda +
• Antoine Pitrou +
• Antonio Linde +
• Antonio Molina +
• Antonio Quinonez +
• Armin Varshokar +
• Artem Bogachev +
• Avi Sen +
• Azeez Oluwafemi +
• Ben Auffarth +
• Bernhard Thiel +
• Bhavesh Poddar +
• BielStela +
• Blair +
• Bob Haffner
• Brett Naul +
• Brock Mendel
• Bryce Guinta +
• Carlos Eduardo Moreira dos Santos +
• Carlos García Márquez +
• Carol Willing
• Cheuk Ting Ho +
• Chitrak Dixit +
• Chris
• Chris Burr +
• Chris Catalfo +
• Chris Mazzullo
• Christian Chwala +
• Cihan Ceyhan +
• Clemens Brunner
• Colin +
• Cornelius Riemenschneider
• Crystal Gong +
• Daan Van Hauwermeiren
• Dan Dixey +
• Daniel Frank +
• Daniel Garrido +
• Daniel Sakuma +
• DataOmbudsman +
• Dave Hirschfeld
• Dave Lewis +
• David Adrián Cañones Castellano +
• David Arcos +
• David C Hall +
• David Fischer
• David Hoese +
• David Lutz +
• David Polo +
• David Stansby
• Dennis Kamau +
• Dillon Niederhut
• Dimitri +
• Dr. Irv
• Dror Atariah
• Eric Chea +
• Eric Kisslinger
• Eric O. LEBIGOT (EOL) +
• FAN-GOD +
• Fabian Retkowski +
• Fer Sar +
• Gabriel de Maeztu +
• Gianpaolo Macario +
• Giftlin Rajaiah
• Gilberto Olimpio +
• Gina +
• Gjelt +
• Graham Inggs +
• Grant Roch
• Grant Smith +
• Grzegorz Konefał +
• Guilherme Beltramini
• HagaiHargil +
• Hamish Pitkeathly +
• Hammad Mashkoor +
• Hannah Ferchland +
• Hans
• Haochen Wu +
• Hissashi Rocha +
• Iain Barr +
• Ibrahim Sharaf ElDén +
• Ignasi Fosch +
• Igor Conrado Alves de Lima +
• Igor Shelvinskyi +
• Imanflow +
• Ingolf Becker
• Israel Saeta Pérez
• Iva Koevska +
• Jakub Nowacki +
• Jan F-F +
• Jan Koch +
• Jan Werkmann
• Janelle Zoutkamp +
• Jason Bandlow +
• Jaume Bonet +
• Jay Alammar +
• Jeff Reback
• Jenna Vergeynst
• Jimmy Woo +
• Jing Qiang Goh +
• Joachim Wagner +
• Joan Martin Miralles +
• Joel Nothman
• Joeun Park +
• John Cant +
• Johnny Metz +
• Jon Mease
• Jonas Schulze +
• Jongwony +
• Jordi Contestí +
• Joris Van den Bossche
• José F. R. Fonseca +
• Jovixe +
• Julio Martinez +
• Jörg Döpfert
• KOBAYASHI Ittoku +
• Kate Surta +
• Kenneth +
• Kevin Kuhl
• Kevin Sheppard
• Krzysztof Chomski
• Ksenia +
• Ksenia Bobrova +
• Kunal Gosar +
• Kurtis Kerstein +
• Kyle Barron +
• Laksh Arora +
• Laurens Geffert +
• Leif Walsh
• Liam Marshall +
• Liam3851 +
• Licht Takeuchi
• Liudmila +
• Ludovico Russo +
• Mabel Villalba +
• Manan Pal Singh +
• Manraj Singh
• Marc +
• Marc Garcia
• Marco Hemken +
• Maria del Mar Bibiloni +
• Mario Corchero +
• Mark Woodbridge +
• Martin Journois +
• Mason Gallo +
• Matias Heikkilä +
• Matt Braymer-Hayes
• Matt Kirk +
• Matt Maybeno +
• Matthew Kirk +
• Matthew Rocklin +
• Matthew Roeschke
• Matthias Bussonnier +
• Max Mikhaylov +
• Maxim Veksler +
• Maximilian Roos
• Maximiliano Greco +
• Michael Penkov
• Michael Röttger +
• Michael Selik +
• Michael Waskom
• Mike~~~
• Mike Kutzma +
• Ming Li +
• Mitar +
• Mitch Negus +
• Montana Low +
• Moritz Münst +
• Mortada Mehyar
• Myles Braithwaite +
• Nate Yoder
• Nicholas Ursa +
• Nick Chmura
• Nikos Karagiannakis +
• Nipun Sadvilkar +
• Nis Martensen +
• Noah +
• Noémi Éltető +
• Olivier Bilodeau +
• Ondrej Kokes +
• Onno Eberhard +
• amuta +
• bolkedebruin
• cbertinato
• cgohlke
• charlie0389 +
• chris-b1
• csfarkas +
• dajcs +
• deflatSOCO +
• derestle-htwg
• discort
• dmanikowski-reef +
• donK23 +
• elrubio +
• fivemok +
• fjiod
• fjetter +
• froessler +
• gabrielclow
• gfyouth
• ghasemnaddaf
• h-vetinari +
• himanshu awasthi +
• ignamv +
• jayfoad +
• jazzmuesli +
• jbrockmendel
• jen w +
• jjames34 +
• joaoavf +
• joders +
• jschendel
• juan huguet +
• l736x +
• luzpaz +
• mdeboc +
• miguelmorin +
• miker985
• miquelcamprodon +
• orereta +
• ottiP +
• peterpanmj +
• rafarui +
• raph-m +
• readyready15728 +
• rmihael +
• samghelms +
• scriptomation +
• sfoo +
• stefansimik +
• stonebig
• tmnhat2001 +
• tomneep +
• topper-123
• tv3141 +
• verakai +
• xpvpc +
• zhanghui +

5.6 Version 0.22

5.6.1 v0.22.0 (December 29, 2017)

This is a major release from 0.21.1 and includes a single, API-breaking change. We recommend that all users upgrade to this version after carefully reading the release note (singular!).

Backwards incompatible API changes

Pandas 0.22.0 changes the handling of empty and all-NA sums and products. The summary is that

• The sum of an empty or all-NA Series is now 0
• The product of an empty or all-NA Series is now 1
• We’ve added a min_count parameter to .sum() and .prod() controlling the minimum number of valid values for the result to be valid. If fewer than min_count non-NA values are present, the result is NA. The default is 0. To return NaN, the 0.21 behavior, use min_count=1.
Some background: In pandas 0.21, we fixed a long-standing inconsistency in the return value of all-NA series depending on whether or not bottleneck was installed. See *Sum/prod of all-NaN or empty Series/DataFrames is now consistently NaN*. At the same time, we changed the sum and prod of an empty Series to also be NaN.

Based on feedback, we’ve partially reverted those changes.

**Arithmetic operations**

The default sum for empty or all-NA Series is now 0.

*pandas 0.21.x*

```
In [1]: pd.Series([]).sum()
Out[1]: nan

In [2]: pd.Series([np.nan]).sum()
Out[2]: nan
```

*pandas 0.22.0*

```
In [1]: pd.Series([]).sum()
Out[1]: 0.0

In [2]: pd.Series([np.nan]).sum()
Out[2]: 0.0
```

The default behavior is the same as pandas 0.20.3 with bottleneck installed. It also matches the behavior of NumPy’s `np.nansum` on empty and all-NA arrays.

To have the sum of an empty series return NaN (the default behavior of pandas 0.20.3 without bottleneck, or pandas 0.21.x), use the `min_count` keyword.

```
In [3]: pd.Series([]).sum(min_count=1)
Out[3]: nan
```

Thanks to the `skipna` parameter, the `.sum` on an all-NA series is conceptually the same as the `.sum` of an empty one with `skipna=True` (the default).

```
In [4]: pd.Series([np.nan]).sum(min_count=1)  # skipna=True by default
Out[4]: nan
```

The `min_count` parameter refers to the minimum number of *non-null* values required for a non-NA sum or product. `Series.prod()` has been updated to behave the same as `Series.sum()`, returning 1 instead.

```
In [5]: pd.Series([]).prod()
Out[5]: 1.0

In [6]: pd.Series([np.nan]).prod()
Out[6]: 1.0

In [7]: pd.Series([]).prod(min_count=1)
Out[7]: nan
```

These changes affect `DataFrame.sum()` and `DataFrame.prod()` as well. Finally, a few less obvious places in pandas are affected by this change.
Grouping by a categorical

Grouping by a Categorical and summing now returns 0 instead of NaN for categories with no observations. The product now returns 1 instead of NaN.

_pandas 0.21.x_

```python
In [8]: grouper = pd.Categorical(['a', 'a'], categories=['a', 'b'])

In [9]: pd.Series([1, 2]).groupby(grouper).sum()
Out[9]:
   a    3.0
   b   NaN
   dtype: float64
```

_pandas 0.22_

```python
In [8]: grouper = pd.Categorical(['a', 'a'], categories=['a', 'b'])

In [9]: pd.Series([1, 2]).groupby(grouper).sum()
Out[9]:
   a    3
   b    0
   Length: 2, dtype: int64
```

To restore the 0.21 behavior of returning NaN for unobserved groups, use `min_count>=1`.

```python
In [10]: pd.Series([1, 2]).groupby(grouper).sum(min_count=1)
Out[10]:
   a    3.0
   b   NaN
   Length: 2, dtype: float64
```

Resample

The sum and product of all-NA bins has changed from NaN to 0 for sum and 1 for product.

_pandas 0.21.x_

```python
In [11]: s = pd.Series([1, 1, np.nan, np.nan],
                   index=pd.date_range('2017', periods=4))
   ....:
   ....: s
Out[11]:
   2017-01-01    1.0
   2017-01-02    1.0
   2017-01-03   NaN
   2017-01-04   NaN
   Freq: D, dtype: float64

In [12]: s.resample('2d').sum()
Out[12]:
   2017-01-01    2.0
   2017-01-03   NaN
   Freq: 2D, dtype: float64
```

_pandas 0.22_
In [11]: s = pd.Series([1, 1, np.nan, np.nan],
                   index=pd.date_range('2017', periods=4))

In [12]: s.resample('2d').sum()
Out[12]:
2017-01-01    2.0
2017-01-03    0.0
Freq: 2D, Length: 2, dtype: float64

To restore the 0.21 behavior of returning NaN, use min_count>=1.

In [13]: s.resample('2d').sum(min_count=1)
Out[13]:
2017-01-01    2.0
2017-01-03   NaN
Freq: 2D, Length: 2, dtype: float64

In particular, upsampling and taking the sum or product is affected, as upsampling introduces missing values even if the original series was entirely valid.

pandas 0.21.x

In [14]: idx = pd.DatetimeIndex(['2017-01-01', '2017-01-02'])

In [15]: pd.Series([1, 2], index=idx).resample('12H').sum()
Out[15]:
2017-01-01 00:00:00    1.0
2017-01-01 12:00:00   NaN
2017-01-02 00:00:00    2.0
Freq: 12H, dtype: float64

pandas 0.22.0

In [14]: idx = pd.DatetimeIndex(['2017-01-01', '2017-01-02'])

In [15]: pd.Series([1, 2], index=idx).resample('12H').sum()
Out[15]:
2017-01-01 00:00:00    1
2017-01-01 12:00:00   0
2017-01-02 00:00:00    2
Freq: 12H, Length: 3, dtype: int64

Once again, the min_count keyword is available to restore the 0.21 behavior.

In [16]: pd.Series([1, 2], index=idx).resample('12H').sum(min_count=1)
Out[16]:
2017-01-01 00:00:00    1.0
2017-01-01 12:00:00   NaN
2017-01-02 00:00:00    2.0
Freq: 12H, Length: 3, dtype: float64
Rolling and expanding

Rolling and expanding already have a `min_periods` keyword that behaves similar to `min_count`. The only case that changes is when doing a rolling or expanding sum with `min_periods=0`. Previously this returned `NaN`, when fewer than `min_periods` non-NA values were in the window. Now it returns 0.

### pandas 0.21.1

```
In [17]: s = pd.Series([np.nan, np.nan])
In [18]: s.rolling(2, min_periods=0).sum()
Out[18]:
0    NaN
1    NaN
dtype: float64
```

### pandas 0.22.0

```
In [17]: s = pd.Series([np.nan, np.nan])
In [18]: s.rolling(2, min_periods=0).sum()
Out[18]:
0    0.0
1    0.0
Length: 2, dtype: float64
```

The default behavior of `min_periods=None`, implying that `min_periods` equals the window size, is unchanged.

### Compatibility

If you maintain a library that should work across pandas versions, it may be easiest to exclude pandas 0.21 from your requirements. Otherwise, all your `sum()` calls would need to check if the `Series` is empty before summing.

With `setuptools`, in your `setup.py` use:

```
install_requires=['pandas!=0.21.*', ...]
```

With `conda`, use

```
requirements:
  run:
    - pandas !=0.21.0, !=0.21.1
```

Note that the inconsistency in the return value for all-NA series is still there for pandas 0.20.3 and earlier. Avoiding pandas 0.21 will only help with the empty case.
Contributors

A total of 1 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Tom Augspurger

5.7 Version 0.21

5.7.1 Version 0.21.1 (December 12, 2017)

This is a minor bug-fix release in the 0.21.x series and includes some small regression fixes, bug fixes and performance improvements. We recommend that all users upgrade to this version.

Highlights include:

- Temporarily restore matplotlib datetime plotting functionality. This should resolve issues for users who implicitly relied on pandas to plot datetimes with matplotlib. See here.
- Improvements to the Parquet IO functions introduced in 0.21.0. See here.

What’s new in v0.21.1

- Restore Matplotlib datetime converter registration
- New features
  - Improvements to the Parquet IO functionality
  - Other enhancements
- Deprecations
- Performance improvements
- Bug fixes
  - Conversion
  - Indexing
  - IO
  - Plotting
  - GroupBy/resample/rolling
  - Reshaping
  - Numeric
  - Categorical
  - String
- Contributors
**Restore Matplotlib datetime converter registration**

Pandas implements some matplotlib converters for nicely formatting the axis labels on plots with `datetime` or `Period` values. Prior to pandas 0.21.0, these were implicitly registered with matplotlib, as a side effect of `import pandas`.

In pandas 0.21.0, we required users to explicitly register the converter. This caused problems for some users who relied on those converters being present for regular `matplotlib.pyplot` plotting methods, so we’re temporarily reverting that change; pandas 0.21.1 again registers the converters on import, just like before 0.21.0.

We’ve added a new option to control the converters: `pd.options.plotting.matplotlib.register_converters`. By default, they are registered. Toggling this to False removes pandas’ formatters and restore any converters we overwrote when registering them (GH18301).

We’re working with the matplotlib developers to make this easier. We’re trying to balance user convenience (automatically registering the converters) with import performance and best practices (importing pandas shouldn’t have the side effect of overwriting any custom converters you’ve already set). In the future we hope to have most of the date-time formatting functionality in matplotlib, with just the pandas-specific converters in pandas. We’ll then gracefully deprecate the automatic registration of converters in favor of users explicitly registering them when they want them.

**New features**

**Improvements to the Parquet IO functionality**

- `DataFrame.to_parquet()` will now write non-default indexes when the underlying engine supports it. The indexes will be preserved when reading back in with `read_parquet()` (GH18581).
- `read_parquet()` now allows to specify the columns to read from a parquet file (GH18154)
- `read_parquet()` now allows to specify kwargs which are passed to the respective engine (GH18216)

**Other enhancements**

- `Timestamp.timestamp()` is now available in Python 2.7. (GH17329)
- `Grouper` and `TimeGrouper` now have a friendly repr output (GH18203).

**Deprecations**

- `pandas.tseries.register` has been renamed to `pandas.plotting.register_matplotlib_converters()` (GH18301)

**Performance improvements**

- Improved performance of plotting large series/dataframes (GH18236).
Bug fixes

Conversion

- Bug in `TimedeltaIndex` subtraction could incorrectly overflow when NaT is present (GH17791)
- Bug in `DatetimeIndex` subtracting datetimelike from DatetimeIndex could fail to overflow (GH18020)
- Bug in `IntervalIndex.copy()` when copying and `IntervalIndex` with non-default `closed` (GH18339)
- Bug in `DataFrame.to_dict()` where columns of datetime that are tz-aware were not converted to required arrays when used with `orient='records'`, raising TypeError (GH18372)
- Bug in `DateTimeIndex` and `date_range()` where mismatching tz-aware start and end timezones would not raise an err if `end.tzinfo` is None (GH18431)
- Bug in `Series.fillna()` which raised when passed a long integer on Python 2 (GH18159).

Indexing

- Bug in a boolean comparison of a `datetime.datetime` and a `datetime64[ns]` dtype Series (GH17965)
- Bug where a `MultiIndex` with more than a million records was not raising `AttributeError` when trying to access a missing attribute (GH18165)
- Bug in `IntervalIndex` constructor when a list of intervals is passed with non-default `closed` (GH18334)
- Bug in `Index.putmask` when an invalid mask passed (GH18368)
- Bug in masked assignment of a `timedelta64[ns]` dtype Series, incorrectly coerced to float (GH18493)

IO

- Bug in class:`pandas.io.stata.StataReader` not converting date/time columns with display formatting addressed (GH17990). Previously columns with display formatting were normally left as ordinal numbers and not converted to datetime objects.
- Bug in `read_csv()` when reading a compressed UTF-16 encoded file (GH18071)
- Bug in `read_csv()` for handling null values in index columns when specifying `na_filter=False` (GH5239)
- Bug in `read_csv()` when reading numeric category fields with high cardinality (GH18186)
- Bug in `DataFrame.to_csv()` when the table had `MultiIndex` columns, and a list of strings was passed in for `header` (GH5539)
- Bug in parsing integer datetime-like columns with specified format in `read_sql` (GH17855).
- Bug in `DataFrame.to_msgpack()` when serializing data of the `numpy.bool_` datatype (GH18390)
- Bug in `read_json()` not decoding when reading line delimited JSON from S3 (GH17200)
- Bug in `pandas.io.json.json_normalize()` to avoid modification of `meta` (GH18610)
- Bug in `to_latex()` where repeated `MultiIndex` values were not printed even though a higher level index differed from the previous row (GH14484)
- Bug when reading NaN-only categorical columns in `HDFStore` (GH18413)
• Bug in `DataFrame.to_latex()` with longtable=True where a latex multicolumn always spanned over three columns (GH17959)

Plotting

• Bug in `DataFrame.plot()` and `Series.plot()` with `DatetimeIndex` where a figure generated by them is not pickleable in Python 3 (GH18439)

GroupBy/resample/rolling

• Bug in `DataFrame.resample(...) .apply(...)` when there is a callable that returns different columns (GH15169)
• Bug in `DataFrame.resample(...)` when there is a time change (DST) and resampling frequency is 12h or higher (GH15549)
• Bug in `pd.DataFrameGroupBy.count()` when counting over a datetimelike column (GH13393)
• Bug in `rolling.var` where calculation is inaccurate with a zero-valued array (GH18430)

Reshaping

• Error message in `pd.merge_asof()` for key datatype mismatch now includes datatype of left and right key (GH18068)
• Bug in `pd.concat` when empty and non-empty DataFrames or Series are concatenated (GH18178 GH18187)
• Bug in `DataFrame.filter(...)` when unicode is passed as a condition in Python 2 (GH13101)
• Bug when merging empty DataFrames when `np.seterr(divide='raise')` is set (GH17776)

Numeric

• Bug in `pd.Series.rolling.skew()` and `rolling.kurt()` with all equal values has floating issue (GH18044)

Categorical

• Bug in `DataFrame.astype()` where casting to ‘category’ on an empty DataFrame causes a segmentation fault (GH18004)
• Error messages in the testing module have been improved when items have different CategoricalDtype (GH18069)
• CategoricalIndex can now correctly take a pd.api.types.CategoricalDtype as its dtype (GH18116)
• Bug in `Categorical.unique()` returning read-only codes array when all categories were NaN (GH18051)
• Bug in `DataFrame.groupby(axis=1)` with a CategoricalIndex (GH18432)
String

*Series.str.split()* will now propagate NaN values across all expanded columns instead of None (GH18450)

Contributors

A total of 46 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Aaron Critchley +
- Alex Rychyk
- Alexander Buchkovsky +
- Alexander Michael Schade +
- Chris Mazzullo
- Cornelius Riemenschneider +
- Dave Hirschfeld +
- David Fischer +
- David Stansby +
- Dror Atariah +
- Eric Kisslinger +
- Hans +
- Ingolf Becker +
- Jan Werkmann +
- Jeff Reback
- Joris Van den Bossche
- Jörg Döpfert +
- Kevin Kuhl +
- Krzysztof Chomski +
- Leif Walsh
- Licht Takeuchi
- Manraj Singh +
- Matt Braymer-Hayes +
- Michael Waskom +
- Mie~~~ +
- Peter Hoffmann +
- Robert Meyer +
- Sam Cohan +
- Sietse Brouwer +
• Sven +
• Tim Swast
• Tom Augspurger
• Wes Turner
• William Ayd +
• Yee Mey +
• bolkedebruin +
• cgohlke
• derestle-htwg +
• fjdiol +
• gabrielclow +
• gyoung
• ghasemnaddaf +
• jbrockmendel
• jschendel
• miker985 +
• topper-123

5.7.2 Version 0.21.0 (October 27, 2017)

This is a major release from 0.20.3 and includes a number of API changes, deprecations, new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

• Integration with Apache Parquet, including a new top-level `read_parquet()` function and `DataFrame.to_parquet()` method, see here.

• New user-facing `pandas.api.types.CategoricalDtype` for specifying categoricals independent of the data, see here.

• The behavior of `sum` and `prod` on all-NaN Series/DataFrames is now consistent and no longer depends on whether bottleneck is installed, and `sum` and `prod` on empty Series now return NaN instead of 0, see here.

• Compatibility fixes for pypy, see here.

• Additions to the `drop`, `reindex` and `rename` API to make them more consistent, see here.

• Addition of the new methods `DataFrame.infer_objects` (see here) and `GroupBy.pipe` (see here).

• Indexing with a list of labels, where one or more of the labels is missing, is deprecated and will raise a KeyError in a future version, see here.

Check the API Changes and deprecations before updating.
• New features
  – Integration with Apache Parquet file format
  – Method `infer_objects` type conversion
  – Improved warnings when attempting to create columns
  – Method `drop` now also accepts index/columns keywords
  – Methods `rename`, `reindex` now also accept axis keyword
  – `CategoricalDtype` for specifying categoricals
  – `GroupBy` objects now have a `pipe` method
  – `Categorical.rename_categories` accepts a dict-like
  – Other enhancements

• Backwards incompatible API changes
  – Dependencies have increased minimum versions
  – Sum/prod of all-NaN or empty Series/DataFrames is now consistently NaN
  – Indexing with a list with missing labels is deprecated
  – NA naming changes
  – Iteration of Series/Index will now return Python scalars
  – Indexing with a Boolean Index
  – `PeriodIndex` resampling
  – Improved error handling during item assignment in `pd.eval`
  – Dtype conversions
  – `MultiIndex` constructor with a single level
  – UTC localization with `Series`
  – Consistency of range functions
  – No automatic Matplotlib converters
  – Other API changes

• Deprecations
  – `Series.select` and `DataFrame.select`
  – `Series.argmax` and `Series.argmin`

• Removal of prior version deprecations/changes

• Performance improvements

• Documentation changes

• Bug fixes
  – Conversion
  – Indexing
  – IO
New features

Integration with Apache Parquet file format

Integration with Apache Parquet, including a new top-level `read_parquet()` and `DataFrame.to_parquet()` method, see here (GH15838, GH17438).

Apache Parquet provides a cross-language, binary file format for reading and writing data frames efficiently. Parquet is designed to faithfully serialize and de-serialize `DataFrame`s, supporting all of the pandas dtypes, including extension dtypes such as datetime with timezones.

This functionality depends on either the pyarrow or fastparquet library. For more details, see the IO docs on Parquet.

Method `infer_objects` type conversion

The `DataFrame.infer_objects()` and `Series.infer_objects()` methods have been added to perform dtype inference on object columns, replacing some of the functionality of the deprecated `convert_objects` method. See the documentation here for more details. (GH11221)

This method only performs soft conversions on object columns, converting Python objects to native types, but not any coercive conversions. For example:

```
In [1]: df = pd.DataFrame({'A': [1, 2, 3],
                      ...:                     'B': np.array([1, 2, 3], dtype='object'),
                      ...:                     'C': ['1', '2', '3'])

In [2]: df.dtypes
Out[2]:
A    int64
B    object
C    object
Length: 3, dtype: object

In [3]: df.infer_objects().dtypes
Out[3]:
A    int64
B    int64
```

(continues on next page)
Note that column 'C' was not converted - only scalar numeric types will be converted to a new type. Other types of conversion should be accomplished using the `to_numeric()` function (or `to_datetime()`, `to_timedelta()`).

```
In [4]: df = df.infer_objects()
In [5]: df['C'] = pd.to_numeric(df['C'], errors='coerce')
In [6]: df.dtypes
Out[6]:
    A    int64
    B    int64
    C    int64
    dtype: object
```

**Improved warnings when attempting to create columns**

New users are often puzzled by the relationship between column operations and attribute access on `DataFrame` instances (GH7175). One specific instance of this confusion is attempting to create a new column by setting an attribute on the `DataFrame`:

```
In [1]: df = pd.DataFrame({'one': [1., 2., 3.]})
In [2]: df.two = [4, 5, 6]
```

This does not raise any obvious exceptions, but also does not create a new column:

```
In [3]: df
Out[3]:
   one
   0 1.0
   1 2.0
   2 3.0
```

Setting a list-like data structure into a new attribute now raises a `UserWarning` about the potential for unexpected behavior. See `Attribute Access`.

**Method `drop` now also accepts index/columns keywords**

The `drop()` method has gained `index/columns` keywords as an alternative to specifying the `axis`. This is similar to the behavior of `reindex (GH12392)`.

For example:

```
In [7]: df = pd.DataFrame(np.arange(8).reshape(2, 4),
                     columns=['A', 'B', 'C', 'D'])
In [8]: df
Out[8]:
   A  B  C  D
```

(continues on next page)
In [9]: df.drop(['B', 'C'], axis=1)
Out[9]:
   A  D
0  0  3
1  4  7
[2 rows x 2 columns]

# the following is now equivalent
In [10]: df.drop(columns=['B', 'C'])
Out[10]:
   A  D
0  0  3
1  4  7
[2 rows x 2 columns]

### Methods rename, reindex now also accept axis keyword

The `DataFrame.rename()` and `DataFrame.reindex()` methods have gained the `axis` keyword to specify the axis to target with the operation (GH12392).

Here’s rename:

```python
In [11]: df = pd.DataFrame({'A': [1, 2, 3], 'B': [4, 5, 6]})

In [12]: df.rename(str.lower, axis='columns')
Out[12]:
      a  b
0   1  4
1   2  5
2   3  6
[3 rows x 2 columns]

In [13]: df.rename(id, axis='index')
Out[13]:
       A    B
94659639659744  1  4
94659639659776  2  5
94659639659808  3  6
[3 rows x 2 columns]
```

And reindex:

```python
In [14]: df.reindex(['A', 'B', 'C'], axis='columns')
Out[14]:
   A  B  C
0  1  4 NaN
```

(continues on next page)
```python
In [15]: df.reindex([0, 1, 3], axis='index')
Out[15]:
   A  B
0  1.0 4.0
1  2.0 5.0
3  NaN NaN
[3 rows x 2 columns]
```

The “index, columns” style continues to work as before.

```python
In [16]: df.rename(index=id, columns=str.lower)
Out[16]:
      a  b
94659639659744  1 4
94659639659776  2 5
94659639659808  3 6
[3 rows x 2 columns]
```

```python
In [17]: df.reindex(index=[0, 1, 3], columns=['A', 'B', 'C'])
Out[17]:
   A  B  C
0  1.0 4.0  NaN
1  2.0 5.0  NaN
3  NaN NaN NaN
[3 rows x 3 columns]
```

We highly encourage using named arguments to avoid confusion when using either style.

**CategoricalDtype for specifying categoricals**

`pandas.api.types.CategoricalDtype` has been added to the public API and expanded to include the categories and ordered attributes. A CategoricalDtype can be used to specify the set of categories and orderedness of an array, independent of the data. This can be useful for example, when converting string data to a Categorical (GH14711, GH15078, GH16015, GH17643):

```python
In [18]: from pandas.api.types import CategoricalDtype

In [19]: s = pd.Series(['a', 'b', 'c', 'a'])  # strings

In [20]: dtype = CategoricalDtype(categories=['a', 'b', 'c', 'd'], ordered=True)

In [21]: s.astype(dtype)
Out[21]:
0  a
1  b
2  c
3  a
```

(continues on next page)
One place that deserves special mention is in `read_csv()`. Previously, with `dtype={'col': 'category'}`, the returned values and categories would always be strings.

```python
In [22]: data = 'A,B
a,1
b,2
c,3'

In [23]: pd.read_csv(StringIO(data), dtype={'B': 'category'}).B.cat.categories
Out[23]: Index([1, 2, 3], dtype='object')
```

Notice the “object” dtype.

With a `CategoricalDtype` of all numerics, datetimes, or timedeltas, we can automatically convert to the correct type.

```python
In [24]: dtype = {'B': CategoricalDtype([1, 2, 3])}

In [25]: pd.read_csv(StringIO(data), dtype=dtype).B.cat.categories
Out[25]: Int64Index([1, 2, 3], dtype='int64')
```

The values have been correctly interpreted as integers.

The `.dtype` property of a `Categorical`, `CategoricalIndex` or a `Series` with categorical type will now return an instance of `CategoricalDtype`. While the repr has changed, `str(CategoricalDtype())` is still the string 'category'. We’ll take this moment to remind users that the preferred way to detect categorical data is to use `pandas.api.types.is_categorical_dtype()`, and not `str(dtype) == 'category'`. See the `CategoricalDtype docs` for more.

**GroupBy objects now have a pipe method**

GroupBy objects now have a `pipe` method, similar to the one on `DataFrame` and `Series`, that allow for functions that take a `GroupBy` to be composed in a clean, readable syntax. (GH17871)

For a concrete example on combining `.groupby` and `.pipe`, imagine having a DataFrame with columns for stores, products, revenue and sold quantity. We’d like to do a groupwise calculation of prices (i.e. revenue/quantity) per store and per product. We could do this in a multi-step operation, but expressing it in terms of piping can make the code more readable.

First we set the data:

```python
In [26]: import numpy as np

In [27]: n = 1000

In [28]: df = pd.DataFrame({'Store': np.random.choice(['Store_1', 'Store_2'], n),
...:                     'Product': np.random.choice(['Product_1',
...:                                                 'Product_2',
...:                                                 'Product_3'
...:                                                 ], n),
...:                     'Revenue': (np.random.random(n) * 50 + 10).round(2),
...:                     'Quantity': np.random.randint(1, 10, size=n))
...

In [29]: df.head(2)
```
Now, to find prices per store/product, we can simply do:

```python
In [30]: (df.groupby(['Store', 'Product'])
    ....:   .pipe(lambda grp: grp.Revenue.sum() / grp.Quantity.sum())
    ....:   .unstack().round(2))
```

```
Out[30]:

<table>
<thead>
<tr>
<th>Product</th>
<th>Product_1</th>
<th>Product_2</th>
<th>Product_3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Store_1</td>
<td>6.73</td>
<td>6.72</td>
<td>7.14</td>
</tr>
<tr>
<td>Store_2</td>
<td>7.59</td>
<td>6.98</td>
<td>7.23</td>
</tr>
</tbody>
</table>
```

[2 rows x 3 columns]

See the documentation for more.

**Categorical.rename_categories accepts a dict-like**

rename_categories() now accepts a dict-like argument for new_categories. The previous categories are looked up in the dictionary's keys and replaced if found. The behavior of missing and extra keys is the same as in DataFrame.rename().

```python
In [31]: c = pd.Categorical(['a', 'a', 'b'])
In [32]: c.rename_categories({"a": "eh", "b": "bee"})
```

```
Out[32]: ['eh', 'eh', 'bee']
Categories (2, object): ['eh', 'bee']
```

**Warning:** To assist with upgrading pandas, rename_categories treats Series as list-like. Typically, Series are considered to be dict-like (e.g. in .rename, .map). In a future version of pandas rename_categories will change to treat them as dict-like. Follow the warning message’s recommendations for writing future-proof code.

```python
In [33]: c.rename_categories(pd.Series([0, 1], index=['a', 'c']))
```

```
FutureWarning:Treating Series 'new_categories' as a list-like and using the values. In a future version, 'rename_categories' will treat Series like a dictionary. For dict-like, use 'new_categories.to_dict()' For list-like, use 'new_categories.values'.
```

```
Out[33]: [0, 0, 1]
Categories (2, int64): [0, 1]
```
Other enhancements

New functions or methods

- `nearest()` is added to support nearest-neighbor upsampling (GH17496).
- `Index` has added support for a `to_frame` method (GH15230).

New keywords

- Added a `skipna` parameter to `infer_dtype()` to support type inference in the presence of missing values (GH17059).
- `Series.to_dict()` and `DataFrame.to_dict()` now support an `into` keyword which allows you to specify the `collections.Mapping` subclass that you would like returned. The default is `dict`, which is backwards compatible. (GH16122)
- `Series.set_axis()` and `DataFrame.set_axis()` now support the `inplace` parameter. (GH14636)
- `Series.to_pickle()` and `DataFrame.to_pickle()` have gained a `protocol` parameter (GH16252). By default, this parameter is set to `HIGHEST_PROTOCOL`.
- `read_feather()` has gained the `nthreads` parameter for multi-threaded operations (GH16359)
- `DataFrame.clip()` and `Series.clip()` have gained an `inplace` argument. (GH15388)
- `crosstab()` has gained a `margins_name` parameter to define the name of the row / column that will contain the totals when `margins=True`. (GH15972)
- `read_json()` now accepts a `chunksize` parameter that can be used when `lines=True`. If `chunksize` is passed, `read_json` now returns an iterator which reads in `chunksize` lines with each iteration. (GH17048)
- `read_json()` and `to_json()` now accept a `compression` argument which allows them to transparently handle compressed files. (GH17798)

Various enhancements

- Improved the import time of pandas by about 2.25x. (GH16764)
- Support for PEP 519 – Adding a file system path protocol on most readers (e.g. `read_csv()`) and writers (e.g. `DataFrame.to_csv()`) (GH13823).
- Added a `__fspath__` method to `pd.HDFStore`, `pd.ExcelFile`, and `pd.ExcelWriter` to work properly with the file system path protocol (GH13823).
- The `validate` argument for `merge()` now checks whether a merge is one-to-one, one-to-many, many-to-one, or many-to-many. If a merge is found to not be an example of specified merge type, an exception of type `MergeError` will be raised. For more, see here (GH16270)
- Added support for PEP 518 (`pyproject.toml`) to the build system (GH16745)
- `RangeIndex.append()` now returns a `RangeIndex` object when possible (GH16212)
- `Series.rename_axis()` and `DataFrame.rename_axis()` with `inplace=True` now return `None` while renaming the axis inplace. (GH15704)
- `api.types.infer_dtype()` now infers decimals. (GH15690)
- `DataFrame.select_dtypes()` now accepts scalar values for include/exclude as well as list-like. (GH16855)
• `date_range()` now accepts ‘YS’ in addition to ‘AS’ as an alias for start of year. (GH9313)
• `date_range()` now accepts ‘Y’ in addition to ‘A’ as an alias for end of year. (GH9313)
• `DataFrame.add_prefix()` and `DataFrame.add_suffix()` now accept strings containing the ‘%’ character. (GH17151)
• Read/write methods that infer compression (`read_csv()`, `read_table()`, `read_pickle()`, and `to_pickle()`) can now infer from path-like objects, such as `pathlib.Path`. (GH17206)
• `read_sas()` now recognizes much more of the most frequently used date (datetime) formats in SAS7BDAT files. (GH15871)
• `DataFrame.items()` and `Series.items()` are now present in both Python 2 and 3 and is lazy in all cases. (GH13918, GH17213)
• `pandas.io.formats.style.Styler.where()` has been implemented as a convenience for `pandas.io.formats.style.Styler.applymap()`. (GH17474)
• `MultiIndex.is_monotonic_decreasing()` has been implemented. Previously returned `False` in all cases. (GH16554)
• `read_excel()` raises `ImportError` with a better message if `xlrd` is not installed. (GH17613)
• `DataFrame.assign()` will preserve the original order of **kwargs for Python 3.6+ users instead of sorting the column names. (GH14207)
• `Series.reindex()`, `DataFrame.reindex()`, `Index.get_indexer()` now support list-like argument for tolerance. (GH17367)

**Backwards incompatible API changes**

**Dependencies have increased minimum versions**

We have updated our minimum supported versions of dependencies (GH15206, GH15543, GH15214). If installed, we now require:

<table>
<thead>
<tr>
<th>Package</th>
<th>Minimum Version</th>
<th>Required</th>
</tr>
</thead>
<tbody>
<tr>
<td>Numpy</td>
<td>1.9.0</td>
<td>X</td>
</tr>
<tr>
<td>Matplotlib</td>
<td>1.4.3</td>
<td></td>
</tr>
<tr>
<td>Scipy</td>
<td>0.14.0</td>
<td></td>
</tr>
<tr>
<td>Bottleneck</td>
<td>1.0.0</td>
<td></td>
</tr>
</tbody>
</table>

Additionally, support has been dropped for Python 3.4 (GH15251).

**Sum/prod of all-NaN or empty Series/DataFrames is now consistently NaN**

**Note:** The changes described here have been partially reverted. See the v0.22.0 Whatsnew for more.

The behavior of `sum` and `prod` on all-NaN Series/DataFrames no longer depends on whether `bottleneck` is installed, and return value of `sum` and `prod` on an empty Series has changed (GH9422, GH15507).

Calling `sum` or `prod` on an empty or all-NaN Series, or columns of a DataFrame, will result in NaN. See the docs.
Previously WITHOUT bottleneck installed:

```
In [2]: s.sum()
Out[2]: np.nan
```

Previously WITH bottleneck:

```
In [2]: s.sum()
Out[2]: 0.0
```

New behavior, without regard to the bottleneck installation:

```
In [34]: s.sum()
Out[34]: 0.0
```

Note that this also changes the sum of an empty Series. Previously this always returned 0 regardless of a bottleneck installation:

```
In [1]: pd.Series([]).sum()
Out[1]: 0
```

but for consistency with the all-NaN case, this was changed to return NaN as well:

```
In [35]: pd.Series([]).sum()
Out[35]: 0.0
```

**Indexing with a list with missing labels is deprecated**

Previously, selecting with a list of labels, where one or more labels were missing would always succeed, returning NaN for missing labels. This will now show a `FutureWarning`. In the future this will raise a `KeyError (GH15747)`. This warning will trigger on a `DataFrame` or a `Series` for using `.loc[]` or `[]` when passing a list-of-labels with at least 1 missing label. See the [deprecation docs](#).

```
In [36]: s = pd.Series([1, 2, 3])
In [37]: s
Out[37]:
0   1
1   2
2   3
Length: 3, dtype: int64

Previous behavior

```
In [4]: s.loc[[1, 2, 3]]
Out[4]:
1   2.0
2   3.0
3   NaN
dtype: float64
```

Current behavior
In [4]: s.loc[[1, 2, 3]]
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-reindex-
˓listlike

Out[4]:
1 2.0
2 3.0
3 NaN
dtype: float64

The idiomatic way to achieve selecting potentially not-found elements is via .reindex()

In [38]: s.reindex([1, 2, 3])
Out[38]:
1 2.0
2 3.0
3 NaN
Length: 3, dtype: float64

Selection with all keys found is unchanged.

In [39]: s.loc[[1, 2]]
Out[39]:
1 2
2 3
Length: 2, dtype: int64

NA naming changes

In order to promote more consistency among the pandas API, we have added additional top-level functions isna() and notna() that are aliases for isnull() and notnull(). The naming scheme is now more consistent with methods like .dropna() and .fillna(). Furthermore in all cases where .isnull() and .notnull() methods are defined, these have additional methods named .isna() and .notna(), these are included for classes Categorical, Index, Series, and DataFrame. (GH15001).

The configuration option pd.options.mode.use_inf_as_null is deprecated, and pd.options.mode.
use_inf_as_na is added as a replacement.

Iteration of Series/Index will now return Python scalars

Previously, when using certain iteration methods for a Series with dtype int or float, you would receive a numpy scalar, e.g. np.int64, rather than a Python int. Issue (GH10904) corrected this for Series.tolist() and list(Series). This change makes all iteration methods consistent, in particular, for __iter__() and .
map(); note that this only affects int/float dtypes. (GH13236, GH13258, GH14216).

In [40]: s = pd.Series([1, 2, 3])
In [41]: s
Out[41]:
0 1
Previously:

```
In [2]: type(list(s)[0])
Out[2]: numpy.int64
```

New behavior:

```
In [42]: type(list(s)[0])
Out[42]: int
```

Furthermore this will now correctly box the results of iteration for `DataFrame.to_dict()` as well.

```
In [43]: d = {'a': [1], 'b': ['b']}
In [44]: df = pd.DataFrame(d)
```

Previously:

```
In [8]: type(df.to_dict()['a'][0])
Out[8]: numpy.int64
```

New behavior:

```
In [45]: type(df.to_dict()['a'][0])
Out[45]: int
```

### Indexing with a Boolean Index

Previously when passing a boolean `Index` to `.loc`, if the index of the `Series/DataFrame` had boolean labels, you would get a label based selection, potentially duplicating result labels, rather than a boolean indexing selection (where `True` selects elements), this was inconsistent how a boolean numpy array indexed. The new behavior is to act like a boolean numpy array indexer. (GH17738)

Previous behavior:

```
In [46]: s = pd.Series([1, 2, 3], index=[False, True, False])
In [47]: s
Out[47]:
False  1
  True  2
  False 3
Length: 3, dtype: int64
```

```
In [59]: s.loc[pd.Index([True, False, True])]
Out[59]:
  True  2
  False 1
  False 3
  True  2
dtype: int64
```
Current behavior

```python
In [48]: s.loc[pd.Index([True, False, True])]
Out[48]:
False  1
False  3
Length: 2, dtype: int64
```

Furthermore, previously if you had an index that was non-numeric (e.g. strings), then a boolean Index would raise a
`KeyError`. This will now be treated as a boolean indexer.

Previously behavior:

```python
In [49]: s = pd.Series([1, 2, 3], index=['a', 'b', 'c'])
In [50]: s
Out[50]:
a  1
b  2
c  3
Length: 3, dtype: int64
In [39]: s.loc[pd.Index([True, False, True])]
KeyError: "None of [Index([True, False, True], dtype='object')] are in the [index]"
```

Current behavior

```python
In [51]: s.loc[pd.Index([True, False, True])]
Out[51]:
a  1
c  3
Length: 2, dtype: int64
```

**PeriodIndex resampling**

In previous versions of pandas, resampling a `Series/DataFrame` indexed by a `PeriodIndex` returned a
`DatetimeIndex` in some cases (GH12884). Resampling to a multiplied frequency now returns a `PeriodIndex`
(GH15944). As a minor enhancement, resampling a `PeriodIndex` can now handle `NaT` values (GH13224)

Previous behavior:

```python
In [1]: pi = pd.period_range('2017-01', periods=12, freq='M')
In [2]: s = pd.Series(np.arange(12), index=pi)
In [3]: resampled = s.resample('2Q').mean()
In [4]: resampled
Out[4]:
2017-03-31  1.0
2017-09-30  5.5
2018-03-31 10.0
Freq: 2Q-DEC, dtype: float64
In [5]: resampled.index
Out[5]: DatetimeIndex(['2017-03-31', '2017-09-30', '2018-03-31'], dtype=˓→'datetime64[ns]', freq='2Q-DEC')
```
New behavior:

```python
In [52]: pi = pd.period_range('2017-01', periods=12, freq='M')
In [53]: s = pd.Series(np.arange(12), index=pi)
In [54]: resampled = s.resample('2Q').mean()
In [55]: resampled
Out[55]:
2017Q1   2.5
2017Q3   8.5
Freq: 2Q-DEC, Length: 2, dtype: float64
In [56]: resampled.index
Out[56]: PeriodIndex(['2017Q1', '2017Q3'], dtype='period[2Q-DEC]', freq='2Q-DEC')
```

Upsampling and calling `.ohlc()` previously returned a `Series`, basically identical to calling `.asfreq()`. OHLC upsampling now returns a `DataFrame` with columns open, high, low and close (GH13083). This is consistent with downsampling and `DatetimeIndex` behavior.

Previous behavior:

```python
In [1]: pi = pd.period_range(start='2000-01-01', freq='D', periods=10)
In [2]: s = pd.Series(np.arange(10), index=pi)
In [3]: s.resample('H').ohlc()
Out[3]:
2000-01-01 00:00 0.0
... ... ... ...
2000-01-10 23:00 NaN
Freq: H, Length: 240, dtype: float64
In [4]: s.resample('M').ohlc()
Out[4]:
          open  high  low  close
2000-01  0.0  9.0  0.0  9.0
```

New behavior:

```python
In [57]: pi = pd.period_range(start='2000-01-01', freq='D', periods=10)
In [58]: s = pd.Series(np.arange(10), index=pi)
In [59]: s.resample('H').ohlc()
Out[59]:
          open  high  low  close
2000-01-01 00:00 0.0  0.0  0.0  0.0
2000-01-01 01:00 NaN NaN NaN NaN
2000-01-01 02:00 NaN NaN NaN NaN
2000-01-01 03:00 NaN NaN NaN NaN
2000-01-01 04:00 NaN NaN NaN NaN
...     ...     ...     ...     ...
2000-01-10 19:00 NaN NaN NaN NaN
2000-01-10 20:00 NaN NaN NaN NaN
2000-01-10 21:00 NaN NaN NaN NaN
2000-01-10 22:00 NaN NaN NaN NaN
```
Improved error handling during item assignment in pd.eval

`pd.eval()` will now raise a `ValueError` when item assignment malfunctions, or inplace operations are specified, but there is no item assignment in the expression (GH16732)

Previously, if you attempted the following expression, you would get a not very helpful error message:

```python
In [3]: pd.eval("a = 1 + 2", target=arr, inplace=True)
...: IndexError: only integers, slices (':`), ellipsis ('`...`'), numpy.newaxis ('`None`') and integer or boolean arrays are valid indices
```

This is a very long way of saying numpy arrays don’t support string-item indexing. With this change, the error message is now this:

```python
In [3]: pd.eval("a = 1 + 2", target=arr, inplace=True)
...: ValueError: Cannot assign expression output to target
```

It also used to be possible to evaluate expressions inplace, even if there was no item assignment:

```python
In [4]: pd.eval("1 + 2", target=arr, inplace=True)
Out[4]: 3
```

However, this input does not make much sense because the output is not being assigned to the target. Now, a `ValueError` will be raised when such an input is passed in:

```python
In [4]: pd.eval("1 + 2", target=arr, inplace=True)
...: ValueError: Cannot operate inplace if there is no assignment
```
Dtype conversions

Previously assignments, `.where()` and `.fillna()` with a `bool` assignment, would coerce to same the type (e.g. int/float), or raise for datetimelikes. These will now preserve the bools with `object` dtypes. (GH16821).

```python
In [62]: s = pd.Series([1, 2, 3])

In [5]: s[1] = True

In [6]: s
Out[6]:
0   1
1   1
2   3
dtype: int64
```

New behavior

```python
In [63]: s[1] = True

In [64]: s
Out[64]:
0   1
1   True
2   3
Length: 3, dtype: object
```

Previously, as assignment to a datetimelike with a non-datetimelike would coerce the non-datetime-like item being assigned (GH14145).

```python
In [65]: s = pd.Series([pd.Timestamp('2011-01-01'), pd.Timestamp('2012-01-01')])

In [1]: s[1] = 1

In [2]: s
Out[2]:
0 2011-01-01 00:00:00.000000000
1 1970-01-01 00:00:00.000000001
Length: 2, dtype: datetime64[ns]
```

These now coerce to `object` dtype.

```python
In [66]: s[1] = 1

In [67]: s
Out[67]:
0 2011-01-01 00:00:00
1 1
Length: 2, dtype: object
```

- Inconsistent behavior in `.where()` with datetimelikes which would raise rather than coerce to `object` (GH16402)
- Bug in assignment against `int64` data with `np.ndarray` with `float64` dtype may keep `int64` dtype (GH14001)
**MultiIndex constructor with a single level**

The MultiIndex constructors no longer squeezes a MultiIndex with all length-one levels down to a regular Index. This affects all the MultiIndex constructors. (GH17178)

Previous behavior:

```
In [2]: pd.MultiIndex.from_tuples([('a',), ('b',)])
Out[2]: Index(['a', 'b'], dtype='object')
```

Length 1 levels are no longer special-cased. They behave exactly as if you had length 2+ levels, so a MultiIndex is always returned from all of the MultiIndex constructors:

```
In [68]: pd.MultiIndex.from_tuples([('a',), ('b',)])
Out[68]: MultiIndex([('a',),
                   ('b',)])
```

**UTC localization with Series**

Previously, `to_datetime()` did not localize datetime Series data when `utc=True` was passed. Now, `to_datetime()` will correctly localize Series with a `datetime64[ns, UTC]` dtype to be consistent with how list-like and Index data are handled. (GH6415).

Previous behavior

```
In [69]: s = pd.Series(['20130101 00:00:00'] * 3)
In [12]: pd.to_datetime(s, utc=True)
```

```
Out[12]:
0  2013-01-01
1  2013-01-01
2  2013-01-01
dtype: datetime64[ns]
```

New behavior

```
In [70]: pd.to_datetime(s, utc=True)
```

```
Out[70]:
0  2013-01-01 00:00:00+00:00
1  2013-01-01 00:00:00+00:00
2  2013-01-01 00:00:00+00:00
Length: 3, dtype: datetime64[ns, UTC]
```

Additionally, DataFrames with datetime columns that were parsed by `read_sql_table()` and `read_sql_query()` will also be localized to UTC only if the original SQL columns were timezone aware datetime columns.
Consistency of range functions

In previous versions, there were some inconsistencies between the various range functions: `date_range()`, `bdate_range()`, `period_range()`, `timedelta_range()`, and `interval_range()` (GH17471).

One of the inconsistent behaviors occurred when the `start`, `end` and `period` parameters were all specified, potentially leading to ambiguous ranges. When all three parameters were passed, `interval_range` ignored the `period` parameter, `period_range` ignored the `end` parameter, and the other range functions raised. To promote consistency among the range functions, and avoid potentially ambiguous ranges, `interval_range` and `period_range` will now raise when all three parameters are passed.

Previous behavior:

```python
In [2]: pd.interval_range(start=0, end=4, periods=6)
Out[2]:
IntervalIndex([0, 1, 2, 3],
closed='right',
dtype='interval[int64]')
```

```python
In [3]: pd.period_range(start='2017Q1', end='2017Q4', periods=6, freq='Q')
Out[3]:
PeriodIndex(['2017Q1', '2017Q2', '2017Q3', '2017Q4', '2018Q1', '2018Q2'],
closed='right',
dtype='period[Q-DEC]', freq='Q-DEC')
```

New behavior:

```python
In [2]: pd.interval_range(start=0, end=4, periods=6)
---------------------------------------------------------------------------
ValueError: Of the three parameters: start, end, and periods, exactly two must be
  specified
```

```python
In [3]: pd.period_range(start='2017Q1', end='2017Q4', periods=6, freq='Q')
---------------------------------------------------------------------------
ValueError: Of the three parameters: start, end, and periods, exactly two must be
  specified
```

Additionally, the endpoint parameter `end` was not included in the intervals produced by `interval_range`. However, all other range functions include `end` in their output. To promote consistency among the range functions, `interval_range` will now include `end` as the right endpoint of the final interval, except if `freq` is specified in a way which skips `end`.

Previous behavior:

```python
In [4]: pd.interval_range(start=0, end=4)
Out[4]:
IntervalIndex([0, 1, 2, 3],
closed='right',
dtype='interval[int64]')
```

New behavior:

```python
In [71]: pd.interval_range(start=0, end=4)
Out[71]:
IntervalIndex([0, 1, 2, 3, 4],
closed='right',
dtype='interval[int64]')
```
No automatic Matplotlib converters

Pandas no longer registers our `date`, `time`, `datetime`, `datetime64`, and `Period` converters with matplotlib when pandas is imported. Matplotlib plot methods (plt.plot, ax.plot,...), will not nicely format the x-axis for `DatetimeIndex` or `PeriodIndex` values. You must explicitly register these methods:

Pandas built-in `Series.plot` and `DataFrame.plot` will register these converters on first-use (GH17710).

**Note:** This change has been temporarily reverted in pandas 0.21.1, for more details see [here](#).

Other API changes

- The Categorical constructor no longer accepts a scalar for the `categories` keyword. (GH16022)
- Accessing a non-existent attribute on a closed `HDFStore` will now raise an `AttributeError` rather than a `ClosedFileError` (GH16301)
- `read_csv()` now issues a `UserWarning` if the `names` parameter contains duplicates (GH17095)
- `read_csv()` now treats 'null' and 'n/a' strings as missing values by default (GH16471, GH16078)
- `pandas.HDFStore`’s string representation is now faster and less detailed. For the previous behavior, use `pandas.HDFStore.info` (GH16503).
- Compression defaults in HDF stores now follow pytables standards. Default is no compression and if `complib` is missing and `complevel` > 0 `zlib` is used (GH15943)
- `Index.get_indexer_non_unique()` now returns a ndarray indexer rather than an `Index`; this is consistent with `Index.get_indexer()` (GH16819)
- Removed the `@slow` decorator from `pandas._testing`, which caused issues for some downstream packages’ test suites. Use `@pytest.mark.slow` instead, which achieves the same thing (GH16850)
- Moved definition of `MergeError` to the `pandas.errors` module.
- The signature of `Series.set_axis()` and `DataFrame.set_axis()` has been changed from `set_axis(axis, labels)` to `set_axis(labels, axis=0)`, for consistency with the rest of the API. The old signature is deprecated and will show a `FutureWarning` (GH14636)
- `Series.argmin()` and `Series.argmax()` will now raise a `TypeError` when used with `object` dtypes, instead of a `ValueError` (GH13595)
- `Period` is now immutable, and will now raise an `AttributeError` when a user tries to assign a new value to the `ordinal` or `freq` attributes (GH17116).
- `to_datetime()` when passed a tz-aware `origin=` kwarg will now raise a more informative `ValueError` rather than a `TypeError` (GH16842)
- `to_datetime()` now raises a `ValueError` when format includes `%W` or `%U` without also including day of the week and calendar year (GH16774)
- Renamed non-functional `index` to `index_col` in `read_stata()` to improve API consistency (GH16342)
- Bug in `DataFrame.drop()` caused boolean labels False and True to be treated as labels 0 and 1 respectively when dropping indices from a numeric index. This will now raise a `ValueError` (GH16877)
- Restricted `DateOffset` keyword arguments. Previously, `DateOffset` subclasses allowed arbitrary keyword arguments which could lead to unexpected behavior. Now, only valid arguments will be accepted. (GH17176)
Deprecations

- DataFrame.from_csv() and Series.from_csv() have been deprecated in favor of read_csv() (GH4191)
- read_excel() has deprecated sheetname in favor of sheet_name for consistency with .to_excel() (GH10559).
- read_excel() has deprecated parse_cols in favor of usecols for consistency with read_csv() (GH4988)
- read_csv() has deprecated the tupleize_cols argument. Column tuples will always be converted to a MultiIndex (GH17060)
- DataFrame.to_csv() has deprecated the tupleize_cols argument. MultiIndex columns will be always written as rows in the CSV file (GH17060)
- The convert parameter has been deprecated in the .take() method, as it was not being respected (GH16948)
- pd.options.html.border has been deprecated in favor of pd.options.display.html.border (GH15793).
- SeriesGroupBy.nth() has deprecated True in favor of 'all' for its kwarg dropna (GH11038).
- DataFrame.as_blocks() is deprecated, as this is exposing the internal implementation (GH17302)
- pd.TimeGrouper is deprecated in favor of pandas.Grouper (GH16747)
- cdate_range has been deprecated in favor of bdate_range(), which has gained weekmask and holidays parameters for building custom frequency date ranges. See the documentation for more details (GH17596)
- passing categories or ordered kwargs to Series.astype() is deprecated, in favor of passing a CategoricalDtype (GH17636)
- .get_value and .set_value on Series, DataFrame, Panel, SparseSeries, and SparseDataFrame are deprecated in favor of using .iat[] or .at[] accessors (GH15269)
- Passing a non-existent column in .to_excel(..., columns=) is deprecated and will raise a KeyError in the future (GH17295)
- raise_on_error parameter to Series.where(), Series.mask(), DataFrame.where(), DataFrame.mask() is deprecated, in favor of errors= (GH14968)
- Using DataFrame.rename_axis() and Series.rename_axis() to alter index or column labels is now deprecated in favor of using .rename. rename_axis may still be used to alter the name of the index or columns (GH17833).
- reindex_axis() has been deprecated in favor of reindex(). See here for more (GH17833).

Series.select and DataFrame.select

The Series.select() and DataFrame.select() methods are deprecated in favor of using df.loc[labels.map(crit)] (GH12401)

```python
In [72]: df = pd.DataFrame({'A': [1, 2, 3]}, index=['foo', 'bar', 'baz'])
```
Series.argmax and Series.argmin

The behavior of `Series.argmax()` and `Series.argmin()` have been deprecated in favor of `Series.idxmax()` and `Series.idxmin()`, respectively (GH16830).

For compatibility with NumPy arrays, `pd.Series` implements `argmax` and `argmin`. Since pandas 0.13.0, `argmax` has been an alias for `pandas.Series.idxmax()`, and `argmin` has been an alias for `pandas.Series.idxmin()`. They return the `label` of the maximum or minimum, rather than the `position`.

We’ve deprecated the current behavior of `Series.argmax` and `Series.argmin`. Using either of these will emit a `FutureWarning`. Use `Series.idxmax()` if you want the label of the maximum. Use `Series.values.argmax()` if you want the position of the maximum. Likewise for the minimum. In a future release `Series.argmax` and `Series.argmin` will return the position of the maximum or minimum.

Removal of prior version deprecations/changes

- `read_excel()` has dropped the `has_index_names` parameter (GH10967)
- The `pd.options.display.height` configuration has been dropped (GH3663)
- The `pd.options.display.line_width` configuration has been dropped (GH2881)
- The `pd.options.display.mpl_style` configuration has been dropped (GH12190)
- Index has dropped the `.sym_diff()` method in favor of `.symmetric_difference()` (GH12591)
- Categorical has dropped the `.order()` and `.sort()` methods in favor of `.sort_values()` (GH12882)
- `eval()` and `DataFrame.eval()` have changed the default of `inplace` from `None` to `False` (GH11149)
- The function `get_offset_name` has been dropped in favor of the `.freqstr` attribute for an offset (GH11834)
- pandas no longer tests for compatibility with hdf5-files created with pandas < 0.11 (GH17404).
Performance improvements

- Improved performance of instantiating SparseDataFrame (GH16773)
- Series.dt no longer performs frequency inference, yielding a large speedup when accessing the attribute (GH17210)
- Improved performance of set_categories() by not materializing the values (GH17508)
- Timestamp.microsecond no longer re-computes on attribute access (GH17331)
- Improved performance of the CategoricalIndex for data that is already categorical dtype (GH17513)
- Improved performance of RangeIndex.min() and RangeIndex.max() by using RangeIndex properties to perform the computations (GH17607)

Documentation changes

- Several NaT method docstrings (e.g. NaT.ctime()) were incorrect (GH17327)
- The documentation has had references to versions < v0.17 removed and cleaned up (GH17442, GH17442, GH17404 & GH17504)

Bug fixes

Conversion

- Bug in assignment against datetime-like data with int may incorrectly convert to datetime-like (GH14145)
- Bug in assignment against int64 data with np.ndarray with float64 dtype may keep int64 dtype (GH14001)
- Fixed the return type of IntervalIndex.is_non_overlapping_monotonic to be a Python bool for consistency with similar attributes/methods. Previously returned a numpy.bool_. (GH17237)
- Bug in IntervalIndex.is_non_overlapping_monotonic when intervals are closed on both sides and overlap at a point (GH16560)
- Bug in Series.fillna() returns frame when inplace=True and value is dict (GH16156)
- Bug in Timestamp.weekday_name returning a UTC-based weekday name when localized to a timezone (GH17354)
- Bug in Timestamp.replace when replacing tzinfo around DST changes (GH15683)
- Bug in Timedelta construction and arithmetic that would not propagate the Overflow exception (GH17367)
- Bug in astype() converting to object dtype when passed extension type classes (DateTimeTZDtype, CategoricalDtype) rather than instances. Now a TypeError is raised when a class is passed (GH17780).
- Bug in to_numeric() in which elements were not always being coerced to numeric when errors='coerce' (GH17007, GH17125)
- Bug in DataFrame and Series constructors where range objects are converted to int32 dtype on Windows instead of int64 (GH16804)
Indexing

- When called with a null slice (e.g. `df.iloc[:])`, the `iloc` and `loc` indexers return a shallow copy of the original object. Previously they returned the original object. (GH13873).
- When called on an unsorted `MultiIndex`, the `loc` indexer now will raise `UnsortedIndexError` only if proper slicing is used on non-sorted levels (GH16734).
- Fixes regression in 0.20.3 when indexing with a string on a `TimedeltaIndex` (GH16896).
- Fixed `TimedeltaIndex.get_loc()` handling of `np.timedelta64` inputs (GH16909).
- Fix `MultiIndex.sort_index()` ordering when ascending argument is a list, but not all levels are specified, or are in a different order (GH16934).
- Fixes bug where indexing with `np.inf` caused an `OverflowError` to be raised (GH16957)
- Bug in reindexing on an empty `CategoricalIndex` (GH16770)
- Fixes `DataFrame.loc` for setting with alignment and tz-aware `DatetimeIndex` (GH16889)
- Avoids `IndexError` when passing an `Index` or `Series` to `iloc` with older numpy (GH17193)
- Allow unicode empty strings as placeholders in multilevel columns in Python 2 (GH17099)
- Bug in `iloc` when used with inplace addition or assignment and an int indexer on a `MultiIndex` causing the wrong indexes to be read from and written to (GH17148)
- Bug in `isin()` in which checking membership in empty `Series` objects raised an error (GH16991)
- Bug in `CategoricalIndex` reindexing in which specified indices containing duplicates were not being respected (GH17323)
- Bug in intersection of `RangeIndex` with negative step (GH17296)
- Bug in `IntervalIndex` where performing a scalar lookup fails for included right endpoints of non-overlapping monotonic decreasing indexes (GH16417, GH17271)
- Bug in `DataFrame.first_valid_index()` and `DataFrame.last_valid_index()` when no valid entry (GH17400)
- Bug in `Series.rename()` when called with a callable, incorrectly alters the name of the `Series`, rather than the name of the `Index`. (GH17407)
- Bug in `String.str_get()` raises `IndexError` instead of inserting NaNs when using a negative index. (GH17704)

IO

- Bug in `read_hdf()` when reading a timezone aware index from fixed format HDFStore (GH17618)
- Bug in `read_csv()` in which columns were not being thoroughly de-duplicated (GH17060)
- Bug in `read_csv()` in which specified column names were not being thoroughly de-duplicated (GH17095)
- Bug in `read_csv()` in which non integer values for the header argument generated an unhelpful / unrelated error message (GH16338)
- Bug in `read_csv()` in which memory management issues in exception handling, under certain conditions, would cause the interpreter to segfault (GH14696, GH16798).
- Bug in `read_csv()` when called with `low_memory=False` in which a CSV with at least one column > 2GB in size would incorrectly raise a `MemoryError` (GH16798).
• Bug in `read_csv()` when called with a single-element list `header` would return a DataFrame of all NaN values (GH7757)

• Bug in `DataFrame.to_csv()` defaulting to ‘ascii’ encoding in Python 3, instead of ‘utf-8’ (GH17097)

• Bug in `read_stata()` where value labels could not be read when using an iterator (GH16923)

• Bug in `read_stata()` where the index was not set (GH16342)

• Bug in `read_html()` where import check fails when run in multiple threads (GH16928)

• Bug in `read_csv()` where automatic delimiter detection caused a `TypeError` to be thrown when a bad line was encountered rather than the correct error message (GH13374)

• Bug in `DataFrame.to_html()` with `notebook=True` where DataFrames with named indices or non-MultiIndex indices had undesired horizontal or vertical alignment for column or row labels, respectively (GH16792)

• Bug in `DataFrame.to_html()` in which there was no validation of the `justify` parameter (GH17527)

• Bug in `HDFStore.select()` when reading a contiguous mixed-data table featuring VLArray (GH17021)

• Bug in `to_json()` where several conditions (including objects with unprintable symbols, objects with deep recursion, overlong labels) caused segfaults instead of raising the appropriate exception (GH14256)

### Plotting

• Bug in plotting methods using `secondary_y` and `fontsize` not setting secondary axis font size (GH12565)

• Bug when plotting `timedelta` and `datetime` dtypes on y-axis (GH16953)

• Line plots no longer assume monotonic x data when calculating xlims, they show the entire lines now even for unsorted x data. (GH11310, GH11471)

• With matplotlib 2.0.0 and above, calculation of x limits for line plots is left to matplotlib, so that its new default settings are applied. (GH15495)

• Bug in `Series.plot.bar` or `DataFrame.plot.bar` with `y` not respecting user-passed `color` (GH16822)

• Bug causing `plotting.parallel_coordinates` to reset the random seed when using random colors (GH17525)

### GroupBy/resample/rolling

• Bug in `DataFrame.resample(...) .size()` where an empty DataFrame did not return a Series (GH14962)

• Bug in `infer_freq()` causing indices with 2-day gaps during the working week to be wrongly inferred as business daily (GH16624)

• Bug in `.rolling(...) .quantile()` which incorrectly used different defaults than `Series. quantile()` and `DataFrame.quantile()` (GH9413, GH16211)

• Bug in `groupby.transform()` that would coerce boolean dtypes back to float (GH16875)

• Bug in `Series.resample(...) .apply()` where an empty Series modified the source index and did not return the name of a Series (GH14313)

• Bug in `.rolling(...) .apply(...)` with a DataFrame with a DatetimeIndex, a window of a timedelta-convertible and `min_periods >= 1` (GH15305)
pandas: powerful Python data analysis toolkit, Release 1.1.1

- Bug in `DataFrame.groupby` where index and column keys were not recognized correctly when the number of keys equaled the number of elements on the groupby axis (GH16859)
- Bug in `groupby.nunique()` with `TimeGrouper` which cannot handle `NaT` correctly (GH17575)
- Bug in `DataFrame.groupby` where a single level selection from a `MultiIndex` unexpectedly sorts (GH17537)
- Bug in `DataFrame.groupby` where spurious warning is raised when `Grouper` object is used to override ambiguous column name (GH17383)
- Bug in `groupby` differs when passes as a list and as a scalar (GH17530)

Sparse

- Bug in `SparseSeries` raises `AttributeError` when a dictionary is passed in as data (GH16905)
- Bug in `SparseDataFrame.fillna()` not filling all NaNs when frame was instantiated from SciPy sparse matrix (GH16112)
- Bug in `SparseSeries.unstack()` and `SparseDataFrame.stack()` (GH16614, GH15045)
- Bug in `make_sparse()` treating two numeric/boolean data, which have same bits, as same when array dtype is object (GH17574)
- `SparseArray.all()` and `SparseArray.any()` are now implemented to handle `SparseArray`, these were used but not implemented (GH17570)

Reshaping

- Joining/Merging with a non unique `PeriodIndex` raised a `TypeError` (GH16871)
- Bug in `crosstab()` where non-aligned series of integers were casted to float (GH17005)
- Bug in merging with categorical dtypes with datetimelikes incorrectly raised a `TypeError` (GH16900)
- Bug when using `isin()` on a large object series and large comparison array (GH16012)
- Fixes regression from 0.20, `Series.aggregate()` and `DataFrame.aggregate()` allow dictionaries as return values again (GH16741)
- Fixes dtype of result with integer dtype input, from `pivot_table()` when called with `margins=True` (GH17013)
- Bug in `crosstab()` where passing two `Series` with the same name raised a `KeyError` (GH13279)
- `Series.argmin()`, `Series.argmax()`, and their counterparts on `DataFrame` and `groupby` objects work correctly with floating point data that contains infinite values (GH13595).
- Bug in `unique()` where checking a tuple of strings raised a `TypeError` (GH17108)
- Bug in `concat()` where order of result index was unpredictable if it contained non-comparable elements (GH17344)
- Fixes regression when sorting by multiple columns on a `datetime64` dtype `Series` with `NaT` values (GH16836)
- Bug in `pivot_table()` where the result’s columns did not preserve the categorical dtype of columns when `dropna` was `False` (GH17842)
- Bug in `DataFrame.drop_duplicates` where dropping with non-unique column names raised a `ValueError` (GH17836)
• Bug in `unstack()` which, when called on a list of levels, would discard the `fillna` argument (GH13971)
• Bug in the alignment of `range` objects and other list-likes with `DataFrame` leading to operations being performed row-wise instead of column-wise (GH17901)

**Numeric**

• Bug in `.clip()` with `axis=1` and a list-like for `threshold` is passed; previously this raised `ValueError` (GH15390)
• `Series.clip()` and `DataFrame.clip()` now treat NA values for upper and lower arguments as `None` instead of raising `ValueError` (GH17276).

**Categorical**

• Bug in `Series.isin()` when called with a categorical (GH16639)
• Bug in the categorical constructor with empty values and categories causing the `.categories` to be an empty `Float64Index` rather than an empty `Index` with object dtype (GH17248)
• Bug in categorical operations with `Series.cat` not preserving the original Series’ name (GH17509)
• Bug in `DataFrame.merge()` failing for categorical columns with boolean/int data types (GH17187)
• Bug in constructing a `Categorical/CategoricalDtype` when the specified `categories` are of categorical type (GH17884).

**PyPy**

• Compatibility with PyPy in `read_csv()` with `usecols=[<unsorted ints>]` and `read_json()` (GH17351)
• Split tests into cases for CPython and PyPy where needed, which highlights the fragility of index matching with `float('nan')`, `np.nan` and `NAT` (GH17351)
• Fix `DataFrame.memory_usage()` to support PyPy. Objects on PyPy do not have a fixed size, so an approximation is used instead (GH17228)

**Other**

• Bug where some inplace operators were not being wrapped and produced a copy when invoked (GH12962)
• Bug in `eval()` where the `inplace` parameter was being incorrectly handled (GH16732)

**Contributors**

A total of 206 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

• 3553x +
• Aaron Barber
• Adam Gleave +
• Adam Smith +
• Adam Shamlian +
• Adrian Liaw +
• Alan Velasco +
• Alan Yee +
• Alex B +
• Alex Lubbock +
• Alex Marchenko +
• Alex Rychyk +
• Amol K +
• Andreas Winkler
• Andrew +
• Andrew
• André Jonasson +
• Becky Sweger
• Berkay +
• Bob Haffner +
• Bran Yang
• Brian Tu +
• Brock Mendel +
• Carol Willing +
• Carter Green +
• Chankey Pathak +
• Chris
• Chris Billington
• Chris Filo Gorgolewski +
• Chris Kerr
• Chris M +
• Chris Mazzullo +
• Christian Prinoth
• Christian Stade-Schuldt
• Christoph Moehl +
• DSM
• Daniel Chen +
• Daniel Grady
• Daniel Himmelstein
• Dave Willmer
• David Cook
• David Gwynne
• David Read +
• Dillon Niederhut +
• Douglas Rudd
• Eric Stein +
• Eric Wieser +
• Erik Fredriksen
• Florian Wilhelm +
• Floris Kint +
• Forbidden Donut
• Gabe F +
• Giftlin +
• Giftlin Rajaiah +
• Giulio Pepe +
• Guilherme Beltramini
• Guillem Borrell +
• Hanmin Qin +
• Hendrik Makait +
• Hugues Valois
• Hussain Tamboli +
• Iva Miholic +
• Jan Novotný +
• Jan Rudolph
• Jean Helie +
• Jean-Baptiste Schiratti +
• Jean-Mathieu Deschenes
• Jeff Knupp +
• Jeff Reback
• Jeff Tratner
• JennaVergeynst
• JimStearns206
• Joel Nothman
• John W. O’Brien
• Jon Crall +
• Jon Mease
• Jonathan J. Helmus +
• Joris Van den Bossche
• Joseph Wagner
• Juarez Bochi
• Julian Kuhlmann +
• Karel De Brabandere
• Kassandra Keeton +
• Keiron Pizzey +
• Keith Webber
• Kernc
• Kevin Sheppard
• Kirk Hansen +
• Licht Takeuchi +
• Lucas Kushner +
• Mahdi Ben Jelloul +
• Makarov Andrey +
• Malgorzata Turzanska +
• Marc Garcia +
• Margaret Sy +
• MarsGuy +
• Matt Bark +
• Matthew Roeschke
• Matti Picus
• Mehmet Ali “Mali” Akmanalp
• Michael Gasvoda +
• Michael Penkov +
• Milo +
• Morgan Stuart +
• Morgan243 +
• Nathan Ford +
• Nick Eubank
• Nick Garvey +
• Oleg Shteynbuk +
• P-Tillmann +
• Pankaj Pandey
• Patrick Luo
• abarber4gh +
• aernlund +
• agustín méndez +
• andymaheshw +
• ante328 +
• aviolog +
• bpraggastis
• cbertinato +
• cclauss +
• chernrick
• chris-b1
• dkamm +
• dwkenefick
• economy
• faic +
• fding253 +
• gfyounng
• guygoldberg +
• hhuuggoo +
• huashuai +
• ian
• iulia +
• jaredsnyder
• jbrockmendel +
• jdeschenes
• jebob +
• jschendel +
• keitakurita
• kernc +
• kiwirob +
• kjford
• linebp
• lloydkirk
• louspotok +
• majiang +
• manikbhandari +
5.8 Version 0.20

5.8.1 Version 0.20.3 (July 7, 2017)

This is a minor bug-fix release in the 0.20.x series and includes some small regression fixes and bug fixes. We recommend that all users upgrade to this version.

What’s new in v0.20.3

- Bug fixes
  - Conversion
  - Indexing
  - IO
  - Plotting
  - Reshaping
Bug fixes

- Fixed a bug in failing to compute rolling computations of a column-MultiIndexed DataFrame (GH16789, GH16825)
- Fixed a pytest marker failing downstream packages’ tests suites (GH16680)

Conversion

- Bug in pickle compat prior to the v0.20.x series, when UTC is a timezone in a Series/DataFrame/Index (GH16608)
- Bug in Series construction when passing a Series with dtype='category' (GH16524).
- Bug in DataFrame.astype() when passing a Series as the dtype kwarg. (GH16717).

Indexing

- Bug in Float64Index causing an empty array instead of None to be returned from .get(np.nan) on a Series whose index did not contain any NaNs (GH8569)
- Bug in MultiIndex.isin causing an error when passing an empty iterable (GH16777)
- Fixed a bug in a slicing DataFrame/Series that have a TimedeltaIndex (GH16637)

IO

- Bug in read_csv() in which files weren’t opened as binary files by the C engine on Windows, causing EOF characters mid-field, which would fail (GH16039, GH16559, GH16675)
- Bug in read_hdf() in which reading a Series saved to an HDF file in ‘fixed’ format fails when an explicit mode='r' argument is supplied (GH16583)
- Bug in DataFrame.to_latex() where bold_rows was wrongly specified to be True by default, whereas in reality row labels remained non-bold whatever parameter provided. (GH16707)
- Fixed an issue with DataFrame.style() where generated element ids were not unique (GH16780)
- Fixed loading a DataFrame with a PeriodIndex, from a format='fixed' HDFStore, in Python 3, that was written in Python 2 (GH16781)
Plotting

- Fixed regression that prevented RGB and RGBA tuples from being used as color arguments (GH16233)
- Fixed an issue with `DataFrame.plot.scatter()` that incorrectly raised a `KeyError` when categorical data is used for plotting (GH16199)

Reshaping

- `PeriodIndex/TimedeltaIndex.join` was missing the `sort=` kwarg (GH16541)
- Bug in joining on a `MultiIndex` with a `category` dtype for a level (GH16627).
- Bug in `merge()` when merging/joining with multiple categorical columns (GH16767)

Categorical

- Bug in `DataFrame.sort_values` not respecting the `kind` parameter with categorical data (GH16793)

Contributors

A total of 20 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Bran Yang
- Chris
- Chris Kerr +
- DSM
- David Gwynne
- Douglas Rudd
- Forbidden Donut +
- Jeff Reback
- Joris Van den Bossche
- Karel De Brabandere +
- Peter Quackenbush +
- Pradyumna Reddy Chinthal +
- Telt +
- Tom Augspurger
- chris-b1
- gfyoung
- ian +
- jdeschenes +
- kjford +
- ri938 +
5.8.2 Version 0.20.2 (June 4, 2017)

This is a minor bug-fix release in the 0.20.x series and includes some small regression fixes, bug fixes and performance improvements. We recommend that all users upgrade to this version.

What’s new in v0.20.2

- **Enhancements**
- **Performance improvements**
- **Bug fixes**
  - Conversion
  - Indexing
  - IO
  - Plotting
  - GroupBy/resample/rolling
  - Sparse
  - Reshaping
  - Numeric
  - Categorical
  - Other
- **Contributors**

**Enhancements**

- Series provides a `to_latex` method (GH16180)
- A new groupby method `ngroup()`, parallel to the existing `cumcount()`, has been added to return the group order (GH11642); see here.

**Performance improvements**

- Performance regression fix when indexing with a list-like (GH16285)
- Performance regression fix for MultiIndexes (GH16319, GH16346)
- Improved performance of `.clip()` with scalar arguments (GH15400)
- Improved performance of groupby with categorical groupers (GH16413)
- Improved performance of `MultiIndex.remove_unused_levels()` (GH16556)
Bug fixes

- Silenced a warning on some Windows environments about “tput: terminal attributes: No such device or address” when detecting the terminal size. This fix only applies to python 3 (GH16496)
- Bug in using pathlib.Path or py.path.local objects with io functions (GH16291)
- Bug in `Index.symmetric_difference()` on two equal MultiIndex’s, results in a TypeError (GH13490)
- Bug in `DataFrame.update()` with overwrite=False and NaN values (GH15593)
- Passing an invalid engine to `read_csv()` now raises an informative ValueError rather than UnboundLocalError. (GH16511)
- Bug in `unique()` on an array of tuples (GH16519)
- Bug in `cut()` when labels are set, resulting in incorrect label ordering (GH16459)
- Fixed a compatibility issue with IPython 6.0’s tab completion showing deprecation warnings on Categoricals (GH16409)

Conversion

- Bug in `to_numeric()` in which empty data inputs were causing a segfault of the interpreter (GH16302)
- Silence numpy warnings when broadcasting DataFrame to Series with comparison ops (GH16378, GH16306)

Indexing

- Bug in `DataFrame.reset_index(level=)` with single level index (GH16263)
- Bug in partial string indexing with a monotonic, but not strictly-monotonic, index incorrectly reversing the slice bounds (GH16515)
- Bug in `MultiIndex.remove_unused_levels()` that would not return a MultiIndex equal to the original. (GH16556)

IO

- Bug in `read_csv()` when comment is passed in a space delimited text file (GH16472)
- Bug in `read_csv()` not raising an exception with nonexistent columns in usecols when it had the correct length (GH14671)
- Bug that would force importing of the clipboard routines unnecessarily, potentially causing an import error on startup (GH16288)
- Bug that raised IndexError when HTML-rendering an empty DataFrame (GH15953)
- Bug in `read_csv()` in which tarfile object inputs were raising an error in Python 2.x for the C engine (GH16530)
- Bug where `DataFrame.to_html()` ignored the index_names parameter (GH16493)
- Bug where `pd.read_hdf()` returns numpy strings for index names (GH13492)
- Bug in `HDFStore.select_as_multiple()` where start/stop arguments were not respected (GH16209)
Plotting

- Bug in `DataFrame.plot` with a single column and a list-like color (GH3486)
- Bug in `plot` where NaT in DatetimeIndex results in Timestamp.min (GH12405)
- Bug in `DataFrame.boxplot` where `figsize` keyword was not respected for non-grouped boxplots (GH11959)

GroupBy/resample/rolling

- Bug in creating a time-based rolling window on an empty DataFrame (GH15819)
- Bug in `rolling.cov()` with offset window (GH16058)
- Bug in `.resample()` and `.groupby()` when aggregating on integers (GH16361)

Sparse

- Bug in construction of `SparseDataFrame` from `scipy.sparse.dok_matrix` (GH16179)

Reshaping

- Bug in `DataFrame.stack` with unsorted levels in MultiIndex columns (GH16323)
- Bug in `pd.wide_to_long()` where no error was raised when i was not a unique identifier (GH16382)
- Bug in `Series.isin()` with a list of tuples (GH16394)
- Bug in construction of a DataFrame with mixed dtypes including an all-NaT column. (GH16395)
- Bug in `DataFrame.agg()` and `Series.agg()` with aggregating on non-callable attributes (GH16405)

Numeric

- Bug in `.interpolate()`, where `limit_direction` was not respected when `limit=None` (default) was passed (GH16282)

Categorical

- Fixed comparison operations considering the order of the categories when both categoricals are unordered (GH16014)
Other

- Bug in `DataFrame.drop()` with an empty-list with non-unique indices (GH16270)

Contributors

A total of 34 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Aaron Barber +
- Andrew +
- Becky Sweger +
- Christian Prinoth +
- Christian Stade-Schuldt +
- DSM
- Erik Fredriksen +
- Hugues Valois +
- Jeff Reback
- Jeff Tratner
- JimStearns206 +
- John W. O’Brien
- Joris Van den Bossche
- Joseph Wagner +
- Keith Webber +
- Mehmet Ali “Mali” Akmanalp +
- Pankaj Pandey
- Patrick Luo +
- Patrick O’Melveny +
- Pietro Battiston
- RobinFiveWords +
- Ryan Hendrickson +
- Simon Baron +
- Tom Augspurger
- WBare +
- bpraggastis +
- chernrick +
- chris-b1
- economy +
- gfyoun
5.8.3 Version 0.20.1 (May 5, 2017)

This is a major release from 0.19.2 and includes a number of API changes, deprecations, new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- New `.agg()` API for Series/DataFrame similar to the groupby-rolling-resample API’s, see here
- Integration with the feather-format, including a new top-level pd.read_feather() and DataFrame.to_feather() method, see here.
- The `.ix` indexer has been deprecated, see here
- Panel has been deprecated, see here
- Addition of an IntervalIndex and Interval scalar type, see here
- Improved user API when grouping by index levels in .groupby(), see here
- Improved support for UInt64 dtypes, see here
- A new orient for JSON serialization, orient='table', that uses the Table Schema spec and that gives the possibility for a more interactive repr in the Jupyter Notebook, see here
- Experimental support for exporting styled DataFrames (DataFrame.style) to Excel, see here
- Window binary corr/cov operations now return a MultiIndexed DataFrame rather than a Panel, as Panel is now deprecated, see here
- Support for S3 handling now uses s3fs, see here
- Google BigQuery support now uses the pandas-gbq library, see here

Warning: Pandas has changed the internal structure and layout of the code base. This can affect imports that are not from the top-level pandas.* namespace, please see the changes here.

Check the API Changes and deprecations before updating.

Note: This is a combined release for 0.20.0 and 0.20.1. Version 0.20.1 contains one additional change for backwards-compatibility with downstream projects using pandas’ utils routines. (GH16250)

What’s new in v0.20.0

- New features
  - Method `.agg()` API for DataFrame/Series
  - Keyword argument `dtype` for data IO
- Method .to_datetime() has gained an origin parameter
- GroupBy enhancements
- Better support for compressed URLs in read_csv
- Pickle file IO now supports compression
- UInt64 support improved
- GroupBy on categoricals
- Table schema output
- SciPy sparse matrix from/to SparseDataFrame
- Excel output for styled DataFrames
- IntervalIndex
- Other enhancements

- Backwards incompatible API changes
  - Possible incompatibility for HDF5 formats created with pandas < 0.13.0
  - Map on Index types now return other Index types
  - Accessing datetime fields of Index now return Index
  - pd.unique will now be consistent with extension types
  - S3 file handling
  - Partial string indexing changes
  - Concat of different float dtypes will not automatically upcast
  - pandas Google BigQuery support has moved
  - Memory usage for Index is more accurate
  - DataFrame.sort_index changes
  - GroupBy describe formatting
  - Window binary corr/cov operations return a MultiIndex DataFrame
  - HDFStore where string comparison
  - Index.intersection and inner join now preserve the order of the left Index
  - Pivot table always returns a DataFrame
  - Other API changes

- Reorganization of the library: privacy changes
  - Modules privacy has changed
  - pandas.errors
  - pandas.testing
  - pandas.plotting
  - Other development changes

- Deprecations
New features

Method agg API for DataFrame/Series

Series & DataFrame have been enhanced to support the aggregation API. This is a familiar API from groupby, window operations, and resampling. This allows aggregation operations in a concise way by using \texttt{agg()} and \texttt{transform()}. The full documentation is here (GH1623).

Here is a sample

\begin{verbatim}
In [1]: df = pd.DataFrame(np.random.randn(10, 3), columns=['A', 'B', 'C'],
...:                   index=pd.date_range('1/1/2000', periods=10))
...:

In [2]: df.iloc[3:7] = np.nan

In [3]: df
\end{verbatim}

\begin{verbatim}
Out[3]:
      A         B         C
2000-01-01  0.469112  -0.282863  -1.509059
2000-01-02  -1.135632   1.212112  -0.173215
2000-01-03   0.119209  -1.044236  -0.861849
2000-01-04        NaN         NaN         NaN
2000-01-05        NaN         NaN         NaN
2000-01-06        NaN         NaN         NaN
2000-01-07        NaN         NaN         NaN
\end{verbatim}
One can operate using string function names, callables, lists, or dictionaries of these.

Using a single function is equivalent to .apply.

```python
In [4]: df.agg('sum')
Out[4]:
A  -1.068226
B  -1.387015
C  -4.892029
Length: 3, dtype: float64
```

Multiple aggregations with a list of functions.

```python
In [5]: df.agg(['sum', 'min'])
Out[5]:
       A       B       C
sum -1.068226 -1.387015 -4.892029
min -1.135632 -1.478427 -1.715002
```

Using a dict provides the ability to apply specific aggregations per column. You will get a matrix-like output of all of the aggregators. The output has one column per unique function. Those functions applied to a particular column will be NaN:

```python
In [6]: df.agg({'A': ['sum', 'min'], 'B': ['min', 'max']})
Out[6]:
        A        B
max  NaN  1.212112
min -1.135632 -1.715002
sum -1.068226     NaN
```

The API also supports a .transform() function for broadcasting results.

```python
In [7]: df.transform(['abs', lambda x: x - x.min()])
Out[7]:
          A        B        C
abs <lambda_0>  abs <lambda_0>  abs <lambda_0>
2000-01-01  0.469112  1.604745  0.282863  1.195563  1.509059  0.205944
2000-01-02  1.135632  0.000000  1.212112  2.690539  0.173215  1.541787
2000-01-03  0.119209  1.254841  1.044236  0.434191  0.861849  0.853153
2000-01-04  NaN      NaN      NaN      NaN      NaN      NaN
2000-01-05  NaN      NaN      NaN      NaN      NaN      NaN
2000-01-06  NaN      NaN      NaN      NaN      NaN      NaN
2000-01-07  NaN      NaN      NaN      NaN      NaN      NaN
2000-01-08  0.113648  1.249281  1.478427  0.000000  0.524988  2.239990
2000-01-09  0.404705  1.540338  0.577046  2.055473  1.715002  0.000000
2000-01-10  1.039268  0.096364  0.370647  1.107780  1.157892  0.557110
```
When presented with mixed dtypes that cannot be aggregated, .agg() will only take the valid aggregations. This is similar to how groupby .agg() works. (GH15015)

```
In [8]: df = pd.DataFrame({'A': [1, 2, 3],
...:                      'B': [1., 2., 3.],
...:                      'C': ['foo', 'bar', 'baz'],
...:                      'D': pd.date_range('20130101', periods=3))

In [9]: df.dtypes
Out[9]:
A     int64
B    float64
C     object
D  datetime64[ns]
Length: 3, dtype: object
```

```
In [10]: df.agg(['min', 'sum'])
Out[10]:
          A  B  C            D
min      1  1.0  bar 2013-01-01
sum      6  6.0 foobarbaz  NaT
```

**Keyword argument dtype for data IO**

The 'python' engine for read_csv(), as well as the read_fwf() function for parsing fixed-width text files and read_excel() for parsing Excel files, now accept the dtype keyword argument for specifying the types of specific columns (GH14295). See the io docs for more information.

```
In [11]: data = "a  b\n1  2\n3  4"

In [12]: pd.read_fwf(StringIO(data)).dtypes
Out[12]:
a     int64
b     int64
Length: 2, dtype: object

In [13]: pd.read_fwf(StringIO(data), dtype={'a': 'float64', 'b': 'object'}).dtypes
Out[13]:
a    float64
b    object
Length: 2, dtype: object
```
Method `.to_datetime()` has gained an `origin` parameter

`.to_datetime()` has gained a new parameter, `origin`, to define a reference date from where to compute the resulting timestamps when parsing numerical values with a specific `unit` specified. (GH11276, GH11745)

For example, with 1960-01-01 as the starting date:

```python
In [14]: pd.to_datetime([1, 2, 3], unit='D', origin=pd.Timestamp('1960-01-01'))
Out[14]: DatetimeIndex(['1960-01-02', '1960-01-03', '1960-01-04'], dtype='datetime64[ns]', freq=None)
```

The default is set at `origin='unix'`, which defaults to 1970-01-01 00:00:00, which is commonly called 'unix epoch' or POSIX time. This was the previous default, so this is a backward compatible change.

```python
In [15]: pd.to_datetime([1, 2, 3], unit='D')
Out[15]: DatetimeIndex(['1970-01-02', '1970-01-03', '1970-01-04'], dtype='datetime64[ns]', freq=None)
```

**GroupBy enhancements**

Strings passed to `DataFrame.groupby()` as the `by` parameter may now reference either column names or index level names. Previously, only column names could be referenced. This allows to easily group by a column and index level at the same time. (GH5677)

```python
In [16]: arrays = [['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux'],
   ...: ['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two']
   ...:
   ...
In [17]: index = pd.MultiIndex.from_arrays(arrays, names=['first', 'second'])
In [18]: df = pd.DataFrame({'A': [1, 1, 1, 1, 2, 2, 3, 3],
   ...:                    'B': np.arange(8)},
   ...:                   index=index)
In [19]: df
Out[19]:
   first  second  
  bar    one    1  0
       two    1  1
  baz    one    1  2
       two    1  3
  foo    one    2  4
       two    2  5
  qux    one    3  6
       two    3  7
[8 rows x 2 columns]
In [20]: df.groupby(['second', 'A']).sum()
Out[20]:
   B
second A
  one  1  2
       2  4
```

(continues on next page)
Better support for compressed URLs in `read_csv`

The compression code was refactored (GH12688). As a result, reading dataframes from URLs in `read_csv()` or `read_table()` now supports additional compression methods: xz, bz2, and zip (GH14570). Previously, only gzip compression was supported. By default, compression of URLs and paths are now inferred using their file extensions. Additionally, support for bz2 compression in the python 2 C-engine improved (GH14874).

```python
In [21]: url = ('https://github.com/{repo}/raw/{branch}/{path}')
   ....:     .format(repo='pandas-dev/pandas',
   ....:             branch='master',
   ....:             path='pandas/tests/io/parser/data/salaries.csv.bz2'))
   ....:

# default, infer compression
In [22]: df = pd.read_csv(url, sep='\t', compression='infer')

# explicitly specify compression
In [23]: df = pd.read_csv(url, sep='\t', compression='bz2')

In [24]: df.head(2)
Out[24]:
     S  X  E  M
0  13876 1  1  1
1  11608 1  3  0

[2 rows x 4 columns]
```

Pickle file IO now supports compression

`read_pickle()`, `DataFrame.to_pickle()` and `Series.to_pickle()` can now read from and write to compressed pickle files. Compression methods can be an explicit parameter or be inferred from the file extension. See the docs here.

```python
In [25]: df = pd.DataFrame({'A': np.random.randn(1000),
   ....:                     'B': 'foo',
   ....:                     'C': pd.date_range('20130101', periods=1000, freq='s')})
   ....:

Using an explicit compression type

In [26]: df.to_pickle("data.pkl.compress", compression="gzip")

In [27]: rt = pd.read_pickle("data.pkl.compress", compression="gzip")

In [28]: rt.head()
```

(continues on next page)
The default is to infer the compression type from the extension (`compression='infer'`):

```python
In [29]: df.to_pickle("data.pkl.gz")
In [30]: rt = pd.read_pickle("data.pkl.gz")
In [31]: rt.head()
Out[31]:
   A   B   C
0 -1.344312 foo 2013-01-01 00:00:00
1  0.844885 foo 2013-01-01 00:00:01
2  1.075770 foo 2013-01-01 00:00:02
3 -0.109050 foo 2013-01-01 00:00:03
4  1.643563 foo 2013-01-01 00:00:04
```

```python
In [32]: df["A"].to_pickle("s1.pkl.bz2")
In [33]: rt = pd.read_pickle("s1.pkl.bz2")
In [34]: rt.head()
Out[34]:
0  -1.344312
1   0.844885
2   1.075770
3  -0.109050
4   1.643563
Name: A, Length: 5, dtype: float64
```

**UInt64 support improved**

Pandas has significantly improved support for operations involving unsigned, or purely non-negative, integers. Previously, handling these integers would result in improper rounding or data-type casting, leading to incorrect results. Notably, a new numerical index, `UInt64Index`, has been created (GH14937)

```python
In [35]: idx = pd.UInt64Index([1, 2, 3])
In [36]: df = pd.DataFrame({'A': ['a', 'b', 'c']}, index=idx)
In [37]: df.head()
Out[37]:
   A
0  a
1  b
2  c
```

- Bug in converting object elements of array-like objects to unsigned 64-bit integers (GH4471, GH14982)
- Bug in `Series.unique()` in which unsigned 64-bit integers were causing overflow (GH14721)
• Bug in DataFrame construction in which unsigned 64-bit integer elements were being converted to objects (GH14881)
• Bug in pd.read_csv() in which unsigned 64-bit integer elements were being improperly converted to the wrong data types (GH14983)
• Bug in pd.unique() in which unsigned 64-bit integers were causing overflow (GH14915)
• Bug in pd.value_counts() in which unsigned 64-bit integers were being erroneously truncated in the output (GH14934)

GroupBy on categoricals

In previous versions, .groupby(..., sort=False) would fail with a ValueError when grouping on a categorical series with some categories not appearing in the data. (GH13179)

In [38]: chromosomes = np.r_[np.arange(1, 23).astype(str), ['X', 'Y']]

In [39]: df = pd.DataFrame({
    ...:     'A': np.random.randint(100),
    ...:     'B': np.random.randint(100),
    ...:     'C': np.random.randint(100),
    ...:     'chromosomes': pd.Categorical(np.random.choice(chromosomes, 100),
    ...:         categories=chromosomes,
    ...:         ordered=True)
    ...: })

In [40]: df

Out[40]:
        A  B   C  chromosomes
0      87  22  81           4
1      87  22  81           3
2      87  22  81          22
3      87  22  81           2
4      87  22  81           6
   ...   ...  ...          ...
95     87  22  81           8
96     87  22  81          11
97     87  22  81           X
98     87  22  81           1
99     87  22  81          19

[100 rows x 4 columns]

Previous behavior:

In [3]: df[df.chromosomes != '1'].groupby('chromosomes', sort=False).sum()
---------------------------------------------------------------------------
ValueError: items in new_categories are not the same as in old categories

New behavior:

In [41]: df[df.chromosomes != '1'].groupby('chromosomes', sort=False).sum()
Out[41]:
   chromosomes  A   B   C
2           348  88  324

(continues on next page)
The new orient 'table' for `DataFrame.to_json()` will generate a Table Schema compatible string representation of the data.

```
In [42]: df = pd.DataFrame(
    ....:     {'A': [1, 2, 3],
    ....:      'B': ['a', 'b', 'c'],
    ....:      'C': pd.date_range('2016-01-01', freq='d', periods=3),
    ....:     index=pd.Index(range(3), name='idx'))
    ....:

In [43]: df
df
```

```
  0 1 a 2016-01-01
  1 2 b 2016-01-02
  2 3 c 2016-01-03
[3 rows x 3 columns]
```

```
In [44]: df.to_json(orient='table')
Out[44]:
       "schema": {"fields": [{"name": "idx", "type": "integer"},
                              {"name": "A", "type": "integer"},
                              {"name": "B", "type": "string"},
                              {"name": "C", "type": "datetime"}],
                  "primaryKey": ["idx"],
                  "pandas_version": "0.20.0"},
       "data": [{"idx": 0, "A": 1, "B": "a", "C": 2016-01-01T00:00:00.000Z"},
                 {"idx": 1, "A": 2, "B": "b", "C": 2016-01-02T00:00:00.000Z"},
                 {"idx": 2, "A": 3, "B": "c", "C": 2016-01-03T00:00:00.000Z"}]
```

See [IO: Table Schema for more information.](#)

Additionally, the repr for `DataFrame` and `Series` can now publish this JSON Table schema representation of the Series or DataFrame if you are using IPython (or another frontend like nteract using the Jupyter messaging protocol). This gives frontends like the Jupyter notebook and nteract more flexibility in how they display pandas objects, since they have more information about the data. You must enable this by setting the `display.html.table_schema` option to `True`.

---

**5.8. Version 0.20**

2801
SciPy sparse matrix from/to SparseDataFrame

Pandas now supports creating sparse dataframes directly from `scipy.sparse.spmatrix` instances. See the documentation for more information. (GH4343)

All sparse formats are supported, but matrices that are not in COOrdinate format will be converted, copying data as needed.

```python
from scipy.sparse import csr_matrix
arr = np.random.random(size=(1000, 5))
arr[arr < .9] = 0
sp_arr = csr_matrix(arr)
sdf = pd.SparseDataFrame(sp_arr)
sdf
```

To convert a SparseDataFrame back to sparse SciPy matrix in COO format, you can use:

```python
sdf.to_coo()
```

Excel output for styled DataFrames

Experimental support has been added to export DataFrame.style formats to Excel using the openpyxl engine. (GH15530)

For example, after running the following, styled.xlsx renders as below:

```python
In [45]: np.random.seed(24)
In [46]: df = pd.DataFrame({'A': np.linspace(1, 10, 10)})
In [47]: df = pd.concat([df, pd.DataFrame(np.random.RandomState(24).randn(10, 4),
                      columns=list('BCDE'))],
                      axis=1)
In [48]: df.iloc[0, 2] = np.nan
In [49]: df
Out[49]:
      A         B         C         D         E
0   1.0  1.329212 NaN -0.316280 -0.990810
1  2.0 -1.070816 -1.438713  0.564417  0.295722
2  3.0 -1.626404  0.219565  0.678805  1.889273
3  4.0  0.961538  0.104011 -0.481165  0.850222
4  5.0  1.453425  1.057737  0.165562  0.515018
5  6.0 -1.336936  0.562861  1.392855 -0.063328
6  7.0  0.121668  1.207603 -0.002040  1.627796
7  8.0  0.354493  1.037528 -0.385684  0.519818
8  9.0  1.686583 -1.325963  1.428984 -2.089354
9 10.0 -0.129820  0.631523 -0.586538  0.290720
[10 rows x 5 columns]
In [50]: styled = (df.style
......: .applymap(lambda val: 'color: %s %s' % ('red' if val < 0 else 'black'))
```

(continues on next page)
pandas has gained an `IntervalIndex` with its own dtype, `interval` as well as the `Interval` scalar type. These allow first-class support for interval notation, specifically as a return type for the categories in `cut()` and `qcut()`. The `IntervalIndex` allows some unique indexing, see the docs. (GH7640, GH8625)

**Warning:** These indexing behaviors of the `IntervalIndex` are provisional and may change in a future version of pandas. Feedback on usage is welcome.

Previous behavior:
The returned categories were strings, representing Intervals

```
In [1]: c = pd.cut(range(4), bins=2)
In [2]: c
Out[2]:
[(-0.003, 1.5], (-0.003, 1.5], (1.5, 3], (1.5, 3]]
Categories (2, object): [(-0.003, 1.5] < (1.5, 3]]
```

New behavior:

```
In [52]: c = pd.cut(range(4), bins=2)
In [53]: c
Out[53]:
```

See the *Style documentation* for more detail.
Furthermore, this allows one to bin other data with these same bins, with NaN representing a missing value similar to other dtypes.

```python
In [55]: pd.cut([0, 3, 5, 1], bins=c.categories)
Out[55]:
[(-0.003, 1.5], (1.5, 3.0], NaN, (-0.003, 1.5]
Categories (2, interval[float64]): [(-0.003, 1.5] < (1.5, 3.0]]
```

An IntervalIndex can also be used in Series and DataFrame as the index.

```python
In [56]: df = pd.DataFrame({'A': range(4),
                      'B': pd.cut([0, 3, 1, 1], bins=c.categories)}).set_index('B')
```

```python
In [57]: df
Out[57]:
   B
A
(-0.003, 1.5]  0
(1.5, 3.0]    1
(-0.003, 1.5]  2
(-0.003, 1.5]  3
[4 rows x 1 columns]
```

Selecting via a specific interval:

```python
In [58]: df.loc[pd.Interval(1.5, 3.0)]
Out[58]:
   A
Name: (1.5, 3.0], Length: 1, dtype: int64
```

Selecting via a scalar value that is contained in the intervals.

```python
In [59]: df.loc[0]
Out[59]:
   A
   B
(-0.003, 1.5]  0
(-0.003, 1.5]  2
(-0.003, 1.5]  3
[3 rows x 1 columns]
```
Other enhancements

- DataFrame.rolling() now accepts the parameter closed='right'|'left'|'both'|'neither' to choose the rolling window-endpoint closedness. See the documentation (GH13965)
- Integration with the feather-format, including a new top-level pd.read_feather() and DataFrame.to_feather() method, see here.
- Series.str.replace() now accepts a callable, as replacement, which is passed to re.sub (GH15055)
- Series.str.replace() now accepts a compiled regular expression as a pattern (GH15446)
- Series.sort_index accepts parameters kind and na_position (GH13589, GH14444)
- DataFrame and DataFrame.groupby() have gained a nunique() method to count the distinct values over an axis (GH14336, GH15197).
- DataFrame has gained a melt() method, equivalent to pd.melt(), for unpivoting from a wide to long format (GH12640).
- pd.read_excel() now preserves sheet order when using sheetname=None (GH9930)
- Multiple offset aliases with decimal points are now supported (e.g. 0.5min is parsed as 30s) (GH8419)
- .isnull() and .notnull() have been added to Index object to make them more consistent with the Series API (GH15300)
- New UnssortedIndexError (subclass of KeyError) raised when indexing/slicing into an unsorted MultiIndex (GH11897). This allows differentiation between errors due to lack of sorting or an incorrect key. See here
- MultiIndex has gained a .to_frame() method to convert to a DataFrame (GH12397)
- pd.cut and pd.qcut now support datetime64 and timedelta64 dtypes (GH14714, GH14798)
- pd.qcut has gained the duplicates='raise'|'drop' option to control whether to raise on duplicated edges (GH7751)
- Series provides a to_excel method to output Excel files (GH8825)
- The usecols argument in pd.read_csv() now accepts a callable function as a value (GH14154)
- The skiprows argument in pd.read_csv() now accepts a callable function as a value (GH10882)
- The nrows and chunksize arguments in pd.read_csv() are supported if both are passed (GH6774, GH15755)
- DataFrame.plot now prints a title above each subplot if suplots=True and title is a list of strings (GH14753)
- DataFrame.plot can pass the matplotlib 2.0 default color cycle as a single string as color parameter, see here. (GH15516)
- Series.interpolate() now supports timedelta as an index type with method='time' (GH6424)
- Addition of a level keyword to DataFrame/Series.rename to rename labels in the specified level of a MultiIndex (GH4160).
- DataFrame.reset_index() will now interpret a tuple index.name as a key spanning across levels of columns, if this is a MultiIndex (GH16164)
- Timedelta.isoformat method added for formatting Timedeltas as an ISO 8601 duration. See the Timedelta docs (GH15136)
- .select_dtypes() now allows the string datetimetz to generically select datetimes with tz (GH14910)
• The `.to_latex()` method will now accept `multicolumn` and `multirow` arguments to use the accompanying LaTeX enhancements

• `pd.merge_asof()` gained the option `direction='backward'|'forward'|'nearest'` (GH14887)

• Series/DataFrame.asfreq() have gained a `fill_value` parameter, to fill missing values (GH3715).

• Series/DataFrame.resample.asfreq have gained a `fill_value` parameter, to fill missing values during resampling (GH3715).

• `pandas.util.hash_pandas_object()` has gained the ability to hash a MultiIndex (GH15224)

• Series/DataFrame.squeeze() have gained the `axis` parameter. (GH15339)

• DataFrame.to_excel() has a new `freeze_panes` parameter to turn on Freeze Panes when exporting to Excel (GH15160)

• `pd.read_html()` will parse multiple header rows, creating a MultiIndex header. (GH13434).

• HTML table output skips `colspan` or `rowspan` attribute if equal to 1. (GH15403)

• `pandas.io.formats.style.Styler` template now has blocks for easier extension, see the example notebook (GH15649)

• `Styler.render()` now accepts **kwargs to allow user-defined variables in the template (GH15649)

• Compatibility with Jupyter notebook 5.0; MultiIndex column labels are left-aligned and MultiIndex row-labels are top-aligned (GH15379)

• TimedeltaIndex now has a custom date-tick formatter specifically designed for nanosecond level precision (GH8711)

• `pd.api.types.union_categoricals` gained the `ignore_ordered` argument to allow ignoring the ordered attribute of unioned categoricals (GH13410). See the categorical union docs for more information.

• DataFrame.to_latex() and DataFrame.to_string() now allow optional header aliases. (GH15536)

• Re-enable the `parse_dates` keyword of `pd.read_excel()` to parse string columns as dates (GH14326)

• Added `.empty` property to subclasses of `Index`. (GH15270)

• Enabled floor division for `Timedelta` and `TimedeltaIndex` (GH15828)

• `pandas.io.json.json_normalize()` gained the option `errors='ignore'|'raise'; the default is `errors='raise'` which is backward compatible. (GH14583)

• `pandas.io.json.json_normalize()` with an empty list will return an empty DataFrame (GH15534)

• `pandas.io.json.json_normalize()` has gained a `sep` option that accepts `str` to separate joined fields; the default is “.”, which is backward compatible. (GH14883)

• `MultiIndex.remove_unused_levels()` has been added to facilitate removing unused levels. (GH15694)

• `pd.read_csv()` will now raise a `ParserError` error whenever any parsing error occurs (GH15913, GH15925)

• `pd.read_csv()` now supports the `error_bad_lines` and `warn_bad_lines` arguments for the Python parser (GH15925)

• The `display.show_dimensions` option can now also be used to specify whether the length of a `Series` should be shown in its repr (GH7117).
- `parallel_coordinates()` has gained a `sort_labels` keyword argument that sorts class labels and the colors assigned to them (GH15908)
- Options added to allow one to turn on/off using `bottleneck` and `numexpr`, see here (GH16157)
- `DataFrame.style.bar()` now accepts two more options to further customize the bar chart. Bar alignment is set with `align='left' | 'mid' | 'zero'`, the default is “left”, which is backward compatible. You can now pass a list of `color=[color_negative, color_positive]` (GH14757)

**Backwards incompatible API changes**

**Possible incompatibility for HDF5 formats created with pandas < 0.13.0**

`pd.TimeSeries` was deprecated officially in 0.17.0, though has already been an alias since 0.13.0. It has been dropped in favor of `pd.Series` (GH15098).

This may cause HDF5 files that were created in prior versions to become unreadable if `pd.TimeSeries` was used. This is most likely to be for pandas < 0.13.0. If you find yourself in this situation, you can use a recent prior version of pandas to read in your HDF5 files, then write them out again after applying the procedure below.

There are a few ways you can work around this. If you have a 0.13.0 or earlier version of pandas installed:

```python
In [2]: s = pd.TimeSeries([1, 2, 3], index=pd.date_range('20130101', periods=3))

In [3]: s
Out[3]:
2013-01-01 1
2013-01-02 2
2013-01-03 3
Freq: D, dtype: int64

In [4]: type(s)
Out[4]: pandas.core.series.TimeSeries

In [5]: s = pd.Series(s)

In [6]: s
Out[6]:
2013-01-01 1
2013-01-02 2
2013-01-03 3
Freq: D, dtype: int64

In [7]: type(s)
Out[7]: pandas.core.series.Series
```

**Map on Index types now return other Index types**

`map` on an Index now returns an Index, not a numpy array (GH12766)

```python
In [60]: idx = pd.Index([1, 2])

In [61]: idx
Out[61]: Int64Index([1, 2], dtype='int64')

In [62]: mi = pd.MultiIndex.from_tuples([(1, 2), (2, 4)])
```

(continues on next page)
In [63]: mi
Out[63]:
MultiIndex([(1, 2),
            (2, 4)],
           )

Previous behavior:

In [5]: idx.map(lambda x: x * 2)
Out[5]: array([2, 4])

In [6]: idx.map(lambda x: (x, x * 2))
Out[6]: array([(1, 2), (2, 4)], dtype=object)

In [7]: mi.map(lambda x: x)
Out[7]: array([(1, 2), (2, 4)], dtype=object)

In [8]: mi.map(lambda x: x[0])
Out[8]: array([1, 2])

New behavior:

In [64]: idx.map(lambda x: x * 2)
Out[64]: Int64Index([2, 4], dtype='int64')

In [65]: idx.map(lambda x: (x, x * 2))
Out[65]: MultiIndex([(1, 2),
                   (2, 4)],
                   )

In [66]: mi.map(lambda x: x)
Out[66]: MultiIndex([(1, 2),
                   (2, 4)],
                   )

In [67]: mi.map(lambda x: x[0])
Out[67]: Int64Index([1, 2], dtype='int64')

map on a Series with datetime64 values may return int64 dtypes rather than int32

In [68]: s = pd.Series(pd.date_range('2011-01-02T00:00', '2011-01-02T02:00', freq='H')
                 .tz_localize('Asia/Tokyo'))

In [69]: s
Out[69]:
0 2011-01-02 00:00:00+09:00
1 2011-01-02 01:00:00+09:00
2 2011-01-02 02:00:00+09:00
Length: 3, dtype: datetime64[ns, Asia/Tokyo]

Previous behavior:

In [9]: s.map(lambda x: x.hour)
Out[9]:
(continues on next page)
0 0
1 1
2 2
dtype: int32

New behavior:

```
In [70]: s.map(lambda x: x.hour)
Out[70]:
0 0
1 1
2 2
Length: 3, dtype: int64
```

**Accessing datetime fields of Index now return Index**

The datetime-related attributes (see here for an overview) of `DatetimeIndex`, `PeriodIndex` and `TimedeltaIndex` previously returned numpy arrays. They will now return a new `Index` object, except in the case of a boolean field, where the result will still be a boolean ndarray. (GH15022)

Previous behaviour:

```
In [1]: idx = pd.date_range("2015-01-01", periods=5, freq='10H')
In [2]: idx.hour
Out[2]: array([ 0, 10, 20, 6, 16], dtype=int32)
```

New behavior:

```
In [71]: idx = pd.date_range("2015-01-01", periods=5, freq='10H')
In [72]: idx.hour
Out[72]: Int64Index([0, 10, 20, 6, 16], dtype='int64')
```

This has the advantage that specific `Index` methods are still available on the result. On the other hand, this might have backward incompatibilities: e.g. compared to numpy arrays, `Index` objects are not mutable. To get the original ndarray, you can always convert explicitly using `np.asarray(idx.hour)`.

**pd.unique will now be consistent with extension types**

In prior versions, using `Series.unique()` and `pandas.unique()` on `Categorical` and tz-aware data-types would yield different return types. These are now made consistent. (GH15903)

- Datetime tz-aware

  Previous behaviour:

  ```
  # Series
  In [5]: pd.Series([pd.Timestamp('20160101', tz='US/Eastern'),
  ...:               pd.Timestamp('20160101', tz='US/Eastern')]).unique()
  Out[5]: array([Timestamp('2016-01-01 00:00:00-0500', tz='US/Eastern')],
  →dtype=object)
  In [6]: pd.unique(pd.Series([pd.Timestamp('20160101', tz='US/Eastern'),
  ```
pandas: powerful Python data analysis toolkit, Release 1.1.1

(continued from previous page)

```python
...:     pd.Timestamp('20160101', tz='US/Eastern'))
Out[6]: array(['2016-01-01T05:00:00.000000000'], dtype='datetime64[ns]')

# Index
In [7]: pd.Index([pd.Timestamp('20160101', tz='US/Eastern'),
...:     pd.Timestamp('20160101', tz='US/Eastern')]).unique()
Out[7]: DatetimeIndex(['2016-01-01 00:00:00-05:00'], dtype='datetime64[ns, US/Eastern]', freq=None)

In [8]: pd.unique([pd.Timestamp('20160101', tz='US/Eastern'),
...:     pd.Timestamp('20160101', tz='US/Eastern')])
Out[8]: array(['2016-01-01T05:00:00.000000000'], dtype='datetime64[ns]')

New behavior:

```python
# Series, returns an array of Timestamp tz-aware
In [73]: pd.Series([pd.Timestamp(r'20160101', tz=r'US/Eastern'),
...:     pd.Timestamp(r'20160101', tz=r'US/Eastern')]).unique()
Out[73]: <DatetimeArray>
['2016-01-01 00:00:00-05:00']
Length: 1, dtype: datetime64[ns, US/Eastern]

In [74]: pd.unique(pd.Series([pd.Timestamp('20160101', tz='US/Eastern'),
...:     pd.Timestamp('20160101', tz='US/Eastern')]))
Out[74]: DatetimeIndex(['2016-01-01 00:00:00-05:00'], dtype='datetime64[ns, US/Eastern]', freq=None)

# Index, returns a DatetimeIndex
In [75]: pd.Index([pd.Timestamp('20160101', tz='US/Eastern'),
...:     pd.Timestamp('20160101', tz='US/Eastern')]).unique()
Out[75]: DatetimeIndex(['2016-01-01 00:00:00-05:00'], dtype='datetime64[ns, US/Eastern]', freq=None)

In [76]: pd.unique(pd.Index([pd.Timestamp('20160101', tz='US/Eastern'),
...:     pd.Timestamp('20160101', tz='US/Eastern')]))
Out[76]: DatetimeIndex(['2016-01-01 00:00:00-05:00'], dtype='datetime64[ns, US/Eastern]', freq=None)
```

- Categoricals

Previous behaviour:

```python
In [1]: pd.Series(list('baabc'), dtype='category').unique()
Out[1]:
[b, a, c]
Categories (3, object): [b, a, c]

In [2]: pd.unique(pd.Series(list('baabc'), dtype='category'))
Out[2]: array(['b', 'a', 'c'], dtype=object)
```

New behavior:
```python
# returns a Categorical
In [77]: pd.Series(list('baabc'), dtype='category').unique()
Out[77]:
['b', 'a', 'c']
Categories (3, object): ['b', 'a', 'c']

In [78]: pd.unique(pd.Series(list('baabc'), dtype='category'))
Out[78]:
['b', 'a', 'c']
Categories (3, object): ['b', 'a', 'c']
```

### S3 file handling

pandas now uses s3fs for handling S3 connections. This shouldn’t break any code. However, since s3fs is not a required dependency, you will need to install it separately, like boto in prior versions of pandas. (GH11915).

### Partial string indexing changes

**DatetimeIndex Partial String Indexing** now works as an exact match, provided that string resolution coincides with index resolution, including a case when both are seconds (GH14826). See Slice vs. Exact Match for details.

```python
In [79]: df = pd.DataFrame({'a': [1, 2, 3]}, pd.DatetimeIndex(['2011-12-31 23:59:59', '2012-01-01 00:00:00', '2012-01-01 00:00:01']))

In [4]: df['2011-12-31 23:59:59']
Out[4]:
   a
2011-12-31 23:59:59  1

In [5]: df['a']['2011-12-31 23:59:59']
Out[5]:
2011-12-31 23:59:59  1
Name: a, dtype: int64

In [4]: df['2011-12-31 23:59:59']
KeyError: '2011-12-31 23:59:59'

In [5]: df['a']['2011-12-31 23:59:59']
Out[5]: 1
```
Concat of different float dtypes will not automatically upcast

Previously, concat of multiple objects with different float dtypes would automatically upcast results to a dtype of float64. Now the smallest acceptable dtype will be used (GH13247)

```python
In [80]: df1 = pd.DataFrame(np.array([1.0], dtype=np.float32, ndmin=2))
In [81]: df1.dtypes
Out[81]:
   0 float32
Length: 1, dtype: object

In [82]: df2 = pd.DataFrame(np.array([np.nan], dtype=np.float32, ndmin=2))
In [83]: df2.dtypes
Out[83]:
   0 float32
Length: 1, dtype: object
```

Previous behavior:

```python
In [7]: pd.concat([df1, df2]).dtypes
Out[7]:
   0 float64
dtype: object
```

New behavior:

```python
In [84]: pd.concat([df1, df2]).dtypes
Out[84]:
   0 float32
Length: 1, dtype: object
```

pandas Google BigQuery support has moved

pandas has split off Google BigQuery support into a separate package pandas-gbq. You can conda install pandas-gbq -c conda-forge or pip install pandas-gbq to get it. The functionality of `read_gbq()` and `DataFrame.to_gbq()` remain the same with the currently released version of pandas-gbq=0.1.4. Documentation is now hosted here (GH15347)

Memory usage for Index is more accurate

In previous versions, showing `memory_usage()` on a pandas structure that has an index, would only include actual index values and not include structures that facilitated fast indexing. This will generally be different for `Index` and `MultiIndex` and less-so for other index types. (GH15237)

Previous behavior:

```python
In [8]: index = pd.Index(['foo', 'bar', 'baz'])
In [9]: index.memory_usage(deep=True)
Out[9]: 180
In [10]: index.get_loc('foo')
```
New behavior:

```python
In [8]: index = pd.Index(['foo', 'bar', 'baz'])
In [9]: index.memory_usage(deep=True)
Out[9]: 180
In [10]: index.get_loc('foo')
Out[10]: 0
In [11]: index.memory_usage(deep=True)
Out[11]: 260
```

### DataFrame.sort_index changes

In certain cases, calling `.sort_index()` on a MultiIndexed DataFrame would return the same DataFrame without seeming to sort. This would happen with a lexsorted, but non-monotonic levels. (GH15622, GH15687, GH14015, GH13431, GH15797)

This is *unchanged* from prior versions, but shown for illustration purposes:

```python
In [85]: df = pd.DataFrame(np.arange(6), columns=['value'],
                        index=pd.MultiIndex.from_product([list('BA'), range(3)]))
In [86]: df
Out[86]:
     value
B 0  0
   1  1
   2  2
A 0  3
   1  4
   2  5
[6 rows x 1 columns]
In [87]: df.index.is_lexsorted()
Out[87]: False
In [88]: df.index.is_monotonic
Out[88]: False
```

Sorting works as expected

```python
In [89]: df.sort_index()
Out[89]:
     value
A 0  3
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

(continued from previous page)

In [90]: df.sort_index().index.is_lexsorted()
Out[90]: True

In [91]: df.sort_index().index.is_monotonic
Out[91]: True

However, this example, which has a non-monotonic 2nd level, doesn’t behave as desired.

In [92]: df = pd.DataFrame({'value': [1, 2, 3, 4]},
                   index=pd.MultiIndex([['a', 'b'], ['bb', 'aa']],
                                    [[0, 0, 1, 1], [0, 1, 0, 1]]))

In [93]: df
Out[93]:
   value
  a bb 1
  aa 2
  b bb 3
  aa 4

Previous behavior:

In [11]: df.sort_index()
Out[11]:
   value
  a bb 1
  aa 2
  b bb 3
  aa 4

In [14]: df.sort_index().index.is_lexsorted()
Out[14]: True

In [15]: df.sort_index().index.is_monotonic
Out[15]: False

New behavior:

In [94]: df.sort_index()
Out[94]:
   value
  a aa 2
  bb 1
  b aa 4
  bb 3

(continues on next page)
In [95]: df.sort_index().index.is_lexsorted()
Out[95]: True

In [96]: df.sort_index().index.is_monotonic
Out[96]: True

GroupBy describe formatting

The output formatting of `groupby.describe()` now labels the `describe()` metrics in the columns instead of the index. This format is consistent with `groupby.agg()` when applying multiple functions at once. (GH4792)

Previous behavior:

```
In [1]: df = pd.DataFrame({'A': [1, 1, 2, 2], 'B': [1, 2, 3, 4]})
In [2]: df.groupby('A').describe()
Out[2]:
   B
A      
 1  count 2.000000
     mean 1.500000
     std  0.707107
     min  1.000000
     25%  1.250000
     50%  1.500000
     75%  1.750000
     max  2.000000
 2  count 2.000000
     mean 3.500000
     std  0.707107
     min  3.000000
     25%  3.250000
     50%  3.500000
     75%  3.750000
     max  4.000000
```

New behavior:

```
In [97]: df = pd.DataFrame({'A': [1, 1, 2, 2], 'B': [1, 2, 3, 4]})
In [98]: df.groupby('A').agg([np.mean, np.std, np.min, np.max])
Out[98]:
   B
A
 1  count 2.000000
     mean 1.500000
     std  0.707107
     min  1.000000
     25%  1.250000
     50%  1.500000
     75%  1.750000
     max  2.000000
 2  count 2.000000
     mean 3.500000
     std  0.707107
     min  3.000000
     25%  3.250000
     50%  3.500000
     75%  3.750000
     max  4.000000
```

(continues on next page)
In [99]: df.groupby('A').agg([np.mean, np.std, np.min, np.max])
Out[99]:
   B
   mean   std  amin  amax
A
1  1.5  0.707107  1   2
2  3.5  0.707107  3   4

Window binary corr/cov operations return a MultiIndex DataFrame

A binary window operation, like .corr() or .cov(), when operating on a .rolling()..expanding().
or .ewm() object, will now return a 2-level MultiIndexed DataFrame rather than a Panel, as Panel
is now deprecated, see here. These are equivalent in function, but a MultiIndexed DataFrame
enjoys more support in pandas. See the section on Windowed Binary Operations for more information. (GH15677)

In [100]: np.random.seed(1234)
In [101]: df = pd.DataFrame(np.random.rand(100, 2),
                     columns=['A', 'B'],
                     index=pd.date_range('20160101',
                                         periods=100, freq='D', name='foo'))
In [102]: df.tail()
Out[102]:
       bar        A        B
foo
2016-04-05  0.640880  0.126205
2016-04-06  0.171465  0.737086
2016-04-07  0.127029  0.369650
2016-04-08  0.604334  0.945553
2016-04-09  0.802374  0.945553

Previous behavior:

In [2]: df.rolling(12).corr()
Out[2]:
<class 'pandas.core.panel.Panel'>
Dimensions: 100 (items) x 2 (major_axis) x 2 (minor_axis)
Items axis: 2016-01-01 00:00:00 to 2016-04-09 00:00:00
Major_axis axis: A to B
Minor_axis axis: A to B

New behavior:
In [103]: res = df.rolling(12).corr()

In [104]: res.tail()
Out[104]:
   bar  A    B
foo  bar
2016-04-07  B -0.132090  1.000000
2016-04-08  A  1.000000 -0.145775
    B -0.145775  1.000000
2016-04-09  A  1.000000  0.119645
    B  0.119645  1.000000

[5 rows x 2 columns]

Retrieving a correlation matrix for a cross-section

In [105]: df.rolling(12).corr().loc['2016-04-07']
Out[105]:
   bar  A    B
foo  bar
2016-04-07  A  1.00000 -0.13209
    B -0.13209  1.00000

[2 rows x 2 columns]

HDFStore where string comparison

In previous versions most types could be compared to string column in a HDFStore usually resulting in an invalid comparison, returning an empty result frame. These comparisons will now raise a TypeError (GH15492)

In [106]: df = pd.DataFrame({'unparsed_date': ["2014-01-01", '2014-01-01']})

In [107]: df.to_hdf('store.h5', 'key', format='table', data_columns=True)

In [108]: df.dtypes
Out[108]:
unparsed_date    object
Length: 1, dtype: object

Previous behavior:

In [4]: pd.read_hdf('store.h5', 'key', where='unparsed_date > ts')
   File "<string>" line 1
   (unparsed_date > 1970-01-01 00:00:01.388552400)
          ^
SyntaxError: invalid token

New behavior:

In [18]: ts = pd.Timestamp('2014-01-01')

In [19]: pd.read_hdf('store.h5', 'key', where='unparsed_date > ts')
   TypeError: Cannot compare 2014-01-01 00:00:00 of type <class 'pandas.tslib.Timestamp'> to string column
Index.intersection and inner join now preserve the order of the left Index

*Index.intersection()* now preserves the order of the calling Index (left) instead of the other Index (right) (GH15582). This affects inner joins, *DataFrame.join()* and *merge()* , and the .align method.

- **Index.intersection**

```python
In [109]: left = pd.Index([2, 1, 0])
In [110]: left
Out[110]: Int64Index([2, 1, 0], dtype='int64')
In [111]: right = pd.Index([1, 2, 3])
In [112]: right
Out[112]: Int64Index([1, 2, 3], dtype='int64')
```

Previous behavior:

```python
In [4]: left.intersection(right)
Out[4]: Int64Index([1, 2], dtype='int64')
```

New behavior:

```python
In [113]: left.intersection(right)
Out[113]: Int64Index([2, 1], dtype='int64')
```

- **DataFrame.join and pd.merge**

```python
In [114]: left = pd.DataFrame({'a': [20, 10, 0]}, index=[2, 1, 0])
In [115]: left
Out[115]:
   a
2  20
1  10
0  0
[3 rows x 1 columns]
In [116]: right = pd.DataFrame({'b': [100, 200, 300]}, index=[1, 2, 3])
In [117]: right
Out[117]:
   b
1  100
2  200
3  300
[3 rows x 1 columns]
```

Previous behavior:

```python
In [4]: left.join(right, how='inner')
Out[4]:
   a  b
1  10  100
2  20  200
```

Chapter 5. Release notes
New behavior:

```
In [118]: left.join(right, how='inner')
Out[118]:
   a  b
2  20  200
1  10  100
[2 rows x 2 columns]
```

Pivot table always returns a DataFrame

The documentation for `pivot_table()` states that a DataFrame is always returned. Here a bug is fixed that allowed this to return a Series under certain circumstance. (GH4386)

```
In [119]: df = pd.DataFrame({'col1': [3, 4, 5],
                     'col2': ['C', 'D', 'E'],
                     'col3': [1, 3, 9]})
In [120]: df
Out[120]:
   col1  col2  col3
0     3     C     1
1     4     D     3
2     5     E     9
[3 rows x 3 columns]
```

Previous behavior:

```
In [2]: df.pivot_table('col1', index=['col3', 'col2'], aggfunc=np.sum)
Out[2]:
     col3  col2
col1
1     C     3
3     D     4
9     E     5
Name: col1, dtype: int64
```

New behavior:

```
In [121]: df.pivot_table('col1', index=['col3', 'col2'], aggfunc=np.sum)
Out[121]:
    col1
  col3  col2
1     C     3
3     D     4
9     E     5
[3 rows x 1 columns]
```
Other API changes

- `numexpr` version is now required to be >= 2.4.6 and it will not be used at all if this requisite is not fulfilled (GH15213).
- `CParserError` has been renamed to `ParserError` in `pd.read_csv()` and will be removed in the future (GH12665).
- `SparseArray.cumsum()` and `SparseSeries.cumsum()` will now always return `SparseArray` and `SparseSeries` respectively (GH12855).
- `DataFrame.applymap()` with an empty `DataFrame` will return a copy of the empty `DataFrame` instead of a `Series` (GH8222).
- `Series.map()` now respects default values of dictionary subclasses with a `__missing__` method, such as `collections.Counter` (GH15999).
- `.loc` has compat with `.ix` for accepting iterators, and NamedTuples (GH15120).
- `interpolate()` and `fillna()` will raise a `ValueError` if the `limit` keyword argument is not greater than 0. (GH9217)
- `pd.read_csv()` will now issue a `ParserWarning` whenever there are conflicting values provided by the dialect parameter and the user (GH14898).
- `pd.read_csv()` will now raise a `ValueError` for the C engine if the quote character is larger than one byte (GH11592).
- `inplace` arguments now require a boolean value, else a `ValueError` is thrown (GH14189).
- `pandas.api.types.is_datetime64_ns_dtype` will now report `True` on a tz-aware dtype, similar to `pandas.api.types.is_datetime64_any_dtype`.
- `DataFrame.asof()` will return a null filled `Series` instead the scalar `NaN` if a match is not found (GH15118).
- Specific support for `copy.copy()` and `copy.deepcopy()` functions on `NDFrame` objects (GH15444).
- `Series.sort_values()` accepts a one element list of bool for consistency with the behavior of `DataFrame.sort_values()` (GH15604).
- `.merge()` and `.join()` on category dtype columns will now preserve the category dtype when possible (GH10409).
- `SparseDataFrame.default_fill_value` will be 0, previously was `nan` in the return from `pd.get_dummies(..., sparse=True)` (GH15594).
- The default behaviour of `Series.str.match` has changed from extracting groups to matching the pattern. The extracting behaviour was deprecated since pandas version 0.13.0 and can be done with the `Series.str.extract` method (GH5224). As a consequence, the `as_indexer` keyword is ignored (no longer needed to specify the new behaviour) and is deprecated.
- `NaT` will now correctly report `False` for datetimelike boolean operations such as `is_month_start` (GH15781).
- `NaT` will now correctly return `np.nan` for `Timedelta` and `Period` accessors such as `days` and `quarter` (GH15782).
- `NaT` will now return `NaT` for `tz_localize` and `tz_convert` methods (GH15830).
- `DataFrame` and `Panel` constructors with invalid input will now raise `ValueError` rather than `PandasError`, if called with scalar inputs and not axes (GH15541).
DataFrame and Panel constructors with invalid input will now raise `ValueError` rather than `pandas.core.common.PandasError`, if called with scalar inputs and not axes; The exception `PandasError` is removed as well. (GH15541)

The exception `pandas.core.common.AmbiguousIndexError` is removed as it is not referenced (GH15541)

Reorganization of the library: privacy changes

Modules privacy has changed

Some formerly public python/c/c++/cython extension modules have been moved and/or renamed. These are all removed from the public API. Furthermore, the `pandas.core`, `pandas.compat`, and `pandas.util` top-level modules are now considered to be PRIVATE. If indicated, a deprecation warning will be issued if you reference these modules. (GH12588)

<table>
<thead>
<tr>
<th>Previous Location</th>
<th>New Location</th>
<th>Deprecated</th>
</tr>
</thead>
<tbody>
<tr>
<td>pandas.lib</td>
<td>pandas._libs.lib</td>
<td>X</td>
</tr>
<tr>
<td>pandas.tslib</td>
<td>pandas._libs.tslib</td>
<td>X</td>
</tr>
<tr>
<td>pandas.computation</td>
<td>pandas.core.computation</td>
<td></td>
</tr>
<tr>
<td>pandas.msgpack</td>
<td>pandas.io.msgpack</td>
<td></td>
</tr>
<tr>
<td>pandas.index</td>
<td>pandas._libs.index</td>
<td></td>
</tr>
<tr>
<td>pandas.algos</td>
<td>pandas._libs.algos</td>
<td></td>
</tr>
<tr>
<td>pandas hashtable</td>
<td>pandas._libs.hashtable</td>
<td></td>
</tr>
<tr>
<td>pandas.indexes</td>
<td>pandas.core.indexes</td>
<td></td>
</tr>
<tr>
<td>pandas.json</td>
<td>pandas._libs.json / pandas.io.json</td>
<td>X</td>
</tr>
<tr>
<td>pandas.parser</td>
<td>pandas._libs.parsers</td>
<td>X</td>
</tr>
<tr>
<td>pandas.formats</td>
<td>pandas.io.formats</td>
<td></td>
</tr>
<tr>
<td>pandas.sparse</td>
<td>pandas.core.sparse</td>
<td></td>
</tr>
<tr>
<td>pandas.tools</td>
<td>pandas.core.reshape</td>
<td>X</td>
</tr>
<tr>
<td>pandas.types</td>
<td>pandas.core.dtypes</td>
<td>X</td>
</tr>
<tr>
<td>pandas.io.sas.saslib</td>
<td>pandas.io.sas._sas</td>
<td></td>
</tr>
<tr>
<td>pandas._join</td>
<td>pandas._libs.join</td>
<td></td>
</tr>
<tr>
<td>pandas._hash</td>
<td>pandas._libs.hashing</td>
<td></td>
</tr>
<tr>
<td>pandas._period</td>
<td>pandas._libs.period</td>
<td></td>
</tr>
<tr>
<td>pandas._sparse</td>
<td>pandas._libs.sparse</td>
<td></td>
</tr>
<tr>
<td>pandas._testing</td>
<td>pandas._libs.testing</td>
<td></td>
</tr>
<tr>
<td>pandas._window</td>
<td>pandas._libs.window</td>
<td></td>
</tr>
</tbody>
</table>

Some new subpackages are created with public functionality that is not directly exposed in the top-level namespace: `pandas.errors`, `pandas.plotting` and `pandas.testing` (more details below). Together with `pandas.api.types` and certain functions in the `pandas.io` and `pandas.tseries` submodules, these are now the public subpackages.

Further changes:

- The function `union_categoricals()` is now importable from `pandas.api.types`, formerly from `pandas.types.concat` (GH15998)

- The type import `pandas.tslib.NaTType` is deprecated and can be replaced by using `type(pandas.NaT)` (GH16146)

- The public functions in `pandas.tools.hashing` deprecated from that locations, but are now importable from `pandas.util` (GH16223)

5.8. Version 0.20
• The modules in pandas.util: decorators, print_versions, doctools, validators, depr_module are now private. Only the functions exposed in pandas.util itself are public (GH16223)

**pandas.errors**

We are adding a standard public module for all pandas exceptions & warnings pandas.errors. (GH14800). Previously these exceptions & warnings could be imported from pandas.core.common or pandas.io.common. These exceptions and warnings will be removed from the *.common locations in a future release. (GH15541)

The following are now part of this API:

```python
['DtypeWarning',
'EmptyDataError',
'OutOfBoundsDatetime',
'ParserError',
'ParserWarning',
'PerformanceWarning',
'UnsortedIndexWarning',
'UnsupportedFunctionCall']
```

**pandas.testing**

We are adding a standard module that exposes the public testing functions in pandas.testing (GH9895). Those functions can be used when writing tests for functionality using pandas objects.

The following testing functions are now part of this API:

• testing.assert_frame_equal()
• testing.assert_series_equal()
• testing.assert_index_equal()

**pandas.plotting**

A new public pandas.plotting module has been added that holds plotting functionality that was previously in either pandas.tools.plotting or in the top-level namespace. See the deprecations sections for more details.

**Other development changes**

• Building pandas for development now requires cython >= 0.23 (GH14831)
• Require at least 0.23 version of cython to avoid problems with character encodings (GH14699)
• Switched the test framework to use pytest (GH13097)
• Reorganization of tests directory layout (GH14854, GH15707).
Deprecations

Deprecate .ix

The .ix indexer is deprecated, in favor of the more strict .iloc and .loc indexers. .ix offers a lot of magic on the inference of what the user wants to do. To wit, .ix can decide to index positionally OR via labels, depending on the data type of the index. This has caused quite a bit of user confusion over the years. The full indexing documentation is here. (GH14218)

The recommended methods of indexing are:

- .loc if you want to label index
- .iloc if you want to positionally index.

Using .ix will now show a DeprecationWarning with a link to some examples of how to convert code here.

```
In [122]: df = pd.DataFrame({'A': [1, 2, 3],
                     ....:       'B': [4, 5, 6],
                     ....:       index=list('abc'))

In [123]: df
Out[123]:
   A  B
  a 1 4
  b 2 5
  c 3 6
[3 rows x 2 columns]
```

Previous behavior, where you wish to get the 0th and the 2nd elements from the index in the ‘A’ column.

```
In [3]: df.ix[[0, 2], 'A']
Out[3]:
   A
  a 1
  c 3
Name: A, dtype: int64
```

Using .loc. Here we will select the appropriate indexes from the index, then use label indexing.

```
In [124]: df.loc[df.index[[0, 2]], 'A']
Out[124]:
   A
  a 1
  c 3
Name: A, Length: 2, dtype: int64
```

Using .iloc. Here we will get the location of the ‘A’ column, then use positional indexing to select things.

```
In [125]: df.iloc[[0, 2], df.columns.get_loc('A')]
Out[125]:
   A
  a 1
  c 3
Name: A, Length: 2, dtype: int64
```
Panel is deprecated and will be removed in a future version. The recommended way to represent 3-D data are with a MultiIndex on a DataFrame via the `to_frame()` method or with the xarray package. Pandas provides a `to_xarray()` method to automate this conversion (GH13563).

```python
In [133]: import pandas._testing as tm

In [134]: p = tm.makePanel()

In [135]: p
Out[135]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 3 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D
```

Convert to a MultiIndex DataFrame

```python
In [136]: p.to_frame()
Out[136]:
          ItemA    ItemB    ItemC
major minor
2000-01-03 A   0.628776 -1.409432  0.209395
  B       0.988138 -1.347533 -0.896581
  C   -0.938153  1.272395 -0.161137
  D  -0.223019 -0.591863 -1.051539
2000-01-04 A   0.186494  1.422986 -0.592886
  B  -0.072608  0.363565  1.104352
  C   1.239072 -1.449567  0.889157
  D  2.123692 -0.414505 -0.319561
2000-01-05 A   0.952478 -2.147855 -1.473116
  B  -0.550603 -0.014752 -0.431550
  C  0.139683 -1.195524  0.288377
  D  0.122273 -1.425795 -0.619993
[12 rows x 3 columns]
```

Convert to an xarray DataArray

```python
In [137]: p.to_xarray()
Out[137]:
xarray.DataArray (items: 3, major_axis: 3, minor_axis: 4)
array([[[ 0.628776,  0.988138, -0.938153, -0.223019],
        [ 0.186494, -0.072608, -1.239072,  2.123692],
        [ 0.952478, -0.550603,  0.139683,  0.122273]],
       [[-1.409432, -1.347533,  1.272395, -0.591863],
        [ 1.422986,  0.363565, -1.449567, -0.414505],
        [-2.147855, -0.014752, -1.195524, -1.425795]],
       [[ 0.209395, -0.896581, -0.161137, -1.051539],
        [-0.592886,  1.104352,  0.889157, -0.319561],
        [-1.473116, -0.431550,  0.288377, -0.619993]])
Coordinates:
  * items   (items) object 'ItemA' 'ItemB' 'ItemC'
(continues on next page)
Deprecate groupby.agg() with a dictionary when renaming

The `.groupby(..).agg(..)`, `.rolling(..).agg(..)`, and `.resample(..).agg(..)` syntax can accept a variable of inputs, including scalars, list, and a dict of column names to scalars or lists. This provides a useful syntax for constructing multiple (potentially different) aggregations.

However, `.agg(..)` can also accept a dict that allows ‘renaming’ of the result columns. This is a complicated and confusing syntax, as well as not consistent between `Series` and `DataFrame`. We are deprecating this ‘renaming’ functionality.

- We are deprecating passing a dict to a grouped/rolled/resampled `Series`. This allowed one to rename the resulting aggregation, but this had a completely different meaning than passing a dictionary to a grouped `DataFrame`, which accepts column-to-aggregations.
- We are deprecating passing a dict-of-dicts to a grouped/rolled/resampled `DataFrame` in a similar manner.

This is an illustrative example:

```python
In [126]: df = pd.DataFrame({'A': [1, 1, 1, 2, 2],
                        'B': range(5),
                        'C': range(5))

In [127]: df.groupby('A').agg({'B': 'sum', 'C': 'min'})
Out[127]:
   B  C
0  3  0
1  7  3
```

Here is a typical useful syntax for computing different aggregations for different columns. This is a natural, and useful syntax. We aggregate from the dict-to-list by taking the specified columns and applying the list of functions. This returns a `MultiIndex` for the columns (this is not deprecated).

```python
In [128]: df.groupby('A').agg({'B': 'sum', 'C': 'min'})
Out[128]:
   B  C
A   3  0
2   7  3
```

Here’s an example of the first deprecation, passing a dict to a grouped `Series`. This is a combination aggregation & renaming:

```python
In [6]: df.groupby('A').B.agg({'foo': 'count'})
FutureWarning: using a dict on a Series for aggregation
```
is deprecated and will be removed in a future version

```
Out[6]:
   foo
  A  
  1  3
  2  2
```

You can accomplish the same operation, more idiomatically by:

```
In [129]: df.groupby('A').B.agg(['count']).rename(columns={'count': 'foo'})
Out[129]:
   foo
  A  
  1  3
  2  2
[2 rows x 1 columns]
```

Here’s an example of the second deprecation, passing a dict-of-dict to a grouped DataFrame:

```
In [23]: (df.groupby('A')
    ...: .agg({'B': {'foo': 'sum'}, 'C': {'bar': 'min'}})
    ...: )
FutureWarning: using a dict with renaming is deprecated and will be removed in a future version
Out[23]:
   B   C
foo  bar
  A
  1  3  0
  2  7  3
```

You can accomplish nearly the same by:

```
In [130]: (df.groupby('A')
    ...: .agg({'B': 'sum', 'C': 'min'})
    ...: .rename(columns={'B': 'foo', 'C': 'bar'})
    ...: )
```

```
Out[130]:
   foo   bar
  A
  1  3  0
  2  7  3
[2 rows x 2 columns]
```
Deprecate .plotting

The `pandas.tools.plotting` module has been deprecated, in favor of the top level `pandas.plotting` module. All the public plotting functions are now available from `pandas.plotting` (GH12548).

Furthermore, the top-level `pandas.scatter_matrix` and `pandas.plot_params` are deprecated. Users can import these from `pandas.plotting` as well.

Previous script:

```python
pd.tools.plotting.scatter_matrix(df)
pd.scatter_matrix(df)
```

Should be changed to:

```python
pd.plotting.scatter_matrix(df)
```

Other deprecations

- `SparseArray.to_dense()` has deprecated the `fill` parameter, as that parameter was not being respected (GH14647)
- `SparseSeries.to_dense()` has deprecated the `sparse_only` parameter (GH14647)
- `Series.repeat()` has deprecated the `reps` parameter in favor of `repeats` (GH12662)
- The `Series` constructor and `.astype` method have deprecated accepting timestamp dtypes without a frequency (e.g. `np.datetime64`) for the `dtype` parameter (GH15524)
- `Index.repeat()` and `MultiIndex.repeat()` have deprecated the `n` parameter in favor of `repeats` (GH12662)
- `Categorical.searchsorted()` and `Series.searchsorted()` have deprecated the `v` parameter in favor of `value` (GH12662)
- `TimedeltaIndex.searchsorted()`, `DatetimeIndex.searchsorted()`, and `PeriodIndex.searchsorted()` have deprecated the key parameter in favor of `value` (GH12662)
- `DataFrame.astype()` has deprecated the `raise_on_error` parameter in favor of `errors` (GH14878)
- `Series.sortlevel` and `DataFrame.sortlevel` have been deprecated in favor of `Series.sort_index` and `DataFrame.sort_index` (GH15099)
- importing `concat` from `pandas.tools.merge` has been deprecated in favor of imports from the `pandas` namespace. This should only affect explicit imports (GH15358)
- `Series/DataFrame/Panel.consolidate()` been deprecated as a public method. (GH15483)
- The `as_indexer` keyword of `Series.str.match()` has been deprecated (ignored keyword) (GH15257).
- The following top-level `pandas.str` functions have been deprecated and will be removed in a future version (GH13790, GH15940)
  - `pd.pnow()`, replaced by `Period.now()`
  - `pd.Term`, is removed, as it is not applicable to user code. Instead use in-line string expressions in the where clause when searching in HDFStore
  - `pd.Expr`, is removed, as it is not applicable to user code.
  - `pd.match()`, is removed.
pandas: powerful Python data analysis toolkit, Release 1.1.1

- pd.groupby(), replaced by using the .groupby() method directly on a Series/DataFrame
- pd.get_store(), replaced by a direct call to pd.HDFStore(...)
- is_any_int_dtype, is_floating_dtype, and is_sequence are deprecated from pandas.api.types (GH16042)

Removal of prior version deprecations/changes

- The pandas.rpy module is removed. Similar functionality can be accessed through the rpy2 project. See the R interfacing docs for more details.
- The pandas.io.ga module with a google-analytics interface is removed (GH11308). Similar functionality can be found in the Google2Pandas package.
- pd.to_datetime and pd.to_timedelta have dropped the coerce parameter in favor of errors (GH13602)
- pandas.stats.fama_macbeth, pandas.stats.ols, pandas.stats.plm and pandas.stats.var, as well as the top-level pandas.fama_macbeth and pandas.ols routines are removed. Similar functionality can be found in the statsmodels package. (GH11898)
- The TimeSeries and SparseTimeSeries classes, aliases of Series and SparseSeries, are removed (GH10890, GH15098).
- Series.is_time_series is dropped in favor of Series.index.is_all_dates (GH15098)
- The deprecated irow, icol, iget and iget_value methods are removed in favor of iloc and iat as explained here (GH10711).
- The deprecated DataFrame.iterkv() has been removed in favor of DataFrame.iteritems() (GH10711)
- The Categorical constructor has dropped the name parameter (GH10632)
- Categorical has dropped support for NaN categories (GH10748)
- The take_last parameter has been dropped from duplicated(), drop_duplicates(), nlargest(), and nsmallest() methods (GH10236, GH10792, GH10920)
- Series, Index, and DataFrame have dropped the sort and order methods (GH10726)
- Where clauses in pytables are only accepted as strings and expressions types and not other data-types (GH12027)
- DataFrame has dropped the combineAdd and combineMult methods in favor of add and mul respectively (GH10735)

Performance improvements

- Improved performance of pd.wide_to_long() (GH14779)
- Improved performance of pd.factorize() by releasing the GIL with object dtype when inferred as strings (GH14859, GH16057)
- Improved performance of timeseries plotting with an irregular DatetimeIndex (or with compat_x=True) (GH15073).
- Improved performance of groupby().cummin() and groupby().cummax() (GH15048, GH15109, GH15561, GH15635)
- Improved performance and reduced memory when indexing with a MultiIndex (GH15245)
- When reading buffer object in `read_sas()` method without specified format, filepath string is inferred rather than buffer object. (GH14947)
- Improved performance of `.rank()` for categorical data (GH15498)
- Improved performance when using `.unstack()` (GH15503)
- Improved performance of merge/join on category columns (GH10409)
- Improved performance of `drop_duplicates()` on bool columns (GH12963)
- Improved performance of `pd.core.groupby.GroupBy.apply` when the applied function used the `.name` attribute of the group DataFrame (GH15062).
- Improved performance of `iloc` indexing with a list or array (GH15504).
- Improved performance of `Series.sort_index()` with a monotonic index (GH15694)
- Improved performance in `pd.read_csv()` on some platforms with buffered reads (GH16039)

### Bug fixes

#### Conversion

- Bug in `Timestamp.replace` now raises `TypeError` when incorrect argument names are given; previously this raised `ValueError` (GH15240)
- Bug in `Timestamp.replace` with compat for passing long integers (GH15030)
- Bug in `Timestamp` returning UTC based time/date attributes when a timezone was provided (GH13303, GH6538)
- Bug in `Timestamp` incorrectly localizing timezones during construction (GH11481, GH15777)
- Bug in `TimedeltaIndex` addition where overflow was being allowed without error (GH14816)
- Bug in `TimedeltaIndex` raising a `ValueError` when boolean indexing with `loc` (GH14946)
- Bug in catching an overflow in `Timestamp + Timedelta/Offset` operations (GH15126)
- Bug in `DatetimeIndex.round()` and `Timestamp.round()` floating point accuracy when rounding by milliseconds or less (GH14440, GH15578)
- Bug in `astype()` where `inf` values were incorrectly converted to integers. Now raises error now with `astype()` for Series and DataFrames (GH14265)
- Bug in `DataFrame(...).apply(to_numeric)` when values are of type `decimal.Decimal`. (GH14827)
- Bug in `describe()` when passing a numpy array which does not contain the median to the `percentiles` keyword argument (GH14908)
- Cleaned up `PeriodIndex` constructor, including raising on floats more consistently (GH13277)
- Bug in using `__deepcopy__` on empty NDFrame objects (GH15370)
- Bug in `.replace()` may result in incorrect dtypes. (GH12747, GH15765)
- Bug in `Series.replace` and `DataFrame.replace` which failed on empty replacement dicts (GH15289)
- Bug in `Series.replace` which replaced a numeric by string (GH15743)
- Bug in `Index` construction with `NaN` elements and integer dtype specified (GH15187)
- Bug in `Series` construction with a `datetimetz` (GH14928)
- Bug in `Series.dt.round()` inconsistent behaviour on `NaT`’s with different arguments (GH14940)
pandas: powerful Python data analysis toolkit, Release 1.1.1

- Bug in `Series` constructor when both `copy=True` and `dtype` arguments are provided (GH15125)
- Incorrect dtyped `Series` was returned by comparison methods (e.g., `lt`, `gt`, ...) against a constant for an empty `DataFrame` (GH15077)
- Bug in `Series.ffill()` with mixed dtypes containing tz-aware datetimes. (GH14956)
- Bug in `DataFrame.fillna()` where the argument `downcast` was ignored when `fillna` value was of type `dict` (GH15277)
- Bug in `.asfreq()`, where frequency was not set for empty `Series` (GH14320)
- Bug in `DataFrame` construction with nulls and datetimes in a list-like (GH15869)
- Bug in `DataFrame.fillna()` with tz-aware datetimes (GH15855)
- Bug in `is_string_dtype`, `is_timedelta64_ns_dtype`, and `is_string_like_dtype` in which an error was raised when `None` was passed in (GH15941)
- Bug in the return type of `pd.unique` on a `Categorical`, which was returning an `ndarray` and not a `Categorical` (GH15903)
- Bug in `Index.to_series()` where the index was not copied (and so mutating later would change the original), (GH15949)
- Bug in indexing with partial string indexing with a len-1 `DataFrame` (GH16071)
- Bug in `Series` construction where passing invalid `dtype` didn’t raise an error. (GH15520)

**Indexing**

- Bug in `Index` power operations with reversed operands (GH14973)
- Bug in `DataFrame.sort_values()` when sorting by multiple columns where one column is of type `int64` and contains `NaT` (GH14922)
- Bug in `DataFrame.reindex()` in which method was ignored when passing columns (GH14992)
- Bug in `DataFrame.loc` with indexing a `MultiIndex` with a `Series` indexer (GH14730, GH15424)
- Bug in `DataFrame.loc` with indexing a `MultiIndex` with a numpy array (GH15434)
- Bug in `Series.asof` which raised if the series contained all `np.nan` (GH15731)
- Bug in `.at` when selecting from a tz-aware column (GH15822)
- Bug in `Series.where()` and `DataFrame.where()` where array-like conditionals were being rejected (GH15414)
- Bug in `Series.where()` where TZ-aware data was converted to float representation (GH15701)
- Bug in `.loc` that would not return the correct `dtype` for scalar access for a `DataFrame` (GH11617)
- Bug in output formatting of a `MultiIndex` when names are integers (GH12223, GH15262)
- Bug in `Categorical.searchsorted()` where alphabetical instead of the provided categorical order was used (GH14522)
- Bug in `Series.iloc` where a `Categorical` object for list-like indexes input was returned, where a `Series` was expected. (GH14580)
- Bug in `DataFrame.isin` comparing datetimelike to empty frame (GH15473)
- Bug in `.reset_index()` when an all `NaN` level of a `MultiIndex` would fail (GH6322)
• Bug in `.reset_index()` when raising error for index name already present in MultiIndex columns (GH16120)

• Bug in creating a MultiIndex with tuples and not passing a list of names; this will now raise ValueError (GH15110)

• Bug in the HTML display with a MultiIndex and truncation (GH14882)

• Bug in the display of `.info()` where a qualifier (+) would always be displayed with a MultiIndex that contains only non-strings (GH15245)

• Bug in `pd.concat()` where the names of MultiIndex of resulting DataFrame are not handled correctly when None is presented in the names of MultiIndex of input DataFrame (GH15787)

• Bug in `DataFrame.sort_index()` and `Series.sort_index()` where na_position doesn’t work with a MultiIndex (GH14784, GH16604)

• Bug in `pd.concat()` when combining objects with a CategoricalIndex (GH16111)

• Bug in indexing with a scalar and a CategoricalIndex (GH16123)

IO

• Bug in `pd.to_numeric()` in which float and unsigned integer elements were being improperly casted (GH14941, GH15005)

• Bug in `pd.read_fwf()` where the skiprows parameter was not being respected during column width inference (GH11256)

• Bug in `pd.read_csv()` in which the dialect parameter was not being verified before processing (GH14898)

• Bug in `pd.read_csv()` in which missing data was being improperly handled with usecols (GH6710)

• Bug in `pd.read_csv()` in which a file containing a row with many columns followed by rows with fewer columns would cause a crash (GH14125)

• Bug in `pd.read_csv()` for the C engine where usecols were being indexed incorrectly with parse_dates (GH14792)

• Bug in `pd.read_csv()` with parse_dates when multi-line headers are specified (GH15376)

• Bug in `pd.read_csv()` with float_precision='round_trip' which caused a segfault when a text entry is parsed (GH15140)

• Bug in `pd.read_csv()` when an index was specified and no values were specified as null values (GH15835)

• Bug in `pd.read_csv()` in which certain invalid file objects caused the Python interpreter to crash (GH15337)

• Bug in `pd.read_csv()` in which invalid values for nrows and chunksize were allowed (GH15767)

• Bug in `pd.read_csv()` for the Python engine in which unhelpful error messages were being raised when parsing errors occurred (GH15910)

• Bug in `pd.read_csv()` in which the skipfooter parameter was not being properly validated (GH15925)

• Bug in `pd.to_csv()` in which there was numeric overflow when a timestamp index was being written (GH15982)

• Bug in `pd.util.hashing.hash_pandas_object()` in which hashing of categoricals depended on the ordering of categories, instead of just their values. (GH15143)

• Bug in `.to_json()` where lines=True and contents (keys or values) contain escaped characters (GH15096)
• Bug in `.to_json()` causing single byte ascii characters to be expanded to four byte unicode (GH15344)
• Bug in `.to_json()` for the C engine where rollover was not correctly handled for case where frac is odd and diff is exactly 0.5 (GH15716, GH15864)
• Bug in `pd.read_json()` for Python 2 where lines=True and contents contain non-ascii unicode characters (GH15132)
• Bug in `pd.read_msgpack()` in which Series categoricals were being improperly processed (GH14901)
• Bug in `pd.read_msgpack()` which did not allow loading of a dataframe with an index of type CategoricalIndex (GH15487)
• Bug in `pd.read_msgpack()` when deserializing a CategoricalIndex (GH15487)
• Bug in `DataFrame.to_records()` with converting a DatetimeIndex with a timezone (GH13937)
• Bug in `DataFrame.to_records()` which failed with unicode characters in column names (GH11879)
• Bug in `.to_sql()` when writing a DataFrame with numeric index names (GH15404).
• Bug in `DataFrame.to_html()` with index=False and max_rows raising in IndexError (GH14998)
• Bug in `pd.read_hdf()` passing a Timestamp to the where parameter with a non date column (GH15492)
• Bug in `DataFrame.to_stata()` and StataWriter which produces incorrectly formatted files to be produced for some locales (GH13856)
• Bug in StataReader and StataWriter which allows invalid encodings (GH15723)
• Bug in the Series repr not showing the length when the output was truncated (GH15962).

Plotting

• Bug in `DataFrame.hist` where plt.tight_layout caused an AttributeError (use matplotlib >= 2.0.1) (GH9351)
• Bug in `DataFrame.boxplot` where fontsize was not applied to the tick labels on both axes (GH15108)
• Bug in the date and time converters pandas registers with matplotlib not handling multiple dimensions (GH16026)
• Bug in `pd.scatter_matrix()` could accept either color or c, but not both (GH14855)

GroupBy/resample/rolling

• Bug in `.groupby(..).resample()` when passed the on= kwarg. (GH15021)
• Properly set __name__ and __qualname__ for Groupby.* functions (GH14620)
• Bug in GroupBy.get_group() failing with a categorical grouper (GH15155)
• Bug in `.groupby(...).rolling(...)` when on is specified and using a DatetimeIndex (GH15130, GH13966)
• Bug in groupby operations with timedelta64 when passing numeric_only=False (GH5724)
• Bug in groupby.apply() coercing object dtypes to numeric types, when not all values were numeric (GH14423, GH15421, GH15670)
• Bug in resample, where a non-string offset argument would not be applied when resampling a timeseries (GH13218)
• Bug in `DataFrame.groupby().describe()` when grouping on `Index` containing tuples (GH14848)
• Bug in `groupby().nunique()` with a datetimelike grouper where bins counts were incorrect (GH13453)
• Bug in `groupby.transform()` that would coerce the resultant dtypes back to the original (GH10972, GH11444)
• Bug in `groupby.agg()` incorrectly localizing timezone on `datetime` (GH15426, GH10668, GH13046)
• Bug in `.rolling/expanding()` functions where `count()` was not counting `np.Inf`, nor handling object dtypes (GH12541)
• Bug in `.rolling()` where `pd.Timedelta` or `datetime.timedelta` was not accepted as a window argument (GH15440)
• Bug in `Rolling.quantile` function that caused a segmentation fault when called with a quantile value outside of the range [0, 1] (GH15463)
• Bug in `DataFrame.resample().median()` if duplicate column names are present (GH14233)

Sparse

• Bug in `SparseSeries.reindex` on single level with list of length 1 (GH15447)
• Bug in repr-formatting a `SparseDataFrame` after a value was set on (a copy of) one of its series (GH15488)
• Bug in `SparseDataFrame` construction with lists not coercing to dtype (GH15682)
• Bug in sparse array indexing in which indices were not being validated (GH15863)

Reshaping

• Bug in `pd.merge_asof()` where `left_index` or `right_index` caused a failure when multiple `by` was specified (GH15676)
• Bug in `pd.merge_asof()` where `left_index/right_index` together caused a failure when tolerance was specified (GH15135)
• Bug in `DataFrame.pivot_table()` where `dropna=True` would not drop all-NaN columns when the columns was a category dtype (GH15193)
• Bug in `pd.melt()` where passing a tuple value for `value_vars` caused a `TypeError` (GH15348)
• Bug in `pd.pivot_table()` where no error was raised when values argument was not in the columns (GH14938)
• Bug in `pd.concat()` in which concatenating with an empty dataframe with `join='inner'` was being improperly handled (GH15328)
• Bug with `sort=True` in `DataFrame.join` and `pd.merge` when joining on indexes (GH15582)
• Bug in `DataFrame.nsmallest` and `DataFrame.nlargest` where identical values resulted in duplicated rows (GH15297)
• Bug in `pandas.pivot_table()` incorrectly raising `UnicodeError` when passing unicode input for `margins` keyword (GH13292)
Numeric

- Bug in `.rank()` which incorrectly ranks ordered categories (GH15420)
- Bug in `.corr()` and `.cov()` where the column and index were the same object (GH14617)
- Bug in `.mode()` where mode was not returned if was only a single value (GH15714)
- Bug in `pd.cut()` with a single bin on an all 0s array (GH15428)
- Bug in `pd.qcut()` with a single quantile and an array with identical values (GH15431)
- Bug in `pandas.tools.utils.cartesian_product()` with large input can cause overflow on windows (GH15265)
- Bug in `.eval()` which caused multi-line evals to fail with local variables not on the first line (GH15342)

Other

- Compat with SciPy 0.19.0 for testing on `.interpolate()` (GH15662)
- Compat for 32-bit platforms for `.qcut/cut`: bins will now be int64 dtype (GH14866)
- Bug in interactions with Qt when a QtApplication already exists (GH14372)
- Avoid use of `np.finfo()` during import pandas removed to mitigate deadlock on Python GIL misuse (GH14641)

Contributors

A total of 204 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Adam J. Stewart +
- Adrian +
- Ajay Saxena
- Akash Tandon +
- Albert Villanova del Moral +
- Aleksey Bilogur +
- Alexis Mignon +
- Amol Kahat +
- Andreas Winkler +
- Andrew Kittredge +
- Anthonios Partheniou
- Arco Bast +
- Ashish Singal +
- Baurzhan Muftakhidinov +
- Ben Kandel
- Ben Thayer +
• Ben Welsh +
• Bill Chambers +
• Brandon M. Burroughs
• Brian +
• Brian McFee +
• Carlos Souza +
• Chris
• Chris Ham
• Chris Warth
• Christoph Gohlke
• Christoph Paulik +
• Christopher C. Aycock
• Clemens Brunner +
• D.S. McNeil +
• DaanVanHauwermeiren +
• Daniel Himmelstein
• Dave Willmer
• David Cook +
• David Gwynne +
• David Hoffman +
• David Krych
• Diego Fernandez +
• Dimitris Spathis +
• Dmitry L +
• Dody Suria Wijaya +
• Dominik Stanczak +
• Dr-Irv
• Dr. Irv +
• Elliott Sales de Andrade +
• Ennemoser Christoph +
• Francesc Alted +
• Fumito Hamamura +
• Giacomo Ferroni
• Graham R. Jeffries +
• Greg Williams +
• Guilherme Beltramini +
• Guilherme Samora +
• Hao Wu +
• Harshit Patni +
• Ilya V. Schurov +
• Iván Vallés Pérez
• Jackie Leng +
• Jaehoon Hwang +
• James Draper +
• James Goppert +
• James McBride +
• James Santucci +
• Jan Schulz
• Jeff Carey
• Jeff Reback
• JennaVergeynst +
• Jim +
• Jim Crist
• Joe Jevnik
• Joel Nothman +
• John +
• John Tucker +
• John W. O’Brien
• John Zwinck
• Jon M. Mease
• Jon Mease
• Jonathan Whitmore +
• Jonathan de Bruin +
• Joost Kranendonk +
• Joris Van den Bossche
• Joshua Bradt +
• Julian Santander
• Julien Marrec +
• Jun Kim +
• Justin Solinsky +
• Kacawi +
• Kamal Kamalaldin +
• Kerby Shedden
• Kernc
• Keshav Ramaswamy
• Kevin Sheppard
• Kyle Kelley
• Larry Ren
• Leon Yin +
• Line Pedersen +
• Lorenzo Cestaro +
• Luca Scarabello
• Lukasz +
• Mahmoud Lababidi
• Mark Mandel +
• Matt Roeschke
• Matthew Brett
• Matthew Roeschke +
• Matti Picus
• Maximilian Roos
• Michael Charlton +
• Michael Felt
• Michael Lamparski +
• Michiel Stock +
• Mikolaj Chwalisz +
• Min RK
• Miroslav Šedivý +
• Mykola Golubyev
• Nate Yoder
• Nathalie Rud +
• Nicholas Ver Halen
• Nick Chmura +
• Nolan Nichols +
• Pankaj Pandey +
• Pawel Kordek
• Pete Huang +
• Peter +
• Peter Csizsek +
• Petio Petrov +
• Phil Ruffwind +
• Pietro Battiston
• Piotr Chromiec
• Prasanjit Prakash +
• Rob Forgione +
• Robert Bradshaw
• Robin +
• Rodolfo Fernandez
• Roger Thomas
• Rouz Azari +
• Sahil Dua
• Sam Foo +
• Sami Salonen +
• Sarah Bird +
• Sarma Tangirala +
• Scott Sanderson
• Sebastian Bank
• Sebastian Gsänger +
• Shawn Heide
• Shyam Saladi +
• Sinhrks
• Stephen Rauch +
• Sébastien de Menten +
• Tara Adiseshan
• Thiago Serafim
• Thoralf Gutierrez +
• Thrasibule +
• Tobias Gustafsson +
• Tom Augspurger
• Tong SHEN +
• Tong Shen +
• TrigonaMinima +
• Uwe +
• Wes Turner
• Wiktor Tomczak +
- WillAyd
- Yaroslav Halchenko
- Yimeng Zhang +
- abaldenko +
- adrian-stepien +
- alexanderchbooth +
- atbd +
- bastewart +
- bmagnusson +
- carlosdanielsantos +
- chaimdemulder +
- chris-b1
- dickreuter +
- discort +
- dr-leo +
- dubourg
- dwkenefick +
- funnycrab +
- gfyoun
- goldenbull +
- hesham.shabana@hotmail.com
- jojomdt +
- linebp +
- manu +
- manuels +
- mattip +
- maxalbert +
- mcocdawc +
- nuffe +
- paul-mannino
- pbreach +
- sakkemo +
- scls19fr
- sinhhrs
- stijnvanhoeey +
- the-nose-knows +
5.9 Version 0.19

5.9.1 Version 0.19.2 (December 24, 2016)

This is a minor bug-fix release in the 0.19.x series and includes some small regression fixes, bug fixes and performance improvements. We recommend that all users upgrade to this version.

Highlights include:
  • Compatibility with Python 3.6
  • Added a Pandas Cheat Sheet. (GH13202).

Enhancements

The pd.merge_asof(), added in 0.19.0, gained some improvements:
  • pd.merge_asof() gained left_index/right_index and left_by/right_by arguments (GH14253)
  • pd.merge_asof() can take multiple columns in by parameter and has specialized dtypes for better performance (GH13936)
Performance improvements

- Performance regression with PeriodIndex (GH14822)
- Performance regression in indexing with getitem (GH14930)
- Improved performance of .replace() (GH12745)
- Improved performance Series creation with a datetime index and dictionary data (GH14894)

Bug fixes

- Compat with python 3.6 for pickling of some offsets (GH14685)
- Compat with python 3.6 for some indexing exception types (GH14684, GH14689)
- Compat with python 3.6 for deprecation warnings in the test suite (GH14681)
- Compat with python 3.6 for Timestamp pickles (GH14689)
- Compat with dateutil==2.6.0; segfault reported in the testing suite (GH14621)
- Allow nanosecond in Timestamp.replace as a kwarg (GH14621)
- Bug in pd.read_csv in which aliasing was being done for na_values when passed in as a dictionary (GH14203)
- Bug in pd.read_csv in which column indices for a dict-like na_values were not being respected (GH14203)
- Bug in pd.read_csv where reading files fails, if the number of headers is equal to the number of lines in the file (GH14515)
- Bug in pd.read_csv for the Python engine in which an unhelpful error message was being raised when multi-char delimiters were not being respected with quotes (GH14582)
- Fix bugs (GH14734, GH13654) in pd.read_sas and pandas.io.sas.sas7bdat.SAS7BDATReader that caused problems when reading a SAS file incrementally.
- Bug in pd.read_csv for the Python engine in which an unhelpful error message was being raised when skipfooter was not being respected by Python’s CSV library (GH13879)
- Bug infillna() in which timezone aware datetime64 values were incorrectly rounded (GH14872)
- Bug in .groupby(..., sort=True) of a non-lexsorted MultiIndex when grouping with multiple levels (GH14776)
- Bug in pd.cut with negative values and a single bin (GH14652)
- Bug in pd.to_numeric where a 0 was not unsigned on a downcast='unsigned' argument (GH14401)
- Bug in plotting regular and irregular timeseries using shared axes (sharex=True or ax.twinx()) (GH13341, GH14322).
- Bug in not propagating exceptions in parsing invalid datetimes, noted in python 3.6 (GH14561)
- Bug in resampling a DatetimeIndex in local TZ, covering a DST change, which would raise AmbiguousTimeError (GH14682)
- Bug in indexing that transformed RecursionError into KeyError or IndexError (GH14554)
- Bug in HDFStore when writing a MultiIndex when using data_columns=True (GH14435)
- Bug in HDFStore.append() when writing a Series and passing a min_itemsize argument containing a value for the index (GH1412)
• Bug when writing to a HDFStore in table format with a min_itemsize value for the index and without asking to append (GH10381)
• Bug in Series.groupby.nunique() raising an IndexError for an empty Series (GH12553)
• Bug in DataFrame.nlargest and DataFrame.nsmallest when the index had duplicate values (GH13412)
• Bug in clipboard functions on linux with python2 with unicode and separators (GH13747)
• Bug in clipboard functions on Windows 10 and python 3 (GH14362, GH12807)
• Bug in .to_clipboard() and Excel compat (GH12529)
• Bug in DataFrame.combine_first() for integer columns (GH14687).
• Bug in pd.read_csv() in which the dtype parameter was not being respected for empty data (GH14712)
• Bug in pd.read_csv() in which the nrows parameter was not being respected for large input when using the C engine for parsing (GH7626)
• Bug in pd.merge_asof() could not handle timezone-aware DatetimeIndex when a tolerance was specified (GH14844)
• Explicit check in to_stata and StataWriter for out-of-range values when writing doubles (GH14618)
• Bug in .plot(kind='kde') which did not drop missing values to generate the KDE Plot, instead generating an empty plot. (GH14821)
• Bug in unstack() if called with a list of column(s) as an argument, regardless of the dtypes of all columns, they get coerced to object (GH11847)

Contributors
A total of 33 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

• Ajay Saxena +
• Ben Kandel
• Chris
• Chris Ham +
• Christopher C. Aycock
• Daniel Himmelstein +
• Dave Willmer +
• Dr-Irv
• Jeff Carey +
• Jeff Reback
• Joe Jevnik
• Joris Van den Bossche
• Julian Santander +
• Kerby Shedden
• Keshav Ramaswamy
5.9.2 Version 0.19.1 (November 3, 2016)

This is a minor bug-fix release from 0.19.0 and includes some small regression fixes, bug fixes and performance improvements. We recommend that all users upgrade to this version.

### What’s new in v0.19.1

- Performance improvements
- Bug fixes
- Contributors

#### Performance improvements

- Fixed performance regression in factorization of Period data (GH14338)
- Fixed performance regression in Series.asof(where) when where is a scalar (GH14461)
- Improved performance in DataFrame.asof(where) when where is a scalar (GH14461)
- Improved performance in .to_json() when lines=True (GH14408)
- Improved performance in certain types of loc indexing with a MultiIndex (GH14551).
Bug fixes

- Source installs from PyPI will now again work without cython installed, as in previous versions (GH14204)
- Compatability with Cython 0.25 for building (GH14496)
- Fixed regression where user-provided file handles were closed in read_csv (c engine) (GH14418).
- Fixed regression in DataFrame.quantile when missing values where present in some columns (GH14357).
- Fixed regression in Index.difference where the freq of a DatetimeIndex was incorrectly set (GH14323)
- Added back pandas.core.common.array_equivalent with a deprecation warning (GH14555).
- Bug in pd.read_csv for the C engine in which quotation marks were improperly parsed in skipped rows (GH14459)
- Bug in pd.read_csv for Python 2.x in which Unicode quote characters were no longer being respected (GH14477)
- Fixed regression in Index.append when categorical indices were appended (GH14545).
- Fixed regression in pd.DataFrame where constructor fails when given dict with None value (GH14381)
- Fixed regression in DatetimeIndex._maybe_cast_slice_bound when index is empty (GH14354).
- Bug in localizing an ambiguous timezone when a boolean is passed (GH14402)
- Bug in TimedeltaIndex addition with a Datetime-like object where addition overflow in the negative direction was not being caught (GH14068, GH14453)
- Bug in string indexing against data with objectIndex may raise AttributeError (GH14424)
- Correctly raise ValueError on empty input to pd.eval() and df.query() (GH13139)
- Bug in RangeIndex.intersection when result is a empty set (GH14364).
- Bug in groupby-transform broadcasting that could cause incorrect dtype coercion (GH14457)
- Bug in Series.__setitem__ which allowed mutating read-only arrays (GH14359).
- Bug in DataFrame.insert where multiple calls with duplicate columns can fail (GH14291)
- pd.merge() will raise ValueError with non-boolean parameters in passed boolean type arguments (GH14434)
- Bug in Timestamp where dates very near the minimum (1677-09) could underflow on creation (GH14415)
- Bug in pd.concat where names of the keys were not propagated to the resulting MultiIndex (GH14252)
- Bug in pd.concat where axis cannot take string parameters 'rows' or 'columns' (GH14369)
- Bug in pd.concat with dataframes heterogeneous in length and tuple keys (GH14438)
- Bug in MultiIndex.set_levels where illegal level values were still set after raising an error (GH13754)
- Bug in DataFrame.to_json where lines=True and a value contained a } character (GH14391)
- Bug in df.groupby causing an AttributeError when grouping a single index frame by a column and the index level (GH14327)
- Bug in df.groupby where TypeError raised when pd.Grouper(key=...) is passed in a list (GH14334)
- Bug in pd.pivot_table may raise TypeError or ValueError when index or columns is not scalar and values is not specified (GH14380)
Contributors

A total of 30 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Adam Chainz +
- Anthonios Partheniou
- Arash Rouhani +
- Ben Kandel
- Brandon M. Burroughs +
- Chris
- Chris Warth
- David Krych +
- Iván Vallés Pérez +
- Jeff Reback
- Joe Jevnik
- Jon M. Mease +
- Jon Mease +
- Joris Van den Bossche
- Josh Owen +
- Keshav Ramaswamy +
- Larry Ren +
- Michael Felt +
- Piotr Chromiec +
- Robert Bradshaw +
- Sinhrks
- Thiago Serafim +
- Tom Bird
- bkandel +
- chris-b1
- dubourg +
- gfyounq
- mattrijk +
- paul-mannino +
- sinhrks
5.9.3 Version 0.19.0 (October 2, 2016)

This is a major release from 0.18.1 and includes number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- `merge_asof()` for asof-style time-series joining, see here
- `.rolling()` is now time-series aware, see here
- `read_csv()` now supports parsing `Categorical` data, see here
- A function `union_categorical()` has been added for combining categoricals, see here
- `PeriodIndex` now has its own `period` dtype, and changed to be more consistent with other `Index` classes. See here
- Sparse data structures gained enhanced support of `int` and `bool` dtypes, see here
- Comparison operations with `Series` no longer ignores the index, see here for an overview of the API changes.
- Introduction of a pandas development API for utility functions, see here.
- Deprecation of `Panel4D` and `PanelND`. We recommend to represent these types of n-dimensional data with the xarray package.
- Removal of the previously deprecated modules `pandas.io.data`, `pandas.io.wb`, `pandas.tools.rplot`.

**Warning:** pandas >= 0.19.0 will no longer silence numpy ufunc warnings upon import, see here.

What’s new in v0.19.0

- **New features**
  - Function `merge_asof` for asof-style time-series joining
  - Method `.rolling()` is now time-series aware
  - Method `read_csv` has improved support for duplicate column names
  - Method `read_csv` supports parsing `Categorical` directly
  - `Categorical` concatenation
  - `Semi-month` offsets
  - `New Index` methods
  - `Google BigQuery` enhancements
  - `Fine-grained NumPy errstate`
  - Method `get_dummies` now returns integer dtypes
  - `Downcast values to smallest possible dtype` in `to_numeric`
  - pandas development API
  - Other enhancements
- **API changes**
- `Series.tolist()` will now return Python types
- `Series` operators for different indexes
  - Arithmetic operators
  - Comparison operators
  - Logical operators
  - Flexible comparison methods
- `Series` type promotion on assignment
- `Function .to_datetime()` changes
- Merging changes
- `Method .describe()` changes
- `Period` changes
  - The `PeriodIndex` now has period dtype
  - `Period('NaT')` now returns `pd.NaT`  
  - `PeriodIndex.values` now returns array of `Period` object
- `Index` + / – no longer used for set operations
- `Index.difference` and `.symmetric_difference` changes
- `Index.unique` consistently returns `Index`
- `MultiIndex constructors, groupby and set_index preserve categorical dtypes`
- `Function read_csv` will progressively enumerate chunks
- Sparse changes
  - Types `int64` and `bool` support enhancements
  - Operators now preserve dtypes
  - Other sparse fixes
- `Indexer` dtype changes
- Other API changes
- **Deprecations**
- **Removal of prior version deprecations(changes**
- **Performance improvements**
- **Bug fixes**
- **Contributors**
New features

Function `merge_asof` for asof-style time-series joining

A long-time requested feature has been added through the `merge_asof()` function, to support asof style joining of time-series (GH1870, GH13695, GH13709, GH13902). Full documentation is here.

The `merge_asof()` performs an asof merge, which is similar to a left-join except that we match on nearest key rather than equal keys.

```python
In [1]: left = pd.DataFrame({'a': [1, 5, 10],
                          'left_val': ['a', 'b', 'c']})
...:
In [2]: right = pd.DataFrame({'a': [1, 2, 3, 6, 7],
                          'right_val': [1, 2, 3, 6, 7]})
...:
In [3]: left
Out[3]:
   a  left_val
0  1      a
1  5      b
2 10      c
[3 rows x 2 columns]
In [4]: right
Out[4]:
   a  right_val
0  1       1
1  2       2
2  3       3
3  6       6
4  7       7
[5 rows x 2 columns]
```

We typically want to match exactly when possible, and use the most recent value otherwise.

```python
In [5]: pd.merge_asof(left, right, on='a')
Out[5]:
   a  left_val  right_val
0  1      a       1
1  5      b       3
2 10      c       7
[3 rows x 3 columns]
```

We can also match rows ONLY with prior data, and not an exact match.

```python
In [6]: pd.merge_asof(left, right, on='a', allow_exact_matches=False)
Out[6]:
   a  left_val  right_val
0  1      a     NaN
1  5      b       3
2 10      c       7
(continues on next page)```
In a typical time-series example, we have trades and quotes and we want to asof-join them. This also illustrates using the by parameter to group data before merging.

```
In [7]: trades = pd.DataFrame({
   ...:     'time': pd.to_datetime(['20160525 13:30:00.023',
   ...:                      '20160525 13:30:00.038',
   ...:                      '20160525 13:30:00.048',
   ...:                      '20160525 13:30:00.048',
   ...:                      '20160525 13:30:00.048']),
   ...:     'ticker': ['MSFT', 'MSFT',
   ...:               'GOOG', 'GOOG', 'AAPL'],
   ...:     'price': [51.95, 51.95,
   ...:                720.77, 720.92, 98.00],
   ...:     'quantity': [75, 155,
   ...:                   100, 100, 100]},
   ...: columns=['time', 'ticker', 'price', 'quantity'])
   ...

In [8]: quotes = pd.DataFrame({
   ...:     'time': pd.to_datetime(['20160525 13:30:00.023',
   ...:                      '20160525 13:30:00.023',
   ...:                      '20160525 13:30:00.030',
   ...:                      '20160525 13:30:00.041',
   ...:                      '20160525 13:30:00.048',
   ...:                      '20160525 13:30:00.072',
   ...:                      '20160525 13:30:00.075']),
   ...:     'ticker': ['GOOG', 'MSFT', 'MSFT', 'MSFT',
   ...:                'GOOG', 'AAPL', 'GOOG', 'MSFT'],
   ...:     'bid': [720.50, 51.95, 51.97, 51.99,
   ...:              720.50, 97.99, 720.50, 52.01],
   ...:     'ask': [720.93, 51.96, 51.98, 52.00,
   ...:              720.93, 98.01, 720.88, 52.03]},
   ...: columns=['time', 'ticker', 'bid', 'ask'])
   ...

In [9]: trades
Out[9]:
                     time  ticker  price  quantity
   0 2016-05-25 13:30:00.023  MSFT    51.95       75
   1 2016-05-25 13:30:00.038  MSFT    51.95      155
   2 2016-05-25 13:30:00.048  GOOG   720.77       100
   3 2016-05-25 13:30:00.048  GOOG   720.92       100
   4 2016-05-25 13:30:00.048  AAPL    98.00       100

[5 rows x 4 columns]

In [10]: quotes
Out[10]:
                     time  ticker  bid   ask
   0 2016-05-25 13:30:00.023  GOOG   720.50   720.93
   1 2016-05-25 13:30:00.023  MSFT    51.95    51.96
   2 2016-05-25 13:30:00.030  MSFT    51.97    51.98
```
An asof merge joins on the on, typically a datetimelike field, which is ordered, and in this case we are using a grouper in the by field. This is like a left-outer join, except that forward filling happens automatically taking the most recent non-NaN value.

```
In [11]: pd.merge_asof(trades, quotes,
....:       on='time',
....:       by='ticker')
```

Out[11]:
```
<table>
<thead>
<tr>
<th>time</th>
<th>ticker</th>
<th>price</th>
<th>quantity</th>
<th>bid</th>
<th>ask</th>
</tr>
</thead>
<tbody>
<tr>
<td>2016-05-25</td>
<td>MSFT</td>
<td>51.95</td>
<td>75</td>
<td>51.95</td>
<td>51.96</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>MSFT</td>
<td>51.95</td>
<td>155</td>
<td>51.97</td>
<td>51.98</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>GOOG</td>
<td>720.77</td>
<td>100</td>
<td>720.50</td>
<td>720.93</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>GOOG</td>
<td>720.92</td>
<td>100</td>
<td>720.50</td>
<td>720.93</td>
</tr>
<tr>
<td>2016-05-25</td>
<td>AAPL</td>
<td>98.00</td>
<td>100</td>
<td>NaN</td>
<td>NaN</td>
</tr>
</tbody>
</table>
```

This returns a merged DataFrame with the entries in the same order as the original left passed DataFrame (trades in this case), with the fields of the quotes merged.

**Method `.rolling()` is now time-series aware**

`.rolling()` objects are now time-series aware and can accept a time-series offset (or convertible) for the window argument (GH13327, GH12995). See the full documentation [here](https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.rolling.html).

```
In [12]: dft = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]},
....:                   index=pd.date_range('20130101 09:00:00',
....:                   periods=5, freq='s'))
```

```
In [13]: dft.rolling(2).sum()
```

Out[13]:
```
<table>
<thead>
<tr>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013-01-01 09:00:00</td>
</tr>
<tr>
<td>2013-01-01 09:00:01</td>
</tr>
<tr>
<td>2013-01-01 09:00:02</td>
</tr>
<tr>
<td>2013-01-01 09:00:03</td>
</tr>
<tr>
<td>2013-01-01 09:00:04</td>
</tr>
</tbody>
</table>
```

This is a regular frequency index. Using an integer window parameter works to roll along the window frequency.
2013-01-01 09:00:00 NaN
2013-01-01 09:00:01 1.0
2013-01-01 09:00:02 3.0
2013-01-01 09:00:03 NaN
2013-01-01 09:00:04 NaN

[5 rows x 1 columns]

In [15]: dft.rolling(2, min_periods=1).sum()
Out[15]:

[5 rows x 1 columns]

Specifying an offset allows a more intuitive specification of the rolling frequency.

In [16]: dft.rolling('2s').sum()
Out[16]:

[5 rows x 1 columns]

Using a non-regular, but still monotonic index, rolling with an integer window does not impart any special calculation.

In [17]: dft = pd.DataFrame({'B': [0, 1, 2, np.nan, 4],
....:                     index=pd.Index([pd.Timestamp('20130101 09:00:00'),
....:                               pd.Timestamp('20130101 09:00:02'),
....:                               pd.Timestamp('20130101 09:00:03'),
....:                               pd.Timestamp('20130101 09:00:04'),
....:                               pd.Timestamp('20130101 09:00:06')],
....:                     name='foo'))
In [18]: dft
Out[18]:

[5 rows x 1 columns]

In [19]: dft.rolling(2).sum()
Out[19]:

(continues on next page)
Using the time-specification generates variable windows for this sparse data.

```python
In [20]: dft.rolling('2s').sum()
Out[20]:
     B
foo
2013-01-01 09:00:00  NaN
2013-01-01 09:00:02  1.0
2013-01-01 09:00:03  3.0
2013-01-01 09:00:05  NaN
2013-01-01 09:00:06   NaN
[5 rows x 1 columns]
```

Furthermore, we now allow an optional `on` parameter to specify a column (rather than the default of the index) in a DataFrame.

```python
In [21]: dft = dft.reset_index()
In [22]: dft
Out[22]:
     foo    B
0 2013-01-01 09:00:00  0.0
1 2013-01-01 09:00:02  1.0
2 2013-01-01 09:00:03  2.0
3 2013-01-01 09:00:05  NaN
4 2013-01-01 09:00:06  4.0
[5 rows x 2 columns]
```

```python
In [23]: dft.rolling('2s', on='foo').sum()
Out[23]:
     foo    B
0 2013-01-01 09:00:00  0.0
1 2013-01-01 09:00:02  1.0
2 2013-01-01 09:00:03  3.0
3 2013-01-01 09:00:05  NaN
4 2013-01-01 09:00:06  4.0
[5 rows x 2 columns]
```
Method `read_csv` has improved support for duplicate column names

Duplicate column names are now supported in `read_csv()` whether they are in the file or passed in as the `names` parameter (GH7160, GH9424)

In [24]: data = '0,1,2
3,4,5'
In [25]: names = ['a', 'b', 'a']

Previous behavior:

In [2]: pd.read_csv(StringIO(data), names=names)
Out[2]:
    a  b  a
   0  2  1  2
   1  5  4  5

The first a column contained the same data as the second a column, when it should have contained the values [0, 3].

New behavior:

In [26]: pd.read_csv(StringIO(data), names=names)

---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-26-a095135d9435> in <module>
----> 1 pd.read_csv(StringIO(data), names=names)
/pandas-release/pandas/pandas/io/parsers.py in read_csv(filepath_or_buffer, sep,
   684 )
   685     return _read(filepath_or_buffer, kwds)
/pandas-release/pandas/pandas/io/parsers.py in _read(filepath_or_buffer, kwds)
   449     _validate_names(kwds.get("names", None))
   450     # Create the parser.
/pandas-release/pandas/pandas/io/parsers.py in _validate_names(names)
   413     if names is not None:
   414         if len(names) != len(set(names)):
   ----> 415             raise ValueError("Duplicate names are not allowed.")
   416     if not is_list_like(names, allow_sets=False):
   417         raise ValueError("Names should be an ordered collection.")

ValueError: Duplicate names are not allowed.
Method **read_csv** supports parsing Categorical directly

The **read_csv()** function now supports parsing a Categorical column when specified as a dtype (GH10153). Depending on the structure of the data, this can result in a faster parse time and lower memory usage compared to converting to Categorical after parsing. See the io docs here.

```python
In [27]: data = 'col1,col2,col3
a,b,1
a,b,2
b,c,d,3'

In [28]: pd.read_csv(StringIO(data))
Out[28]:
       col1  col2  col3
0      a     b     1
1      a     b     2
2      b     c     3
[3 rows x 3 columns]

In [29]: pd.read_csv(StringIO(data)).dtypes
Out[29]:
       col1  col2  col3
object   object  int64

In [30]: pd.read_csv(StringIO(data), dtype='category').dtypes
Out[30]:
       col1  col2  col3
category category category

Individual columns can be parsed as a Categorical using a dict specification

```python
In [31]: pd.read_csv(StringIO(data), dtype={'col1': 'category'}).dtypes
Out[31]:
       col1  col2  col3
category  object  int64

In [32]: df = pd.read_csv(StringIO(data), dtype='category')

In [33]: df.dtypes
Out[33]:
       col1  col2  col3
category category category

Note: The resulting categories will always be parsed as strings (object dtype). If the categories are numeric they can be converted using the **to_numeric()** function, or as appropriate, another converter such as **to_datetime()**.

```python
In [34]: df['col3']
Out[34]:
0  1
1  2
```

(continues on next page)
2 3
Name: col3, Length: 3, dtype: category
Categories (3, object): ['1', '2', '3']

In [35]: df['col3'].cat.categories = pd.to_numeric(df['col3'].cat.categories)

In [36]: df['col3']
Out[36]:
0 1
1 2
2 3
Name: col3, Length: 3, dtype: category
Categories (3, int64): [1, 2, 3]

Categorical concatenation

- A function `union_categoricals()` has been added for combining categoricals, see [Unioning Categoricals](GH13361, GH13763, GH13846, GH14173)

```
In [37]: from pandas.api.types import union_categoricals
In [38]: a = pd.Categorical(['b', 'c'])
In [39]: b = pd.Categorical(['a', 'b'])
In [40]: union_categoricals([a, b])
Out[40]:
['b', 'c', 'a', 'b']
Categories (3, object): ['b', 'c', 'a']
```

- `concat` and `append` now can concat category dtypes with different categories as object dtype (GH13524)

```
In [41]: s1 = pd.Series(['a', 'b'], dtype='category')
In [42]: s2 = pd.Series(['b', 'c'], dtype='category')

Previous behavior:
```
In [1]: pd.concat([s1, s2])
ValueError: incompatible categories in categorical concat
```

New behavior:
```
In [43]: pd.concat([s1, s2])
Out[43]:
      0   a
      1   b
      0   b
      1   c
Length: 4, dtype: object
```
Semi-month offsets

Pandas has gained new frequency offsets, SemiMonthEnd (‘SM’) and SemiMonthBegin (‘SMS’). These provide date offsets anchored (by default) to the 15th and end of month, and 15th and 1st of month respectively. (GH1543)

```python
In [44]: from pandas.tseries.offsets import SemiMonthEnd, SemiMonthBegin
```

**SemiMonthEnd:**

```python
In [45]: pd.Timestamp('2016-01-01') + SemiMonthEnd()
Out[45]: Timestamp('2016-01-15 00:00:00')
```

```python
In [46]: pd.date_range('2015-01-01', freq='SM', periods=4)
```

**SemiMonthBegin:**

```python
In [47]: pd.Timestamp('2016-01-01') + SemiMonthBegin()
Out[47]: Timestamp('2016-01-15 00:00:00')
```

```python
In [48]: pd.date_range('2015-01-01', freq='SMS', periods=4)
```

Using the anchoring suffix, you can also specify the day of month to use instead of the 15th.

```python
In [49]: pd.date_range('2015-01-01', freq='SMS-16', periods=4)
Out[49]: DatetimeIndex(['2015-01-01', '2015-01-16', '2015-02-01', '2015-02-16'], dtype='datetime64[ns]', freq='SMS-16')
```

```python
In [50]: pd.date_range('2015-01-01', freq='SM-14', periods=4)
Out[50]: DatetimeIndex(['2015-01-14', '2015-01-31', '2015-02-14', '2015-02-28'], dtype='datetime64[ns]', freq='SM-14')
```

New Index methods

The following methods and options are added to Index, to be more consistent with the Series and DataFrame API.

Index now supports the `.where()` function for same shape indexing (GH13170)

```python
In [51]: idx = pd.Index(['a', 'b', 'c'])
In [52]: idx.where([True, False, True])
Out[52]: Index(['a', nan, 'c'], dtype='object')
```

Index now supports `.dropna()` to exclude missing values (GH6194)

```python
In [53]: idx = pd.Index([1, 2, np.nan, 4])
In [54]: idx.dropna()
Out[54]: Float64Index([1.0, 2.0, 4.0], dtype='float64')
```

For MultiIndex, values are dropped if any level is missing by default. Specifying `how='all'` only drops values where all levels are missing.
Index now supports .str.extractall() which returns a DataFrame, see the docs here (GH10008, GH13156)

Index.astype() now accepts an optional boolean argument copy, which allows optional copying if the requirements on dtype are satisfied (GH13209)

Google BigQuery enhancements

- The read_gbq() method has gained the dialect argument to allow users to specify whether to use BigQuery’s legacy SQL or BigQuery’s standard SQL. See the docs for more details (GH13615).
- The to_gbq() method now allows the DataFrame column order to differ from the destination table schema (GH11359).
Fine-grained NumPy errstate

Previous versions of pandas would permanently silence numpy’s ufunc error handling when pandas was imported. Pandas did this in order to silence the warnings that would arise from using numpy ufuncs on missing data, which are usually represented as NaNs. Unfortunately, this silenced legitimate warnings arising in non-pandas code in the application. Starting with 0.19.0, pandas will use the numpy.errstate context manager to silence these warnings in a more fine-grained manner, only around where these operations are actually used in the pandas code base. (GH13109, GH13145)

After upgrading pandas, you may see new RuntimeWarnings being issued from your code. These are likely legitimate, and the underlying cause likely existed in the code when using previous versions of pandas that simply silenced the warning. Use numpy.errstate around the source of the RuntimeWarning to control how these conditions are handled.

Method get_dummies now returns integer dtypes

The pd.get_dummies function now returns dummy-encoded columns as small integers, rather than floats (GH8725). This should provide an improved memory footprint.

Previous behavior:

```python
In [1]: pd.get_dummies(['a', 'b', 'a', 'c']).dtypes
Out[1]:
a float64
b float64
c float64
dtype: object
```

New behavior:

```python
In [61]: pd.get_dummies(['a', 'b', 'a', 'c']).dtypes
Out[61]:
a uint8
b uint8
c uint8
Length: 3, dtype: object
```

Downcast values to smallest possible dtype in to_numeric

pd.to_numeric() now accepts a downcast parameter, which will downcast the data if possible to smallest specified numerical dtype (GH13352)

```python
In [62]: s = ['1', 2, 3]

In [63]: pd.to_numeric(s, downcast='unsigned')
Out[63]: array([1, 2, 3], dtype=uint8)

In [64]: pd.to_numeric(s, downcast='integer')
Out[64]: array([1, 2, 3], dtype=int8)
```
pandas development API

As part of making pandas API more uniform and accessible in the future, we have created a standard sub-package of pandas, pandas.api to hold public API’s. We are starting by exposing type introspection functions in pandas.api.types. More sub-packages and officially sanctioned API’s will be published in future versions of pandas (GH13147, GH13634)

The following are now part of this API:

```
In [65]: import pprint
In [66]: from pandas.api import types
In [67]: func = [f for f in dir(types) if not f.startswith('_')]
In [68]: pprint.pprint(func)
['CategoricalDtype', 'DatetimeTZDtype', 'IntervalDtype', 'PeriodDtype', 'infer_dtype', 'is_array_like', 'is_bool', 'is_bool_dtype', 'is_categorical', 'is_categorical_dtype', 'is_complex', 'is_complex_dtype', 'is_datetime64_any_dtype', 'is_datetime64_dtype', 'is_datetime64_ns_dtype', 'is_datetime64tz_dtype', 'is_dict_like', 'is_dtype_equal', 'is_extension_array_dtype', 'is_extension_type', 'is_file_like', 'is_float', 'is_float_dtype', 'is_hashable', 'is_int64_dtype', 'is_integer', 'is_integer_dtype', 'is_interval', 'is_interval_dtype', 'is_iterator', 'is_list_like', 'is_named_tuple', 'is_number', 'is_numeric_dtype', 'is_object_dtype', 'is_period_dtype', 'is_re', 'is_re_compilable', 'is_scalar', 'is_signed_integer_dtype', 'is_sparse', 'is_string_dtype',
```
Note: Calling these functions from the internal module pandas.core.common will now show a DeprecationWarning (GH13990)

Other enhancements

- **Timestamp** can now accept positional and keyword parameters similar to datetime.datetime() (GH10758, GH11630)

```python
In [69]: pd.Timestamp(2012, 1, 1)
Out[69]: Timestamp('2012-01-01 00:00:00')

In [70]: pd.Timestamp(year=2012, month=1, day=1, hour=8, minute=30)
Out[70]: Timestamp('2012-01-01 08:30:00')
```

- The `resample()` function now accepts a `on=` or `level=` parameter for resampling on a datetimelike column or MultiIndex level (GH13500)

```python
In [71]: df = pd.DataFrame({'date': pd.date_range('2015-01-01', freq='W', periods=5),
                      'a': np.arange(5),
                      index=pd.MultiIndex.from_arrays([pd.date_range('2015-01-01', freq='W', periods=5),
                                                      [1, 2, 3, 4, 5]],
                                                      names=['v', 'd']))

In [72]: df
Out[72]:
   date      a
 v d
1 2015-01-04 2015-01-04 0
2 2015-01-11 2015-01-11 1
3 2015-01-18 2015-01-18 2
4 2015-01-25 2015-01-25 3
5 2015-02-01 2015-02-01 4
[5 rows x 2 columns]

In [73]: df.resample('M', on='date').sum()
Out[73]:
     a
date
2015-01-31 6
```

(continues on next page)
• The `.get_credentials()` method of GbqConnector can now first try to fetch the application default credentials. See the docs for more details (GH13577).

• The `.tz_localize()` method of DatetimeIndex and Timestamp has gained the errors keyword, so you can potentially coerce nonexistent timestamps to NaT. The default behavior remains to raising a NonExistentTimeError (GH13057)

• `.to_hdf/read_hdf()` now accept path objects (e.g. pathlib.Path, py.path.local) for the file path (GH11773)

• The `pd.read_csv()` with engine='python' has gained support for the decimal (GH12933), na_filter (GH13321) and the memory_map option (GH13381).

• Consistent with the Python API, `pd.read_csv()` will now interpret +inf as positive infinity (GH13274)

• The `pd.read_html()` has gained support for the na_values, converters, keep_default_na options (GH13461)

• Categorical.astype() now accepts an optional boolean argument copy, effective when dtype is categorical (GH13209)

• DataFrame has gained the .asof() method to return the last non-NaN values according to the selected subset (GH13358)

• The DataFrame constructor will now respect key ordering if a list of OrderedDict objects are passed in (GH13304)

• `pd.read_html()` has gained support for the decimal option (GH12907)

• Series has gained the properties .is_monotonic, .is_monotonic_increasing, .is_monotonic_decreasing, similar to Index (GH13336)

• DataFrame.to_sql() now allows a single value as the SQL type for all columns (GH11886).

• Series.append now supports the ignore_index option (GH13677)

• `.to_stata()` and StataWriter can now write variable labels to Stata dta files using a dictionary to make column names to labels (GH13535, GH13536)

• `.to_stata()` and StataWriter will automatically convert datetime64[ns] columns to Stata format %tc, rather than raising a ValueError (GH12259)

• `read_stata()` and StataReader raise with a more explicit error message when reading Stata files with repeated value labels when convert_categoricals=True (GH13923)

• DataFrame.style will now render sparsified MultiIndexes (GH11655)

• DataFrame.style will now show column level names (e.g. DataFrame.columns.names)(GH13775)
• DataFrame has gained support to re-order the columns based on the values in a row using `df.sort_values(by='...', axis=1)` (GH10806)

```
In [75]: df = pd.DataFrame({'A': [2, 7], 'B': [3, 5], 'C': [4, 8]},
   ....:     index=['row1', 'row2'])
In [76]: df
Out[76]:
     A  B  C
row1 2  3  4
row2 7  5  8
[2 rows x 3 columns]
In [77]: df.sort_values(by='row2', axis=1)
Out[77]:
     B  A  C
row1 3  2  4
row2 5  7  8
[2 rows x 3 columns]
```

• Added documentation to I/O regarding the perils of reading in columns with mixed dtypes and how to handle it (GH13746)

• `to_html()` now has a `border` argument to control the value in the opening `<table>` tag. The default is the value of the `html.border` option, which defaults to 1. This also affects the notebook HTML repr, but since Jupyter’s CSS includes a border-width attribute, the visual effect is the same. (GH11563).

• Raise `ImportError` in the `sql` functions when `sqlalchemy` is not installed and a connection string is used (GH11920).

• Compatibility with matplotlib 2.0. Older versions of pandas should also work with matplotlib 2.0 (GH13333)

• `Timestamp`, `Period`, `DatetimeIndex`, `PeriodIndex` and `.dt` accessor have gained a `.is_leap_year` property to check whether the date belongs to a leap year. (GH13727)

• `astype()` will now accept a dict of column name to data types mapping as the `dtype` argument. (GH12086)

• The `pd.read_json` and `DataFrame.to_json` has gained support for reading and writing json lines with `lines` option see `Line delimited json` (GH9180)

• `read_excel()` now supports the `true_values` and `false_values` keyword arguments (GH13347)

• `groupby()` will now accept a scalar and a single-element list for specifying `level` on a non-`MultiIndex` grouper. (GH13907)

• Non-convertible dates in an excel date column will be returned without conversion and the column will be `object` dtype, rather than raising an exception (GH10001).

• `pd.Timedelta(None)` is now accepted and will return `NaT`, mirroring `pd.Timestamp` (GH13687)

• `pd.read_stata()` can now handle some format 111 files, which are produced by SAS when generating Stata dta files (GH11526)

• `Series` and `Index` now support `divmod` which will return a tuple of series or indices. This behaves like a standard binary operator with regards to broadcasting rules (GH14208).
API changes

Series.tolist() will now return Python types

Series.tolist() will now return Python types in the output, mimicking NumPy .tolist() behavior (GH10904)

```
In [78]: s = pd.Series([1, 2, 3])
```

Previous behavior:

```
In [7]: type(s.tolist()[0])
Out[7]: <class 'numpy.int64'>
```

New behavior:

```
In [79]: type(s.tolist()[0])
Out[79]: int
```

Series operators for different indexes

Following Series operators have been changed to make all operators consistent, including DataFrame (GH1134, GH4581, GH13538)

- Series comparison operators now raise ValueError when index are different.
- Series logical operators align both index of left and right hand side.

**Warning:** Until 0.18.1, comparing Series with the same length, would succeed even if the .index are different (the result ignores .index). As of 0.19.0, this will raise ValueError to be more strict. This section also describes how to keep previous behavior or align different indexes, using the flexible comparison methods like .eq.

As a result, Series and DataFrame operators behave as below:

**Arithmetic operators**

Arithmetic operators align both index (no changes).

```
In [80]: s1 = pd.Series([1, 2, 3], index=list('ABC'))
In [81]: s2 = pd.Series([2, 2, 2], index=list('ABD'))
In [82]: s1 + s2
Out[82]:
     A  3.0
     B  4.0
     C   NaN
     D   NaN
Length: 4, dtype: float64
```
In [83]: df1 = pd.DataFrame([1, 2, 3], index=list('ABC'))

In [84]: df2 = pd.DataFrame([2, 2, 2], index=list('ABD'))

In [85]: df1 + df2
Out[85]:
0    3.0
A    4.0
B     NaN
C     NaN
D     NaN
[4 rows x 1 columns]

Comparison operators

Comparison operators raise `ValueError` when `.index` are different.

**Previous behavior** (Series):
Series compared values ignoring the `.index` as long as both had the same length:

In [1]: s1 == s2
Out[1]:
A   False
B    True
C   False
dtype: bool

**New behavior** (Series):

In [2]: s1 == s2
Out[2]:
ValueError: Can only compare identically-labeled Series objects

**Note:** To achieve the same result as previous versions (compare values based on locations ignoring `.index`), compare both `.values`.

In [86]: s1.values == s2.values
Out[86]: array([False, True, False])

If you want to compare Series aligning its `.index`, see flexible comparison methods section below:

In [87]: s1.eq(s2)
Out[87]:
A   False
B    True
C   False
D   False
Length: 4, dtype: bool

**Current behavior** (DataFrame, no change):
Logical operators

Logical operators align both .index of left and right hand side.

Previous behavior (Series), only left hand side index was kept:

```python
In [4]: s1 = pd.Series([True, False, True], index=list('ABC'))
In [5]: s2 = pd.Series([True, True, True], index=list('ABD'))
In [6]: s1 & s2
Out[6]:
A   True
B   False
C   False
dtype: bool
```

New behavior (Series):

```python
In [88]: s1 = pd.Series([True, False, True], index=list('ABC'))
In [89]: s2 = pd.Series([True, True, True], index=list('ABD'))
In [90]: s1 & s2
Out[90]:
A   True
B   False
C   False
D   False
Length: 4, dtype: bool
```

Note: Series logical operators fill a NaN result with False.

Note: To achieve the same result as previous versions (compare values based on only left hand side index), you can use reindex_like:

```python
In [91]: s1 & s2.reindex_like(s1)
Out[91]:
A   True
B   False
C   False
D   False
Length: 3, dtype: bool
```

Current behavior (DataFrame, no change):

```python
In [92]: df1 = pd.DataFrame([True, False, True], index=list('ABC'))
In [93]: df2 = pd.DataFrame([True, True, True], index=list('ABD'))
In [94]: df1 & df2
```(continues on next page)
Flexible comparison methods

Series flexible comparison methods like `eq`, `ne`, `le`, `lt`, `ge` and `gt` now align both index. Use these operators if you want to compare two Series which has the different index.

```python
In [95]: s1 = pd.Series([1, 2, 3], index=['a', 'b', 'c'])
In [96]: s2 = pd.Series([2, 2, 2], index=['b', 'c', 'd'])
In [97]: s1.eq(s2)
Out[97]:
   a   False
   b    True
   c   False
   d   False
Length: 4, dtype: bool
In [98]: s1.ge(s2)
Out[98]:
   a   False
   b    True
   c    True
   d   False
Length: 4, dtype: bool
```

Previously, this worked the same as comparison operators (see above).

Series type promotion on assignment

A Series will now correctly promote its dtype for assignment with incompat values to the current dtype (GH13234)

```python
In [99]: s = pd.Series()

Previous behavior:

In [2]: s['a'] = pd.Timestamp("2016-01-01")
In [3]: s['b'] = 3.0
TypeError: invalid type promotion

New behavior:

In [100]: s['a'] = pd.Timestamp("2016-01-01")
```

(continues on next page)
Function `.to_datetime()` changes

Previously if `.to_datetime()` encountered mixed integers/floats and strings, but no datetimes with errors='coerce' it would convert all to NaT.

**Previous behavior:**

```
In [2]: pd.to_datetime([1, 'foo'], errors='coerce')
Out[2]: DatetimeIndex(['NaT', 'NaT'], dtype='datetime64[ns]', freq=None)
```

**Current behavior:**

This will now convert integers/floats with the default unit of ns.

```
In [104]: pd.to_datetime([1, 'foo'], errors='coerce')
Out[104]: DatetimeIndex(['1970-01-01 00:00:00.000000001', 'NaT'], dtype='datetime64[ns]', freq=None)
```

**Bug fixes related to `.to_datetime()`:**

- Bug in `pd.to_datetime()` when passing integers or floats, and no unit and errors='coerce' (GH13180).
- Bug in `pd.to_datetime()` when passing invalid data types (e.g. bool); will now respect the errors keyword (GH13176)
- Bug in `pd.to_datetime()` which overflowed on `int8` and `int16` dtypes (GH13451)
- Bug in `pd.to_datetime()` raise AttributeError with NaN and the other string is not valid when errors='ignore' (GH12424)
- Bug in `pd.to_datetime()` did not cast floats correctly when unit was specified, resulting in truncated datetime (GH13834)

**Merging changes**

Merging will now preserve the dtype of the join keys (GH8596)

```
In [105]: df1 = pd.DataFrame({'key': [1], 'v1': [10]})
In [106]: df1
Out[106]:
   key  v1
0   1  10
```
In [107]: df2 = pd.DataFrame({'key': [1, 2], 'v1': [20, 30]})

In [108]: df2
Out[108]:
     key  v1
0     1  20
1     2  30
[2 rows x 2 columns]

Previous behavior:

In [5]: pd.merge(df1, df2, how='outer')
Out[5]:
     key  v1
0  1.0  10.0
1  1.0  20.0
2  2.0  30.0

In [6]: pd.merge(df1, df2, how='outer').dtypes
Out[6]:
key  float64
v1   float64
dtype: object

New behavior:

We are able to preserve the join keys

In [109]: pd.merge(df1, df2, how='outer')
Out[109]:
     key  v1_x  v1_y
0     1    10.0  20
1     2      NaN  30
[2 rows x 3 columns]

In [110]: pd.merge(df1, df2, how='outer').dtypes
Out[110]:
key     int64
v1_x    int64
v1_y    int64
Length: 2, dtype: object

Of course if you have missing values that are introduced, then the resulting dtype will be upcast, which is unchanged from previous.
In [112]: pd.merge(df1, df2, how='outer', on='key').dtypes
Out[112]:
key     int64
v1_x    float64
v1_y    int64
Length: 3, dtype: object

Method .describe() changes

Percentile identifiers in the index of a .describe() output will now be rounded to the least precision that keeps them distinct (GH13104)

In [113]: s = pd.Series([0, 1, 2, 3, 4])
In [114]: df = pd.DataFrame([0, 1, 2, 3, 4])

Previous behavior:
The percentiles were rounded to at most one decimal place, which could raise ValueError for a data frame if the percentiles were duplicated.

In [3]: s.describe(percentiles=[0.0001, 0.0005, 0.001, 0.999, 0.9995, 0.9999])
Out[3]:
      count      mean      std      min      0.0%      0.1%      0.1%      0.1%      50%      99.9%      100.0%      100.0%      max
dtype: float64
In [4]: df.describe(percentiles=[0.0001, 0.0005, 0.001, 0.999, 0.9995, 0.9999])
Out[4]:
... 
ValueError: cannot reindex from a duplicate axis

New behavior:

In [115]: s.describe(percentiles=[0.0001, 0.0005, 0.001, 0.999, 0.9995, 0.9999])
Out[115]:
      count      mean      std      min      0.01%      0.05%      0.1%      0.1%      50%      99.9%      100.0%      100.0%      max
dtype: float64
Furthermore:

- Passing duplicated percentiles will now raise a `ValueError`.
- Bug in `.describe()` on a DataFrame with a mixed-dtype column index, which would previously raise a `TypeError` (GH13288)

### Period changes

The `PeriodIndex` now has period `dtype`. The period `dtype` is a pandas extension `dtype` like `category` or the `timezone aware dtype` ([datetime64[ns, tz]](GH13941)). As a consequence of this change, `PeriodIndex` no longer has an integer `dtype`:

#### Previous behavior:

```python
In [1]: pi = pd.PeriodIndex(['2016-08-01'], freq='D')

In [2]: pi
Out[2]: PeriodIndex(['2016-08-01'], dtype='int64', freq='D')

In [3]: pd.api.types.is_integer_dtype(pi)
Out[3]: True

In [4]: pi.dtype
Out[4]: dtype('int64')
```

#### New behavior:

```python
In [1]: pi = pd.PeriodIndex(['2016-08-01'], freq='D')

In [2]: pi
Out[2]: PeriodIndex(['2016-08-01'], dtype='period[D]', freq='D')

In [3]: pd.api.types.is_integer_dtype(pi)
Out[3]: False

In [4]: pi.dtype
Out[4]: PeriodIndex(['2016-08-01'], dtype='period[D]', freq='D')
```
In [117]: pi = pd.PeriodIndex(['2016-08-01'], freq='D')

In [118]: pi
Out[118]: PeriodIndex(['2016-08-01'], dtype='period[D]', freq='D')

In [119]: pd.api.types.is_integer_dtype(pi)
Out[119]: False

In [120]: pd.api.types.is_period_dtype(pi)
Out[120]: True

In [121]: pi.dtype
Out[121]: period[D]

In [122]: type(pi.dtype)
Out[122]: pandas.core.dtypes.dtypes.PeriodDtype

Period('NaT') now returns pd.NaT

Previously, Period has its own Period('NaT') representation different from pd.NaT. Now Period('NaT') has been changed to return pd.NaT. (GH12759, GH13582)

Previous behavior:

In [5]: pd.Period('NaT', freq='D')
Out[5]: Period('NaT', 'D')

New behavior:

These result in pd.NaT without providing freq option.

In [123]: pd.Period('NaT')
Out[123]: NaT

In [124]: pd.Period(None)
Out[124]: NaT

To be compatible with Period addition and subtraction, pd.NaT now supports addition and subtraction with int. Previously it raised ValueError.

Previous behavior:

In [5]: pd.NaT + 1
...:
ValueError: Cannot add integral value to Timestamp without freq.

New behavior:

In [125]: pd.NaT + 1
Out[125]: NaT

In [126]: pd.NaT - 1
Out[126]: NaT
**PeriodIndex.values now returns array of Period object**

`.values` is changed to return an array of `Period` objects, rather than an array of integers (GH13988).

**Previous behavior:**

```python
In [6]: pi = pd.PeriodIndex(['2011-01', '2011-02'], freq='M')
In [7]: pi.values
Out[7]: array([492, 493])
```

**New behavior:**

```python
In [127]: pi = pd.PeriodIndex(['2011-01', '2011-02'], freq='M')
In [128]: pi.values
Out[128]: array([<Period('2011-01', 'M')>, <Period('2011-02', 'M')>], dtype=object)
```

**Index + / – no longer used for set operations**

Addition and subtraction of the base Index type and of DatetimeIndex (not the numeric index types) previously performed set operations (set union and difference). This behavior was already deprecated since 0.15.0 (in favor using the specific `.union()` and `.difference()` methods), and is now disabled. When possible, + and − are now used for element-wise operations, for example for concatenating strings or subtracting datetimes (GH8227, GH14127).

**Previous behavior:**

```python
In [1]: pd.Index(['a', 'b']) + pd.Index(['a', 'c'])
FutureWarning: using '+' to provide set union with Indexes is deprecated, use '|' or .__union__()
Out[1]: Index(['a', 'b', 'c'], dtype='object')
```

**New behavior:** the same operation will now perform element-wise addition:

```python
In [129]: pd.Index(['a', 'b']) + pd.Index(['a', 'c'])
Out[129]: Index(['aa', 'bc'], dtype='object')
```

Note that numeric Index objects already performed element-wise operations. For example, the behavior of adding two integer Indexes is unchanged. The base `Index` is now made consistent with this behavior.

```python
In [130]: pd.Index([1, 2, 3]) + pd.Index([2, 3, 4])
Out[130]: Int64Index([3, 5, 7], dtype='int64')
```

Further, because of this change, it is now possible to subtract two DatetimeIndex objects resulting in a TimedeltaIndex:

**Previous behavior:**

```python
In [1]: (pd.DatetimeIndex(['2016-01-01', '2016-01-02']))
...: − pd.DatetimeIndex(['2016-01-02', '2016-01-03']))
FutureWarning: using '-' to provide set differences with datetimelike Indexes is deprecated, use .difference()
Out[1]: DatetimeIndex(['2016-01-01'], dtype='datetime64[ns]', freq=None)
```

**New behavior:**

```python
In [131]: (pd.DatetimeIndex(['2016-01-01', '2016-01-02']))
.....: − pd.DatetimeIndex(['2016-01-02', '2016-01-03']))
```
Index.difference and symmetric_difference changes

Index.difference and Index.symmetric_difference will now, more consistently, treat NaN values as any other values. (GH13514)

```python
In [132]: idx1 = pd.Index([1, 2, 3, np.nan])
In [133]: idx2 = pd.Index([0, 1, np.nan])

Previous behavior:

```python
In [3]: idx1.difference(idx2)
Out[3]: Float64Index([nan, 2.0, 3.0], dtype='float64')
In [4]: idx1.symmetric_difference(idx2)
Out[4]: Float64Index([0.0, nan, 2.0, 3.0], dtype='float64')
```

New behavior:

```python
In [134]: idx1.difference(idx2)
Out[134]: Float64Index([2.0, 3.0], dtype='float64')
In [135]: idx1.symmetric_difference(idx2)
Out[135]: Float64Index([0.0, 2.0, 3.0], dtype='float64')
```

Index.unique consistently returns Index

Index.unique() now returns unique values as an Index of the appropriate dtype. (GH13395). Previously, most Index classes returned np.ndarray, and DatetimeIndex, TimedeltaIndex and PeriodIndex returned Index to keep metadata like timezone.

Previous behavior:

```python
In [1]: pd.Index([1, 2, 3]).unique()
Out[1]: array([1, 2, 3])
In [2]: pd.DatetimeIndex(['2011-01-01', '2011-01-02', ...
   ...:     '2011-01-03'], tz='Asia/Tokyo').unique()
Out[2]: DatetimeIndex(['2011-01-01 00:00:00+09:00', '2011-01-02 00:00:00+09:00',
   ...:     '2011-01-03 00:00:00+09:00'],
   ...:     dtype='datetime64[ns, Asia/Tokyo]', freq=None)
```

New behavior:

```python
In [136]: pd.Index([1, 2, 3]).unique()
Out[136]: Int64Index([1, 2, 3], dtype='int64')
In [137]: pd.DatetimeIndex(['2011-01-01', '2011-01-02', '2011-01-03'],
   ...:     tz='Asia/Tokyo').unique()
```

(continues on next page)
MultiIndex constructors, groupby and set_index preserve categorical dtypes

MultiIndex.from_arrays and MultiIndex.from_product will now preserve categorical dtype in MultiIndex levels (GH13743, GH13854).

```
In [138]: cat = pd.Categorical(['a', 'b'], categories=list("bac"))
In [139]: lvl1 = ['foo', 'bar']
In [140]: midx = pd.MultiIndex.from_arrays([cat, lvl1])
In [141]: midx
```

```
MultiIndex([('a', 'foo'),
             ('b', 'bar')])
```

Previous behavior:
```
In [4]: midx.levels[0]
Out[4]: Index(['b', 'a', 'c'], dtype='object')
In [5]: midx.get_level_values[0]
Out[5]: Index(['a', 'b'], dtype='object')
```

New behavior: the single level is now a CategoricalIndex:
```
In [142]: midx.levels[0]
Out[142]: CategoricalIndex(['b', 'a', 'c'], categories=['b', 'a', 'c'], ordered=False, dtype='category')
In [143]: midx.get_level_values(0)
Out[143]: CategoricalIndex(['a', 'b'], categories=['b', 'a', 'c'], ordered=False, dtype='category')
```

An analogous change has been made to MultiIndex.from_product. As a consequence, groupby and set_index also preserve categorical dtypes in indexes

```
In [144]: df = pd.DataFrame({"A": [0, 1], "B": [10, 11], "C": cat})
In [145]: df_grouped = df.groupby(by=['A', 'C']).first()
In [146]: df_set_idx = df.set_index(['A', 'C'])
```

Previous behavior:
```
In [11]: df_grouped.index.levels[1]
Out[11]: Index(['b', 'a', 'c'], dtype='object', name='C')
```
In [12]: df_grouped.reset_index().dtypes
Out[12]:
A    int64
C    object
B   float64
dtype: object

In [13]: df_set_idx.index.levels[1]
Out[13]: Index(['b', 'a', 'c'], dtype='object', name='C')
In [14]: df_set_idx.reset_index().dtypes
Out[14]:
A    int64
C    object
B    int64
dtype: object

New behavior:

In [147]: df_grouped.index.levels[1]
Out[147]: CategoricalIndex(['b', 'a', 'c'], categories=['b', 'a', 'c'], ordered=False,
-> name='C', dtype='category')
In [148]: df_grouped.reset_index().dtypes
Out[148]:
A    int64
C  category
B   float64
Length: 3, dtype: object
In [149]: df_set_idx.index.levels[1]
Out[149]: CategoricalIndex(['b', 'a', 'c'], categories=['b', 'a', 'c'], ordered=False,
-> name='C', dtype='category')
In [150]: df_set_idx.reset_index().dtypes
Out[150]:
A    int64
C  category
B    int64
Length: 3, dtype: object

Function read_csv will progressively enumerate chunks

When read_csv() is called with chunksize=n and without specifying an index, each chunk used to have an independently generated index from 0 to n−1. They are now given instead a progressive index, starting from 0 for the first chunk, from n for the second, and so on, so that, when concatenated, they are identical to the result of calling read_csv() without the chunksize= argument (GH12185).

In [151]: data = 'A,B
     0,1
     2,3
     4,5
     6,7'

Previous behavior:

In [2]: pd.concat(pd.read_csv(StringIO(data), chunksize=2))
Out[2]:
   A  B
 0  0  0
 1  1  1
 2  2  2
 3  3  3
 4  4  4
 5  5  5
 6  6  6
 7  7  7

(continues on next page)
New behavior:

In [152]: pd.concat(pd.read_csv(StringIO(data), chunksize=2))
Out[152]:
    A  B
0 0  1
1 2  3
2 4  5
3 6  7
[4 rows x 2 columns]

Sparse changes

These changes allow pandas to handle sparse data with more dtypes, and for work to make a smoother experience with data handling.

Types int64 and bool support enhancements

Sparse data structures now gained enhanced support of int64 and bool dtype (GH667, GH13849).

Previously, sparse data were float64 dtype by default, even if all inputs were of int or bool dtype. You had to specify dtype explicitly to create sparse data with int64 dtype. Also, fill_value had to be specified explicitly because the default was np.nan which doesn’t appear in int64 or bool data.

In [1]: pd.SparseArray([1, 2, 0, 0])
Out[1]:
[1.0, 2.0, 0.0, 0.0]
Fill: nan
IntIndex
Indices: array([0, 1, 2, 3], dtype=int32)

# specifying int64 dtype, but all values are stored in sp_values because
# fill_value default is np.nan
In [2]: pd.SparseArray([1, 2, 0, 0], dtype=np.int64)
Out[2]:
[1, 2, 0, 0]
Fill: nan
IntIndex
Indices: array([0, 1, 2, 3], dtype=int32)

In [3]: pd.SparseArray([1, 2, 0, 0], dtype=np.int64, fill_value=0)
Out[3]:
[1, 2, 0, 0]
Fill: 0
IntIndex
Indices: array([0, 1], dtype=int32)
As of v0.19.0, sparse data keeps the input dtype, and uses more appropriate fill_value defaults (0 for int64 dtype, False for bool dtype).

```python
In [153]: pd.SparseArray([1, 2, 0, 0], dtype=np.int64)
Out[153]:
[1, 2, 0, 0]
Fill: 0
IntIndex
Indices: array([0, 1], dtype=int32)

In [154]: pd.SparseArray([True, False, False, False])
Out[154]:
[True, False, False, False]
Fill: False
IntIndex
Indices: array([0], dtype=int32)
```

See the docs for more details.

**Operators now preserve dtypes**

- Sparse data structure now can preserve dtype after arithmetic ops (GH13848)

```python
s = pdSparseSeries([0, 2, 0, 1], fill_value=0, dtype=np.int64)
s.dtype
s + 1
```

- Sparse data structure now support astype to convert internal dtype (GH13900)

```python
s = pdSparseSeries([1., 0., 2., 0.], fill_value=0)
s
s.astype(np.int64)
```

astype fails if data contains values which cannot be converted to specified dtype. Note that the limitation is applied to fill_value which default is np.nan.

```python
In [7]: pdSparseSeries([1., np.nan, 2., np.nan]).astype(np.int64)
Out[7]:
ValueError: unable to coerce current fill_value nan to int64 dtype
```

**Other sparse fixes**

- Subclassed SparseDataFrame and SparseSeries now preserve class types when slicing or transposing. (GH13787)
- SparseArray with bool dtype now supports logical (bool) operators (GH14000)
- Bug in SparseSeries with MultiIndex [] indexing may raise IndexError (GH13144)
- Bug in SparseSeries with MultiIndex [] indexing result may have normal Index (GH13144)
- Bug in SparseDataFrame in which axis=None did not default to axis=0 (GH13048)
- Bug in SparseSeries and SparseDataFrame creation with object dtype may raise TypeError (GH11633)
- Bug in `SparseDataFrame` doesn’t respect passed `SparseArray` or `SparseSeries`’s dtype and `fill_value` (GH13866)
- Bug in `SparseArray` and `SparseSeries` don’t apply ufunc to `fill_value` (GH13853)
- Bug in `SparseSeries.abs` incorrectly keeps negative `fill_value` (GH13853)
- Bug in single row slicing on multi-type `SparseDataFrame` s, types were previously forced to float (GH13917)
- Bug in `SparseSeries` slicing changes integer dtype to float (GH8292)
- Bug in `SparseDataFrame` comparison ops may raise `TypeError` (GH13001)
- Bug in `SparseDataFrame.isnull` raises `ValueError` (GH8276)
- Bug in `SparseSeries` representation with bool dtype may raise `IndexError` (GH13110)
- Bug in `SparseSeries` and `SparseDataFrame` of bool or int64 dtype may display its values like float64 dtype (GH13110)
- Bug in sparse indexing using `SparseArray` with bool dtype may return incorrect result (GH13985)
- Bug in `SparseArray` created from `SparseSeries` may lose dtype (GH13999)
- Bug in `SparseSeries` comparison with dense returns normal `Series` rather than `SparseSeries` (GH13999)

### Indexer dtype changes

**Note:** This change only affects 64 bit python running on Windows, and only affects relatively advanced indexing operations

Methods such as `Index.get_indexer` that return an indexer array, coerce that array to a “platform int”, so that it can be directly used in 3rd party library operations like `numpy.take`. Previously, a platform int was defined as `np.int_` which corresponds to a C integer, but the correct type, and what is being used now, is `np.intp`, which corresponds to the C integer size that can hold a pointer (GH3033, GH13972).

These types are the same on many platform, but for 64 bit python on Windows, `np.int_` is 32 bits, and `np.intp` is 64 bits. Changing this behavior improves performance for many operations on that platform.

**Previous behavior:**

```
In [1]: i = pd.Index(['a', 'b', 'c'])
In [2]: i.get_indexer(['b', 'b', 'c']).dtype
Out[2]: dtype('int32')
```

**New behavior:**

```
In [1]: i = pd.Index(['a', 'b', 'c'])
In [2]: i.get_indexer(['b', 'b', 'c']).dtype
Out[2]: dtype('int64')
```
Other API changes

- `Timestamp.to_pydatetime` will issue a `UserWarning` when `warn=True`, and the instance has a non-zero number of nanoseconds, previously this would print a message to stdout (GH14101).
- `Series.unique()` with datetime and timezone now returns return array of `Timestamp` with timezone (GH13565).
- `Panel.to_sparse()` will raise a `NotImplementedError` exception when called (GH13778).
- `Index.reshape()` will raise a `NotImplementedError` exception when called (GH12882).
- `.filter()` enforces mutual exclusion of the keyword arguments (GH12399).
- `eval`’s upcasting rules for `float32` types have been updated to be more consistent with NumPy’s rules. New behavior will not upcast to `float64` if you multiply a pandas `float32` object by a scalar `float64` (GH12388).
- An `UnsupportedFunctionCall` error is now raised if NumPy ufuncs like `np.mean` are called on groupby or resample objects (GH12811).
- `__setitem__` will no longer apply a callable rhs as a function instead of storing it. Call `where` directly to get the previous behavior (GH13299).
- Calls to `.sample()` will respect the random seed set via `numpy.random.seed(n)` (GH13161).
- `Styler.apply` is now more strict about the outputs your function must return. For `axis=0` or `axis=1`, the output shape must be identical. For `axis=None`, the output must be a DataFrame with identical columns and index labels (GH13222).
- `Float64Index.astype(int)` will now raise `ValueError` if `Float64Index` contains NaN values (GH13149).
- `TimedeltaIndex.astype(int)` and `DatetimeIndex.astype(int)` will now return `Int64Index` instead of `np.array` (GH13209).
- Passing `Period` with multiple frequencies to normal `Index` now returns `Index` with `object` dtype (GH13664).
- `PeriodIndex.fillna` with `Period` has different freq now coerces to `object` dtype (GH13664).
- Faceted boxplots from `DataFrame.boxplot(by=col)` now return a `Series` when `return_type` is not `None`. Previously these returned an `OrderedDict`. Note that when `return_type=None`, the default, these still return a 2-D NumPy array (GH12216, GH7096).
- `pd.read_hdf` will now raise a `ValueError` instead of `KeyError`, if a mode other than `r`, `r+` and `a` is supplied. (GH13623)
- `pd.read_csv()`, `pd.read_table()`, and `pd.read_hdf()` raise the built-in `FileNotFoundError` exception for Python 3.x when called on a nonexistent file; this is back-ported as `IOError` in Python 2.x (GH14086).
- More informative exceptions are passed through the csv parser. The exception type would now be the original exception type instead of `CPARSERERROR` (GH13652).
- `pd.read_csv()` in the C engine will now issue a `ParserWarning` or raise a `ValueError` when `sep` encoded is more than one character long (GH14065)
- `DataFrame.values` will now return `float64` with a `DataFrame` of mixed `int64` and `uint64` dtypes, conforming to `np.find_common_type` (GH10364, GH13917).
- `.groupby().groups` will now return a dictionary of `Index` objects, rather than a dictionary of `np.ndarray` or lists (GH14293).
Deprecations

- Series.reshape and Categorical.reshape have been deprecated and will be removed in a subsequent release (GH12882, GH12882)
- PeriodIndex.to_datetime has been deprecated in favor of PeriodIndex.to_timestamp (GH8254)
- Timestamp.to_datetime has been deprecated in favor of Timestamp.to_pydatetime (GH8254)
- Index.to_datetime and DatetimeIndex.to_datetime have been deprecated in favor of pd.to_datetime (GH8254)
- pandas.core.datetools module has been deprecated and will be removed in a subsequent release (GH14094)
- SparseList has been deprecated and will be removed in a future version (GH13784)
- DataFrame.to_html() and DataFrame.to_latex() have dropped the colSpace parameter in favor of col_space (GH13857)
- DataFrame.to_sql() has deprecated the flavor parameter, as it is superfluous when SQLAlchemy is not installed (GH13611)
- Deprecated read_csv keywords:
  - compact_ints and use_unsigned have been deprecated and will be removed in a future version (GH13320)
  - buffer_lines has been deprecated and will be removed in a future version (GH13360)
  - as_recarray has been deprecated and will be removed in a future version (GH13373)
  - skip_footer has been deprecated in favor of skipfooter and will be removed in a future version (GH13349)
- top-level pd.ordered_merge() has been renamed to pd.merge_ordered() and the original name will be removed in a future version (GH13358)
- Timestamp.offset property (and named arg in the constructor), has been deprecated in favor of freq (GH12160)
- pd.tseries.util.pivot_annual is deprecated. Use pivot_table as alternative, an example is here (GH736)
- pd.tseries.util.isleapyear has been deprecated and will be removed in a subsequent release. Datetime-like now have a .is_leap_year property (GH13727)
- Panel4D and PanelND constructors are deprecated and will be removed in a future version. The recommended way to represent these types of n-dimensional data are with the xarray package. Pandas provides a to_xarray() method to automate this conversion (GH13564).
- pandas.tseries.frequencies.get_standard_freq is deprecated. Use pandas.tseries.frequencies.to_offset(freq).rule_code instead (GH13874)
- pandas.tseries.frequencies.to_offset's freqstr keyword is deprecated in favor of freq (GH13874)
- Categorical.from_array has been deprecated and will be removed in a future version (GH13854)
Removal of prior version deprecations/changes

- The SparsePanel class has been removed (GH13778)
- The pd.sandbox module has been removed in favor of the external library pandas-qt (GH13670)
- The pandas.io.data and pandas.io.wb modules are removed in favor of the pandas-datareader package (GH13724).
- The pandas.tools.rplot module has been removed in favor of the seaborn package (GH13855)
- DataFrame.to_csv() has dropped the engine parameter, as was deprecated in 0.17.1 (GH11274, GH13419)
- pd.DataFrame.to_dict() has dropped the outtype parameter in favor of orient (GH13627, GH8486)
- pd.Categorical has dropped setting of the ordered attribute directly in favor of the set_ordered method (GH13671)
- pd.Categorical has dropped the levels attribute in favor of categories (GH8376)
- DataFrame.to_sql() has dropped the mysql option for the flavor parameter (GH13611)
- Panel.shift() has dropped the lags parameter in favor of periods (GH14041)
- pd.Index has dropped the diff method in favor of difference (GH13669)
- pd.DataFrame has dropped the to_wide method in favor of to_panel (GH14039)
- Series.to_csv has dropped the nanRep parameter in favor of na_rep (GH13804)
- Series.xs, DataFrame.xs, Panel.xs, Panel.major_xs, and Panel.minor_xs have dropped the copy parameter (GH13781)
- str.split has dropped the return_type parameter in favor of expand (GH13701)
- Removal of the legacy time rules (offset aliases), deprecated since 0.17.0 (this has been alias since 0.8.0) (GH13590, GH13868). Now legacy time rules raises ValueError. For the list of currently supported offsets, see here.
- The default value for the return_type parameter for DataFrame.plot.box and DataFrame.boxplot changed from None to "axes". These methods will now return a matplotlib axes by default instead of a dictionary of artists. See here (GH6581).
- The tquery and uquery functions in the pandas.io.sql module are removed (GH5950).

Performance improvements

- Improved performance of sparse IntIndex.intersect (GH13082)
- Improved performance of sparse arithmetic with BlockIndex when the number of blocks are large, though recommended to use IntIndex in such cases (GH13082)
- Improved performance of DataFrame.quantile() as it now operates per-block (GH11623)
- Improved performance of float64 hash table operations, fixing some very slow indexing and groupby operations in python 3 (GH13166, GH13334)
- Improved performance of DataFrameGroupBy.transform (GH12737)
- Improved performance of Index and Series.duplicated (GH10235)
- Improved performance of Index.difference (GH12044)
• Improved performance of `RangeIndex.is_monotonic_increasing` and `is_monotonic_decreasing` (GH13749)
• Improved performance of datetime string parsing in `DatetimeIndex` (GH13692)
• Improved performance of hashing `Period` (GH12817)
• Improved performance of `factorize` of datetime with timezone (GH13750)
• Improved performance of by lazily creating indexing hashtables on larger Indexes (GH14266)
• Improved performance of `groupby.groups` (GH14293)
• Unnecessary materializing of a MultiIndex when introspecting for memory usage (GH14308)

Bug fixes

• Bug in `groupby().shift()`, which could cause a segfault or corruption in rare circumstances when grouping by columns with missing values (GH13813)
• Bug in `groupby().cumsum()` calculating `cumprod` when `axis=1` (GH13994)
• Bug in `pd.to_timedelta()` in which the `errors` parameter was not being respected (GH13613)
• Bug in `io.json.json_normalize()`, where non-ascii keys raised an exception (GH13213)
• Bug when passing a not-default-indexed `Series` as `xerr` or `yerr` in `.plot()` (GH11858)
• Bug in area plot draws legend incorrectly if subplot is enabled or legend is moved after plot (matplotlib 1.5.0 is required to draw area plot legend properly) (GH9161, GH13544)
• Bug in `DataFrame` assignment with an object-dtyped `Index` where the resultant column is mutable to the original object. (GH13522)
• Bug in matplotlib `AutoDataFormatter`; this restores the second scaled formatting and re-adds micro-second scaled formatting (GH13131)
• Bug in selection from a `HDFStore` with a fixed format and `start` and/or `stop` specified will now return the selected range (GH8287)
• Bug in `Categorical.from_codes()` where an unhelpful error was raised when an invalid ordered parameter was passed in (GH14058)
• Bug in `Series` construction from a tuple of integers on windows not returning default dtype (int64) (GH13646)
• Bug in `TimedeltaIndex` addition with a Datetime-like object where addition overflow was not being caught (GH14068)
• Bug in `.groupby(..).resample(..)` when the same object is called multiple times (GH13174)
• Bug in `.to_records()` when index name is a unicode string (GH13172)
• Bug in calling `.memory_usage()` on object which doesn’t implement (GH12924)
• Regression in `Series.quantile` with nans (also shows up in `.median()` and `.describe()`); furthermore now names the `Series` with the quantile (GH13098, GH13146)
• Bug in `SeriesGroupBy.transform` with datetime values and missing groups (GH13191)
• Bug where empty `Series` were incorrectly coerced in datetime-like numeric operations (GH13844)
• Bug in `Categorical` constructor when passed a `Categorical` containing datetimes with timezones (GH14190)
• Bug in `Series.str.extractall()` with str index raises `ValueError` (GH13156)
Bug in Series.str.extractall() with single group and quantifier (GH13382)

Bug in DatetimeIndex and Period subtraction raises ValueError or AttributeError rather than TypeError (GH13078)

Bug in Index and Series created with NaN and NaT mixed data may not have datetime64 dtype (GH13324)

Bug in Index and Series may ignore np.datetime64('nat') and np.timedelta64('nat') to infer dtype (GH13324)

Bug in PeriodIndex and Period subtraction raises AttributeError (GH13071)

Bug in PeriodIndex construction returning a float64 index in some circumstances (GH13067)

Bug in .resample(..) with a PeriodIndex not changing its freq appropriately when empty (GH13067)

Bug in .resample(..) with a PeriodIndex not retaining its type or name with an empty DataFrame appropriately when empty (GH13212)

Bug in groupby(..).apply(..) when the passed function returns scalar values per group (GH13468).

Bug in groupby(..).resample(..) where passing some keywords would raise an exception (GH13235)

Bug in .tz_convert on a tz-aware DateTimeIndex that relied on index being sorted for correct results (GH13306)

Bug in .tz_localize with dateutil.tz.tzlocal may return incorrect result (GH13583)

Bug in DatetimeTZDtype dtype with dateutil.tz.tzlocal cannot be regarded as valid dtype (GH13583)

Bug in pd.read_hdf() where attempting to load an HDF file with a single dataset, that had one or more categorical columns, failed unless the key argument was set to the name of the dataset. (GH13231)

Bug in .rolling() that allowed a negative integer window in construction of the Rolling() object, but would later fail on aggregation (GH13383)

Bug in Series indexing with tuple-valued data and a numeric index (GH13509)

Bug in printing pd.DataFrame where unusual elements with the object dtype were causing segfaults (GH13717)

Bug in ranking Series which could result in segfaults (GH13445)

Bug in various index types, which did not propagate the name of passed index (GH12309)

Bug in DatetimeIndex, which did not honour the copy=True (GH13205)

Bug in DatetimeIndex.is_normalized returns incorrectly for normalized date_range in case of local timezones (GH13459)

Bug in pd.concat and .append may coerces datetime64 and timedelta64 to object dtype containing python built-in datetime or timedelta rather than Timestamp or Timedelta (GH13626)

Bug in PeriodIndex.append may raises AttributeError when the result is object dtype (GH13221)

Bug in CategoricalIndex.append may accept normal list (GH13626)

Bug in pd.concat and .append with the same timezone get reset to UTC (GH7795)

Bug in Series and DataFrame .append raises AmbiguousTimeError if data contains datetime near DST boundary (GH13626)

Bug in DataFrame.to_csv() in which float values were being quoted even though quotations were specified for non-numeric values only (GH12922, GH13259)
• Bug in `DataFrame.describe()` raising `ValueError` with only boolean columns (GH13898)
• Bug in `MultiIndex` slicing where extra elements were returned when level is non-unique (GH12896)
• Bug in `.str.replace` does not raise `TypeError` for invalid replacement (GH13438)
• Bug in `MultiIndex.from_arrays` which didn’t check for input array lengths matching (GH13599)
• Bug in `cartesian_product` and `MultiIndex.from_product` which may raise with empty input arrays (GH12258)
• Bug in `pd.read_csv()` which may cause a segfault or corruption when iterating in large chunks over a stream/file under rare circumstances (GH13703)
• Bug in `pd.read_csv()` which caused errors to be raised when a dictionary containing scalars is passed in for `na_values` (GH12224)
• Bug in `pd.read_csv()` which caused BOM files to be incorrectly parsed by not ignoring the BOM (GH4793)
• Bug in `pd.read_csv()` with `engine='python'` which raised errors when a numpy array was passed in for `usecols` (GH12546)
• Bug in `pd.read_csv()` where the index columns were being incorrectly parsed when parsed as dates with a `thousands` parameter (GH14066)
• Bug in `pd.read_csv()` with `engine='python'` in which NaN values weren’t being detected after data was converted to numeric values (GH13314)
• Bug in `pd.read_csv()` in which the `nrows` argument was not properly validated for both engines (GH10476)
• Bug in `pd.read_csv()` with `engine='python'` in which infinities of mixed-case forms were not being interpreted properly (GH13274)
• Bug in `pd.read_csv()` with `engine='python'` in which trailing NaN values were not being parsed (GH13320)
• Bug in `pd.read_csv()` with `engine='python'` when reading from a `tempfile.TemporaryFile` on Windows with Python 3 (GH13398)
• Bug in `pd.read_csv()` that prevents `usecols` kwarg from accepting single-byte unicode strings (GH13219)
• Bug in `pd.read_csv()` that prevents `usecols` from being an empty set (GH13402)
• Bug in `pd.read_csv()` in the C engine where the NULL character was not being parsed as NULL (GH14012)
• Bug in `pd.read_csv()` with `engine='c'` in which NULL `quotechar` was not accepted even though `quoting` was specified as `None` (GH13411)
• Bug in `pd.read_csv()` with `engine='c'` in which fields were not properly cast to float when quoting was specified as non-numeric (GH13411)
• Bug in `pd.read_csv()` in Python 2.x with non-UTF8 encoded, multi-character separated data (GH13404)
• Bug in `pd.read_csv()`, where aliases for utf-xx (e.g. UTF-xx, UTF_xx, utf_xx) raised `UnicodeDecodeError` (GH13549)
• Bug in `pd.read_csv`, `pd.read_table`, `pd.read_fwf`, `pd.read_stata` and `pd.read_sas` where files were opened by parsers but not closed if both `chunksize` and `iterator` were `None`. (GH13940)
• Bug in `StataReader`, `StataWriter`, `XportReader` and `SAS7BDATReader` where a file was not properly closed when an error was raised. (GH13940)
• Bug in `pd.pivot_table()` where `margins_name` is ignored when `aggfunc` is a list (GH13354)
• Bug in `pd.Series.str.zfill`, `center`, `ljust`, `rjust`, and `pad` when passing non-integers, did not raise `TypeError` (GH13598)
• Bug in checking for any null objects in a `TimedeltaIndex`, which always returned `True` (GH13603)
• Bug in `Series` arithmetic raises `TypeError` if it contains datetime-like as `object` `dtype` (GH13043)
• Bug in `Series.isnull()` and `Series.notnull()` ignore `Period('NaT')` (GH13737)
• Bug in `.fillna(value=np.nan)` incorrectly raises `KeyError` on a category `dtype` `Series` (GH14021)
• Bug in extension `dtype` creation where the created types were not is/identical (GH13285)
• Bug in `.resample(..)` where incorrect warnings were triggered by IPython introspection (GH13618)
• Bug in `NaT - Period` raises `AttributeError` (GH13071)
• Bug in `Series` comparison may output incorrect result if rhs contains `NaT` with `object` `dtype` (GH13069)
• Bug in `.shift` raises `AmbiguousTimeError` if data contains datetime near DST boundary (GH13926)
• Bug in `pd.read_hdf()` returns incorrect result when a `DataFrame` with a `categorical` column and a query which doesn’t match any values (GH13792)
• Bug in `.iloc` when indexing with a non lexsorted `MultiIndex` (GH13797)
• Bug in `.loc` when indexing with date strings in a reverse sorted `DatetimeIndex` (GH14316)
• Bug in `Series` comparison operators when dealing with zero dim NumPy arrays (GH13006)
• Bug in `.combine_first` may return incorrect `dtype` (GH7630, GH10567)
• Bug in `groupby` where `apply` returns different result depending on whether first result is `None` or not (GH12824)
• Bug in `groupby(..).nth()` where the group key is included inconsistently if called after `.head()`/. `.tail()` (GH12839)
• Bug in `.to_html`, `.to_latex` and `.to_string` silently ignore custom datetime formatter passed through the formatters key word (GH10690)
• Bug in `DataFrame.iterrows()`, not yielding a `Series` subclass if defined (GH13977)
• Bug in `pd.to_numeric` when `errors='coerce'` and input contains non-hashable objects (GH13324)
• Bug in invalid `Timedelta` arithmetic and comparison may raise `ValueError` rather than `TypeError` (GH13624)
• Bug in invalid datetime parsing in `to_datetime` and `DatetimeIndex` may raise `TypeError` rather than `ValueError` (GH11169, GH11287)
• Bug in `Index` created with tz-aware `Timestamp` and mismatched tz option incorrectly coerces timezone (GH13692)
• Bug in `DatetimeIndex` with nanosecond frequency does not include timestamp specified with `end` (GH13672)
• Bug in `Series` when setting a slice with a `np.timedelta64` (GH14155)
• Bug in `Index` raises `OutOfBoundsDatetime` if `datetime` exceeds `datetime64[ns]` bounds, rather than coercing to object dtype (GH13663)
• Bug in `Index` may ignore specified `datetime64` or `timedelta64` passed as dtype (GH13981)
• Bug in `DatetimeIndex` may raise `OutOfBoundsDatetime` if input `np.datetime64` has other unit than `ns` (GH9114)
• Bug in `Series` creation with `np.datetime64` which has other unit than `ns` as object dtype results in incorrect values (GH13876)
• Bug in `resample` with timedelta data where data was casted to float (GH13119)
• Bug in `pd.isnull()` or `pd.notnull()` raise `TypeError` if input datetime-like has other unit than `ns` (GH13389)
• Bug in `pd.merge()` may raise `TypeError` if input datetime-like has other unit than `ns` (GH13389)
• Bug in `HDFStore/read_hdf()` discarded `DatetimeIndex.name` if `tz` was set (GH13884)
• Bug in `Categorical.remove_unused_categories()` changes `.codes` dtype to platform int (GH13261)
• Bug in `groupby` with `as_index=False` returns all NaN’s when grouping on multiple columns including a categorical one (GH13204)
• Bug in `df.groupby(...)[...].where` with `Int64Index` raised an error (GH13731)
• Bug in the CSS classes assigned to `DataFrame.style` for index names. Previously they were assigned "col_heading level<\n> col<\n>" where \n was the number of levels + 1. Now they are assigned "index_name level<\n>" where \n is the correct level for that MultiIndex.
• Bug where `pd.read_gbq()` could throw `ImportError: No module named discovery` as a result of a naming conflict with another python package called `apiclient` (GH13454)
• Bug in `Index.union` returns an incorrect result with a named empty index (GH13432)
• Bugs in `Index.difference` and `DataFrame.join` raise in Python3 when using mixed-integer indexes (GH13432, GH12814)
• Bug in `subtract` tz-aware `datetime.datetime` from tz-aware `datetime64` series (GH14088)
• Bug in `.to_excel()` when `DataFrame` contains a MultiIndex which contains a label with a NaN value (GH13511)
• Bug in invalid frequency offset string like “D1”, “-2-3H” may not raise `ValueError` (GH13930)
• Bug in `concat` and `groupby` for hierarchical frames with `RangeIndex` levels (GH13542)
• Bug in `Series.str.contains()` for Series containing only NaN values of object dtype (GH14171)
• Bug in `agg()` function on groupby dataframe changes dtype of `datetime64[ns]` column to `float64` (GH12821)

• Bug in using NumPy ufunc with `PeriodIndex` to add or subtract integer raise `IncompatibleFrequency`. Note that using standard operator like `+` or `-` is recommended, because standard operators use more efficient path (GH13980)

• Bug in operations on `NaT` returning `float` instead of `datetime64[ns]` (GH12941)

• Bug in `Series` flexible arithmetic methods (like `.add()`) raises `ValueError` when `axis=None` (GH13894)

• Bug in `DataFrame.to_csv()` with `MultiIndex` columns in which a stray empty line was added (GH6618)

• Bug in `DatetimeIndex`, `TimedeltaIndex` and `PeriodIndex.equals()` may return `True` when input isn’t `Index` but contains the same values (GH13107)

• Bug in assignment against datetime with timezone may not work if it contains datetime near DST boundary (GH14146)

• Bug in `pd.eval()` and HDFStore query truncating long float literals with python 2 (GH14241)

• Bug in `Index` raises `KeyError` displaying incorrect column when column is not in the df and columns contains duplicate values (GH13822)

• Bug in `Period` and `PeriodIndex` creating wrong dates when frequency has combined offset aliases (GH13874)

• Bug in `.to_string()` when called with an integer `line_width` and `index=False` raises an UnboundLocalError exception because `idx` referenced before assignment.

• Bug in `eval()` where the `resolvers` argument would not accept a list (GH14095)

• Bugs in `stack`, `get_dummies`, `make_axis_dummies` which don’t preserve categorical dtypes in (multi)indexes (GH13854)

• `PeriodIndex` can now accept `list` and `array` which contains `pd.NaT` (GH13430)

• Bug in `df.groupby` where `.median()` returns arbitrary values if grouped dataframe contains empty bins (GH13629)

• Bug in `Index.copy()` where name parameter was ignored (GH14302)

**Contributors**

A total of 117 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

• Adrien Emery +
• Alex Alekseyev
• Alex Vig +
• Allen Riddell +
• Amol +
• Amol Agrawal +
• Andy R. Terrel +
• Anthonios Partheniou
• Ben Kandel +
• Bob Baxley +
• Brett Rosen +
• Camilo Cota +
• Chris
• Chris Grinolds
• Chris Warth
• Christian Hudon
• Christopher C. Aycock
• Daniel Silajdi +
• Douglas McNeil
• Drewrey Lupton +
• Eduardo Blancas Reyes +
• Elliot Marsden +
• Evan Wright
• Felix Marczinowski +
• Francis T. O’Donovan
• Geraint Duck +
• Giacomo Ferroni +
• Grant Roch +
• Gábor Lipták
• Haleemur Ali +
• Hassan Shamim +
• Iulius Curt +
• Ivan Nazarov +
• Jeff Reback
• Jeffrey Gerard +
• Jenn Olsen +
• Jim Crist
• Joe Jevnik
• John Evans +
• John Freeman
• John Liekezer +
• John W. O’Brien
• John Zwinck +
• Johnny Gill +
• Jordan Erenrich +
• Joris Van den Bossche
• Josh Howes +
• Jozef Brandys +
• Ka Wo Chen
• Kamil Sindi +
• Kerby Shedden
• Kernc +
• Kevin Sheppard
• Matthieu Brucher +
• Maximilian Roos
• Michael Scherer +
• Mike Graham +
• Mortada Mehyar
• Muhammad Haseeb Tariq +
• Nate George +
• Neil Parley +
• Nicolas Bonnotte
• OXPHOS
• Pan Deng / Zora +
• Paul +
• Paul Mestemaker +
• Pauli Virtanen
• Pawel Kordek +
• Pietro Battiston
• Piotr Jucha +
• Ravi Kumar Nimmi +
• Robert Gieseke
• Robert Kern +
• Roger Thomas
• Roy Keyes +
• Russell Smith +
• Sahil Dua +
• Sanjiv Lobo +
• Sašo Stanovnik +
• Shawn Heide +
• Sinhrks
• Stephen Kappel +
• Steve Choi +
• Stewart Henderson +
• Sudarshan Konge +
• Thomas A Caswell
• Tom Augspurger
• Tom Bird +
• Uwe Hoffmann +
• WillAyd +
• Xiang Zhang +
• YG-Riku +
• Yadunandan +
• Yaroslav Halchenko
• Yuichiro Kaneko +
• adneu
• agraboso +
• babakkeyvani +
• c123w +
• chris-b1
• cmazzullo +
• conquistador1492 +
• cr3 +
• dsm054
• gfyoung
• harshul1610 +
• iamsimha +
• jackieleng +
• mpuels +
• pijucha +
• priyankjain +
• sinhrks
• wcwagner +
• yui-knk +
• zhangjinjie +
• znmean +
5.10 Version 0.18

5.10.1 Version 0.18.1 (May 3, 2016)

This is a minor bug-fix release from 0.18.0 and includes a large number of bug fixes along with several new features, enhancements, and performance improvements. We recommend that all users upgrade to this version.

Highlights include:

- `.groupby(...)` has been enhanced to provide convenient syntax when working with `.rolling(...)`, `.expanding(...)` and `.resample(...)` per group, see [here](#).
- `pd.to_datetime()` has gained the ability to assemble dates from a DataFrame, see [here](#).
- Method chaining improvements, see [here](#).
- Custom business hour offset, see [here](#).
- Many bug fixes in the handling of sparse, see [here](#).
- Expanded the Tutorials section with a feature on modern pandas, courtesy of @TomAugsburger. (GH13045).

What’s new in v0.18.1

- **New features**
  - Custom business hour
  - Method `.groupby(...)` syntax with window and resample operations
  - Method chaining improvements
    - Methods `.where()` and `.mask()`
    - Methods `.loc[]`, `.iloc[]`, `.ix[]`
    - Indexing with `[]`
  - Partial string indexing on DatetimeIndex when part of a MultiIndex
  - Assembling datetimes
  - Other enhancements
- **Sparse changes**
- **API changes**
  - Method `.groupby(...).nth()` changes
  - NumPy function compatibility
  - Using `.apply` on GroupBy resampling
  - Changes in `read_csv` exceptions
  - Method `to_datetime` error changes
  - Other API changes
  - Deprecations
New features

Custom business hour

The CustomBusinessHour is a mixture of BusinessHour and CustomBusinessDay which allows you to specify arbitrary holidays. For details, see Custom Business Hour (GH11514)

```python
In [1]: from pandas.tseries.offsets import CustomBusinessHour
In [2]: from pandas.tseries.holiday import USFederalHolidayCalendar
In [3]: bhour_us = CustomBusinessHour(calendar=USFederalHolidayCalendar())
```

Friday before MLK Day

```python
In [4]: import datetime
In [5]: dt = datetime.datetime(2014, 1, 17, 15)
In [6]: dt + bhour_us
Out[6]: Timestamp('2014-01-17 16:00:00')
```

Tuesday after MLK Day (Monday is skipped because it’s a holiday)

```python
In [7]: dt + bhour_us * 2
Out[7]: Timestamp('2014-01-20 09:00:00')
```

Method .groupby(...) syntax with window and resample operations

 groupby(...) has been enhanced to provide convenient syntax when working with .rolling(...), .expanding(...) and .resample(...) per group, see (GH12486, GH12738).

You can now use .rolling(...) and .expanding(...) as methods on groupbys. These return another deferred object (similar to what .rolling() and .expanding() do on ungrouped pandas objects). You can then operate on these RollingGroupby objects in a similar manner.

Previously you would have to do this to get a rolling window mean per-group:

```python
                     ...:                   'B': np.arange(40))
In [9]: df
Out[9]:
     A  B
0   1  0
1   1  1
2   1  2
```
In [10]: df.groupby('A').apply(lambda x: x.rolling(4).B.mean())

Out[10]:
A
1   0   NaN
   1   NaN
   2   NaN
   3   1.5
   4   2.5
   ... 
35  35  33.5
36  34.5
37  35.5
38  36.5
39  37.5
Name: B, Length: 40, dtype: float64

Now you can do:

In [11]: df.groupby('A').rolling(4).B.mean()

Out[11]:
A
1   0   NaN
   1   NaN
   2   NaN
   3   1.5
   4   2.5
   ... 
35  35  33.5
36  34.5
37  35.5
38  36.5
39  37.5
Name: B, Length: 40, dtype: float64

For .resample(..) type of operations, previously you would have to:

In [12]: df = pd.DataFrame({'date': pd.date_range(start='2016-01-01',
        periods=4,
        freq='W'),
        'group': [1, 1, 2, 2],
        'val': [5, 6, 7, 8]}).set_index('date')

In [13]: df
Out[13]:

(continues on next page)
In [14]: df.groupby('group').apply(lambda x: x.resample('1D').ffill())

Out[14]:

<table>
<thead>
<tr>
<th>group</th>
<th>val</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>date</td>
<td></td>
</tr>
<tr>
<td>2016-01-03</td>
<td>1 5</td>
</tr>
<tr>
<td>2016-01-10</td>
<td>1 6</td>
</tr>
<tr>
<td>2016-01-17</td>
<td>2 7</td>
</tr>
<tr>
<td>2016-01-24</td>
<td>2 8</td>
</tr>
</tbody>
</table>

[4 rows x 2 columns]

Now you can do:

In [15]: df.groupby('group').resample('1D').ffill()

Out[15]:

<table>
<thead>
<tr>
<th>group</th>
<th>val</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>date</td>
<td></td>
</tr>
<tr>
<td>2016-01-03</td>
<td>1 5</td>
</tr>
<tr>
<td>2016-01-04</td>
<td>1 5</td>
</tr>
<tr>
<td>2016-01-05</td>
<td>1 5</td>
</tr>
<tr>
<td>2016-01-06</td>
<td>1 5</td>
</tr>
<tr>
<td>2016-01-07</td>
<td>1 5</td>
</tr>
<tr>
<td>...</td>
<td></td>
</tr>
<tr>
<td>2016-01-20</td>
<td>2 7</td>
</tr>
<tr>
<td>2016-01-21</td>
<td>2 7</td>
</tr>
<tr>
<td>2016-01-22</td>
<td>2 7</td>
</tr>
<tr>
<td>2016-01-23</td>
<td>2 7</td>
</tr>
<tr>
<td>2016-01-24</td>
<td>2 8</td>
</tr>
</tbody>
</table>

[16 rows x 2 columns]
Method chaining improvements

The following methods / indexers now accept a `callable`. It is intended to make these more useful in method chains, see the documentation. (GH11485, GH12533)

- `where()` and `mask()`
- `loc[]`, `iloc[]` and `ix[]`
- `[]` indexing

Methods `where()` and `mask()`

These can accept a callable for the condition and other arguments.

```python
In [16]: df = pd.DataFrame({'A': [1, 2, 3], 'B': [4, 5, 6], 'C': [7, 8, 9]})
In [17]: df.where(lambda x: x > 4, lambda x: x + 10)
Out[17]:
   A  B  C
0  5  14  7
1  12  5  8
2  13  6  9
[3 rows x 3 columns]
```

Methods `loc[]`, `iloc[]`, `ix[]`

These can accept a callable, and a tuple of callable as a slicer. The callable can return a valid boolean indexer or anything which is valid for these indexer’s input.

```python
# callable returns bool indexer
In [18]: df.loc[lambda x: x.A >= 2, lambda x: x.sum() > 10]
Out[18]:
   B  C
0  11  14  7
1  12  5  8
2  13  6  9
[2 rows x 2 columns]

# callable returns list of labels
In [19]: df.loc[lambda x: [1, 2], lambda x: ['A', 'B']]  
Out[19]:
   A  B
0  1  2
1  2  3
[2 rows x 2 columns]
```
Indexing with `[]`

Finally, you can use a callable in [ ] indexing of Series, DataFrame and Panel. The callable must return a valid input for [ ] indexing depending on its class and index type.

```
In [20]: df[lambda x: 'A']
Out[20]:
   0  1
0  2  3
Name: A, Length: 3, dtype: int64
```

Using these methods / indexers, you can chain data selection operations without using temporary variable.

```
In [21]: bb = pd.read_csv('data/baseball.csv', index_col='id')

In [22]: (bb.groupby(['year', 'team'])
            .sum()
            .loc[lambda df: df.r > 100])
Out[22]:
         stint  g  ab  r  X2b  X3b  hr  rbi  sb  cs  bb  so  hbp  sh  sf  gidp
    year team
2007   CIN    6  379  745  101  203  35   2  36  125.0  10.0  1.0  105  127.0  14.
      DET    5  301 1062  162  283  54   4  37  144.0  24.0   7.0  97  176.0  3.
      HOU    4  311  926 109  218  47   6  14  77.0  10.0  4.0  60  212.0  3.
      LAN    11 413 1021 153  293  47   3  36  154.0  7.0  5.0  114  141.0  8.
      NYN    13 622 1854 240  509 101   3  61 243.0  22.0  4.0  174  310.0 24.
      SFN    5 482 1305 198  337  67   6 40 171.0  26.0  7.0  235  188.0 51.
      TEX    2 198  729 115  200  40   4 28 115.0  21.0  4.0  73  140.0  4.
      TOR    4 459 1408 187  378  96   2 58 223.0  4.0  2.0  190  265.0 16.
      TTX    2 198  729 115  200  40   4 28 115.0  21.0  4.0  73  140.0  4.
[8 rows x 18 columns]
```

Partial string indexing on `DatetimeIndex` when part of a `MultiIndex`

Partial string indexing now matches on `DateTimeIndex` when part of a `MultiIndex` (GH10331)

```
In [23]: dft2 = pd.DataFrame(
            np.random.randn(20, 1),
    columns=['A'],
    index=pd.MultiIndex.from_product([pd.date_range('20130101', periods=10, freq='12H'), ['a', 'b']]))
```

(continues on next page)
In [24]: dft2
Out[24]:

     A
2013-01-01  00:00:00 a  0.469112
     b  -0.282863
2013-01-01  12:00:00 a -1.509059
     b  -1.135632
2013-01-02  00:00:00 a  1.212112
     b  -1.212112
...                          ...
2013-01-04  12:00:00 b  0.271860
2013-01-05  00:00:00 a -0.424972
     b  0.567020
2013-01-05  12:00:00 a  0.276232
     b -1.087401

[20 rows x 1 columns]

In [25]: dft2.loc['2013-01-05']
Out[25]:

     A
2013-01-05  00:00:00 a -0.424972
     b  0.567020
2013-01-05  12:00:00 a  0.276232
     b -1.087401

[4 rows x 1 columns]

On other levels

In [26]: idx = pd.IndexSlice

In [27]: dft2 = dft2.swaplevel(0, 1).sort_index()

In [28]: dft2
Out[28]:

     A
     a 2013-01-01  00:00:00  0.469112
     2013-01-01  12:00:00 -1.509059
     2013-01-02  00:00:00  1.212112
     2013-01-02  12:00:00  0.119209
     2013-01-03  00:00:00 -0.861849
     ...                          ...
     b 2013-01-03  12:00:00  1.071804
     2013-01-04  00:00:00 -0.706771
     2013-01-04  12:00:00  0.271860
     2013-01-05  00:00:00  0.567020
     2013-01-05  12:00:00 -1.087401

[20 rows x 1 columns]

In [29]: dft2.loc[idx[:, '2013-01-05'], :]
Out[29]:

     A
     a 2013-01-05  00:00:00 -0.424972
     2013-01-05  12:00:00  0.276232
     b 2013-01-05  00:00:00  0.567020

(continues on next page)
Assembling datetimes

`pd.to_datetime()` has gained the ability to assemble datetimes from a passed in DataFrame or a dict. (GH8158).

```python
In [30]: df = pd.DataFrame({'year': [2015, 2016],
                       'month': [2, 3],
                       'day': [4, 5],
                       'hour': [2, 3]})

In [31]: df
Out[31]:
    year month  day  hour
0  2015     2     4     2
1  2016     3     5     3

[2 rows x 4 columns]
```

Assembling using the passed frame.

```python
In [32]: pd.to_datetime(df)
Out[32]:
0  2015-02-04 02:00:00
1  2016-03-05 03:00:00
Length: 2, dtype: datetime64[ns]
```

You can pass only the columns that you need to assemble.

```python
In [33]: pd.to_datetime(df[['year', 'month', 'day']])
Out[33]:
0  2015-02-04
1  2016-03-05
Length: 2, dtype: datetime64[ns]
```

Other enhancements

- `pd.read_csv()` now supports `delim_whitespace=True` for the Python engine (GH12958)
- `pd.read_csv()` now supports opening ZIP files that contains a single CSV, via extension inference or explicit `compression='zip'` (GH12175)
- `pd.read_csv()` now supports opening files using xz compression, via extension inference or explicit `compression='xz'` is specified; xz compressions is also supported by `DataFrame.to_csv` in the same way (GH11852)
- `pd.read_msgpack()` now always gives writeable ndarrays even when compression is used (GH12359).
- `pd.read_msgpack()` now supports serializing and de-serializing categoricals with msgpack (GH12573)
- `.to_json()` now supports `NDFrames` that contain categorical and sparse data (GH10778)
• `interpolate()` now supports method='akima' (GH7588).

• `pd.read_excel()` now accepts path objects (e.g. `pathlib.Path`, `py.path.local`) for the file path, in line with other `read_*` functions (GH12655)

• Added `.weekday_name` property as a component to `DatetimeIndex` and the `.dt` accessor. (GH11128)

• `Index.take` now handles `allow_fill` and `fill_value` consistently (GH12631)

```python
In [34]: idx = pd.Index([1., 2., 3., 4.], dtype='float')
# default, allow_fill=True, fill_value=None
In [35]: idx.take([2, -1])
Out[35]: Float64Index([3.0, 4.0], dtype='float64')
In [36]: idx.take([2, -1], fill_value=True)
Out[36]: Float64Index([3.0, nan], dtype='float64')
```

• `Index` now supports `.str.get_dummies()` which returns `MultiIndex`, see Creating Indicator Variables (GH10008, GH10103)

```python
In [37]: idx = pd.Index(["a|b", 'a|c', 'b|c'])
In [38]: idx.str.get_dummies('|')
Out [38]: MultiIndex([(1, 1, 0),
  (1, 0, 1),
  (0, 1, 1)], names=['a', 'b', 'c'])
```

• `pd.crosstab()` has gained a `normalize` argument for normalizing frequency tables (GH12569). Examples in the updated docs [here](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#using-nested-arrays).

• `.resample(..).interpolate()` is now supported (GH12925)

• `.isin()` now accepts passed sets (GH12988)

### Sparse changes

These changes conform sparse handling to return the correct types and work to make a smoother experience with indexing.

`SparseArray.take` now returns a scalar for scalar input, `SparseArray` for others. Furthermore, it handles a negative indexer with the same rule as `Index` (GH10560, GH12796)

```python
s = pd.SparseArray([np.nan, np.nan, 1, 2, 3, np.nan, 4, 5, np.nan, 6])
s.take(0)
s.take([1, 2, 3])
```

• Bug in `SparseSeries[]` indexing with Ellipsis raises `KeyError` (GH9467)

• Bug in `SparseArray[]` indexing with tuples are not handled properly (GH12966)

• Bug in `SparseSeries.loc[]` with list-like input raises `TypeError` (GH10560)

• Bug in `SparseSeries.iloc[]` with scalar input may raise `IndexError` (GH10560)

• Bug in `SparseSeries.loc[]`, `.iloc[]` with slice returns `SparseArray`, rather than `SparseSeries` (GH10560)
• Bug in `SparseDataFrame.loc[]`, `.iloc[]` may result in dense `Series`, rather than `SparseSeries` (GH12787)

• Bug in `SparseArray` addition ignores `fill_value` of right hand side (GH12910)

• Bug in `SparseArray` mod raises `AttributeError` (GH12910)

• Bug in `SparseArray` pow calculates `1 ** np.nan` as `np.nan` which must be `1` (GH12910)

• Bug in `SparseArray` comparison output may incorrect result or raise `ValueError` (GH12971)

• Bug in `SparseSeries.__repr__` raises `TypeError` when it is longer than `max_rows` (GH10560)

• Bug in `SparseSeries.shape` ignores `fill_value` (GH10452)

• Bug in `SparseSeries` and `SparseArray` may have different `dtype` from its dense values (GH12908)

• Bug in `SparseSeries.to_frame()` results in `DataFrame`, rather than `SparseDataFrame` (GH9850)

• Bug in `SparseSeries.value_counts()` does not count `fill_value` (GH6749)

• Bug in `SparseArray.to_dense()` does not preserve `dtype` (GH10648)

• Bug in `SparseArray.to_dense()` incorrectly handle `fill_value` (GH12797)

• Bug in `SparseSeries.reindex` incorrectly handle `fill_value` (GH12797)

• Bug in `pd.concat()` of `SparseSeries` results in dense (GH10536)

• Bug in `pd.concat()` of `SparseDataFrame` incorrectly handle `fill_value` (GH9765)

• Bug in `pd.concat()` of `SparseDataFrame` may raise `AttributeError` (GH12174)

• Bug in `SparseArray.shift()` may raise `NameError` or `TypeError` (GH12908)

**API changes**

**Method .groupby(..).nth() changes**

The index in `.groupby(..).nth()` output is now more consistent when the `as_index` argument is passed (GH11039):

```python
In [39]: df = pd.DataFrame({'A': ['a', 'b', 'a'],
                      'B': [1, 2, 3]})

In [40]: df
Out[40]:
   A  B
0  a  1
1  b  2
2  a  3
[3 rows x 2 columns]
```

Previous behavior:

```python
In [3]: df.groupby('A', as_index=True)['B'].nth(0)
Out[3]:
   0  1
0  1
1  2
Name: B, dtype: int64
```

(continues on next page)
In [4]: df.groupby('A', as_index=False)['B'].nth(0)
Out[4]:
    0  1
    1  2
Name: B, dtype: int64

New behavior:

In [41]: df.groupby('A', as_index=True)['B'].nth(0)
Out[41]:
   A
  a 1
  b 2
Name: B, Length: 2, dtype: int64

In [42]: df.groupby('A', as_index=False)['B'].nth(0)
Out[42]:
    0  1
    1  2
Name: B, Length: 2, dtype: int64

Furthermore, previously, a .groupby would always sort, regardless if sort=False was passed with .nth().

In [43]: np.random.seed(1234)
In [44]: df = pd.DataFrame(np.random.randn(100, 2), columns=['a', 'b'])
In [45]: df['c'] = np.random.randint(0, 4, 100)

Previous behavior:

In [4]: df.groupby('c', sort=True).nth(1)
Out[4]:
   a  b
  c
  0 -0.334077  0.002118
  1  0.036142 -2.074978
  2 -0.720589  0.887163
  3  0.859588 -0.636524

In [5]: df.groupby('c', sort=False).nth(1)
Out[5]:
   a  b
  c
  0 -0.334077  0.002118
  1  0.036142 -2.074978
  2 -0.720589  0.887163
  3  0.859588 -0.636524

New behavior:

In [46]: df.groupby('c', sort=True).nth(1)
Out[46]:
   a  b
  c
  0 -0.334077  0.002118
  1  0.036142 -2.074978
  2 -0.720589  0.887163
  3  0.859588 -0.636524

(continues on next page)
0 -0.334077  0.002118
1  0.036142 -2.074978
2 -0.720589  0.887163
3  0.859588 -0.636524

[4 rows x 2 columns]

```
In [47]: df.groupby('c', sort=False).nth(1)
Out[47]:
   a    b
  c
2 -0.720589  0.887163
3  0.859588 -0.636524
0 -0.334077  0.002118
1  0.036142 -2.074978
[4 rows x 2 columns]
```

### NumPy function compatibility

Compatibility between pandas array-like methods (e.g. `sum` and `take`) and their `numpy` counterparts has been greatly increased by augmenting the signatures of the `pandas` methods so as to accept arguments that can be passed in from `numpy`, even if they are not necessarily used in the `pandas` implementation (GH12644, GH12638, GH12687)

- `.searchsorted()` for `Index` and `TimedeltaIndex` now accept a `sorter` argument to maintain compatibility with `numpy`'s `searchsorted` function (GH12238)
- Bug in `numpy` compatibility of `np.round()` on a `Series` (GH12600)

An example of this signature augmentation is illustrated below:

```python
sp = pd.SparseDataFrame([1, 2, 3])
sp

Previous behaviour:

```
In [2]: np.cumsum(sp, axis=0)
...
TypeError: cumsum() takes at most 2 arguments (4 given)
```

New behaviour:

```python
np.cumsum(sp, axis=0)
```

### Using `.apply` on `GroupBy` resampling

Using `apply` on resampling groupby operations (using a `pd.TimeGrouper`) now has the same output types as similar `apply` calls on other groupby operations. (GH11742).

```
in [48]: df = pd.DataFrame({'date': pd.to_datetime(['10/10/2000', '11/10/2000']),
          'value': [10, 13]})
       ....:
       ....:
```
In [49]: df
Out[49]:
    date  value
0  2000-10-10   10
1  2000-11-10   13
[2 rows x 2 columns]

Previous behavior:

In [1]: df.groupby(pd.TimeGrouper(key='date',
                             ...:     freq='M')).apply(lambda x: x.value.sum())
Out[1]:
    ...:     TypeError: cannot concatenate a non-NDFrame object
# Output is a Series
In [2]: df.groupby(pd.TimeGrouper(key='date',
                             ...:     freq='M')).apply(lambda x: x['value'].sum())
Out[2]:
    date    value
2000-10-31    10
2000-11-30    13
dtype: int64

New behavior:

# Output is a Series
In [55]: df.groupby(pd.TimeGrouper(key='date',
                             ...:     freq='M')).apply(lambda x: x['value'].sum())
Out[55]:
    date    value
2000-10-31    10
2000-11-30    13
Freq: M, dtype: int64
# Output is a DataFrame
In [56]: df.groupby(pd.TimeGrouper(key='date',
                             ...:     freq='M')).apply(lambda x: x[['value']].sum())
Out[56]:
    value
    date
    2000-10-31    10
    2000-11-30    13

Changes in read_csv exceptions

In order to standardize the read_csv API for both the c and python engines, both will now raise an EmptyDataError, a subclass of ValueError, in response to empty columns or header (GH12493, GH12506)

Previous behaviour:

In [1]: import io
In [2]: df = pd.read_csv(io.StringIO(''), engine='c')
ValueError: No columns to parse from file

In [3]: df = pd.read_csv(io.StringIO(''), engine='python')
...
StopIteration

New behaviour:

In [1]: df = pd.read_csv(io.StringIO(''), engine='c')
...
pandas.io.common.EmptyDataError: No columns to parse from file

In [2]: df = pd.read_csv(io.StringIO(''), engine='python')
...
pandas.io.common.EmptyDataError: No columns to parse from file

In addition to this error change, several others have been made as well:

• CPARSERERROR now sub-classes ValueError instead of just a Exception (GH12551)
• A CPARSERERROR is now raised instead of a generic Exception in read_csv when the c engine cannot parse a column (GH12506)
• A ValueError is now raised instead of a generic Exception in read_csv when the c engine encounters a NaN value in an integer column (GH12506)
• A ValueError is now raised instead of a generic Exception in read_csv when true_values is specified, and the c engine encounters an element in a column containing unencodable bytes (GH12506)
• pandas.parser.OverflowError exception has been removed and has been replaced with Python’s built-in OverflowError exception (GH12506)
• pd.read_csv() no longer allows a combination of strings and integers for the usecols parameter (GH12678)

**Method to_datetime error changes**

Bugs in pd.to_datetime() when passing a unit with convertible entries and errors='coerce' or non-convertible with errors='ignore'. Furthermore, an OutOfBoundsDateime exception will be raised when an out-of-range value is encountered for that unit when errors='raise'. (GH11758, GH13052, GH13059)

Previous behaviour:

In [27]: pd.to_datetime(1420043460, unit='s', errors='coerce')
Out[27]: NaT

In [28]: pd.to_datetime(11111111, unit='D', errors='ignore')
OverflowError: Python int too large to convert to C long

In [29]: pd.to_datetime(11111111, unit='D', errors='raise')
OverflowError: Python int too large to convert to C long

New behaviour:

In [2]: pd.to_datetime(1420043460, unit='s', errors='coerce')
Out[2]: Timestamp('2014-12-31 16:31:00')
In [3]: pd.to_datetime(11111111, unit='D', errors='ignore')
Out[3]: 11111111

In [4]: pd.to_datetime(11111111, unit='D', errors='raise')
OutOfBoundsDatetime: cannot convert input with unit 'D'

Other API changes

• `.swaplevel()` for Series, DataFrame, Panel, and MultiIndex now features defaults for its first two parameters `i` and `j` that swap the two innermost levels of the index. (GH12934)

• `.searchsorted()` for Index and TimedeltaIndex now accept a sorter argument to maintain compatibility with numpy's searchsorted function (GH12238)

• `Period` and `PeriodIndex` now raises `IncompatibleFrequency` error which inherits `ValueError` rather than raw `ValueError` (GH12615)

• `Series.apply` for category dtype now applies the passed function to each of the `.categories` (and not the `.codes`), and returns a category dtype if possible (GH12473)

• `read_csv` will now raise a `TypeError` if `parse_dates` is neither a boolean, list, or dictionary (matches the doc-string) (GH5636)

• The default for `.query()/.eval()` is now `engine=None`, which will use `numexpr` if it’s installed; otherwise it will fallback to the python engine. This mimics the pre-0.18.1 behavior if `numexpr` is installed (and which, previously, if `numexpr` was not installed, `.query()/.eval() would raise). (GH12749)

• `pd.show_versions()` now includes pandas_datareader version (GH12740)

• Provide a proper `__name__` and `__qualname__` attributes for generic functions (GH12021)

• `pd.concat(ignore_index=True)` now uses `RangeIndex` as default (GH12695)

• `pd.merge()` and `DataFrame.join()` will show a `UserWarning` when merging/joining a single- with a multi-leveled dataframe (GH9455, GH12219)

• Compat with `scipy > 0.17` for deprecated `piecewise_polynomial` interpolation method; support for the replacement `from_derivatives` method (GH12887)

Deprecations

• The method name `Index.sym_diff()` is deprecated and can be replaced by `Index.symmetric_difference()` (GH12591)

• The method name `Categorical.sort()` is deprecated in favor of `Categorical.sort_values()` (GH12882)
Performance improvements

- Improved speed of SAS reader (GH12656, GH12961)
- Performance improvements in .groupby(..).cumcount () (GH11039)
- Improved memory usage in pd.read_csv() when using skiprows=an_integer (GH13005)
- Improved performance of DataFrame.to_sql when checking case sensitivity for tables. Now only checks if table has been created correctly when table name is not lower case. (GH12876)
- Improved performance of Period construction and time series plotting (GH12903, GH11831).
- Improved performance of .str.encode() and .str.decode() methods (GH13008)
- Improved performance of to_numeric if input is numeric dtype (GH12777)
- Improved performance of sparse arithmetic with IntIndex (GH13036)

Bug fixes

- usecols parameter in pd.read_csv is now respected even when the lines of a CSV file are not even (GH12203)
- Bug in groupby.transform(..) when axis=1 is specified with a non-monotonic ordered index (GH12713)
- Bug in Period and PeriodIndex creation raises KeyError if freq="Minute" is specified. Note that “Minute” freq is deprecated in v0.17.0, and recommended to use freq="T" instead (GH11854)
- Bug in .resample(...).count () with a PeriodIndex always raising a TypeError (GH12774)
- Bug in .resample(...) with a PeriodIndex casting to a DatetimeIndex when empty (GH12868)
- Bug in .resample(...) with a PeriodIndex when resampling to an existing frequency (GH12770)
- Bug in printing data which contains Period with different freq raises ValueError (GH12615)
- Bug in Series construction with Categorical and dtype='category' is specified (GH12574)
- Bugs in concatenation with a coercible dtype was too aggressive, resulting in different dtypes in output formatting when an object was longer than display.max_rows (GH12411, GH12045, GH11594, GH10571, GH12211)
- Bug in float_format option with option not being validated as a callable. (GH12706)
- Bug in GroupBy.filter when dropna=False and no groups fulfilled the criteria (GH12768)
- Bug in __name__ of .cum* functions (GH12021)
- Bug in .astype() of a Float64Index/Int64Index to an Int64Index (GH12881)
- Bug in round tripping an integer based index in .to_json()/.read_json() when orient='index' (the default) (GH12866)
- Bug in plotting Categorical dtypes cause error when attempting stacked bar plot (GH13019)
- Compat with >= numpy 1.11 for NaT comparisons (GH12969)
- Bug in .drop() with a non-unique MultiIndex. (GH12701)
- Bug in .concat of datetime tz-aware and naive DataFrames (GH12467)
- Bug in correctly raising a ValueError in .resample(..).fillna(..) when passing a non-string (GH12952)
• Bug fixes in various encoding and header processing issues in `pd.read_sas()` (GH12659, GH12654, GH12647, GH12809)

• Bug in `pd.crosstab()` where would silently ignore `aggfunc` if `values=None` (GH12569).

• Potential segfault in `DataFrame.to_json` when serialising `datetime.time` (GH11473).

• Potential segfault in `DataFrame.to_json` when attempting to serialise 0d array (GH11299).

• Segfault in `to_json` when attempting to serialise a `DataFrame` or `Series` with non-ndarray values; now supports serialization of category, sparse, and `datetime64[ns, tz]` dtypes (GH10778).

• Bug in `DataFrame.to_json` with unsupported dtype not passed to default handler (GH12554).

• Bug in `.align` not returning the sub-class (GH12983)

• Bug in aligning a `Series` with a `DataFrame` (GH13037)

• Bug in ABCPanel in which `Panel4D` was not being considered as a valid instance of this generic type (GH12810)

• Bug in consistency of `.name` on `.groupby(..).apply(..)` cases (GH12363)

• Bug in `Timestamp.__repr__` that caused `pprint` to fail in nested structures (GH12622)

• Bug in `Timedelta.min` and `Timedelta.max`; the properties now report the true minimum/maximum `timedeltas` as recognized by pandas. See the documentation. (GH12727)

• Bug in `.quantile()` with interpolation may coerce to `float` unexpectedly (GH12772)

• Bug in `.quantile()` with empty `Series` may return scalar rather than empty `Series` (GH12772)

• Bug in `.loc` with out-of-bounds in a large indexer would raise `IndexError` rather than `KeyError` (GH12527)

• Bug in resampling when using a `TimedeltaIndex` and `.asfreq()`, would previously not include the final fencepost (GH12527)

• Bug in equality testing with a `Categorical` in a `DataFrame` (GH12564)

• Bug in `GroupBy.first()`, `.last()` returns incorrect row when `TimeGrouper` is used (GH7453)

• Bug in `pd.read_csv()` with the `c` engine when specifying `skiprows` with newlines in quoted items (GH10911, GH12775)

• Bug in `DataFrame` timezone lost when assigning tz-aware `datetime` `Series` with alignment (GH12981)

• Bug in `.value_counts()` when normalize=True and dropna=True where nulls still contributed to the normalized count (GH12558)

• Bug in `Series.value_counts()` loses name if its dtype is `category` (GH12835)

• Bug in `Series.value_counts()` loses timezone info (GH12835)

• Bug in `Series.value_counts(normalize=True)` with `Categorical` raises `UnboundLocalError` (GH12835)

• Bug in `Panel.fillna()` ignoring inplace=True (GH12633)

• Bug in `pd.read_csv()` when specifying `names`, `usecols`, and `parse_dates` simultaneously with the `c` engine (GH9755)

• Bug in `pd.read_csv()` when specifying `delim_whitespace=True` and `lineterminator` simultaneously with the `c` engine (GH12912)

• Bug in `Series.rename`, `DataFrame.rename` and `DataFrame.rename_axis` not treating `Series` as mappings to relabel (GH12623).
• Clean in .rolling.min and .rolling.max to enhance dtype handling (GH12373)
• Bug in groupby where complex types are coerced to float (GH12902)
• Bug in Series.map raises TypeError if its dtype is category or tz-aware datetime (GH12473)
• Bugs on 32bit platforms for some test comparisons (GH12972)
• Bug in index coercion when falling back from RangeIndex construction (GH12893)
• Better error message in window functions when invalid argument (e.g., a float window) is passed (GH12669)
• Bug in slicing subclassed DataFrame defined to return subclassed Series may return normal Series (GH1159)
• Bug in .str accessor methods may raise ValueError if input has name and the result is DataFrame or MultiIndex (GH12617)
• Bug in DataFrame.last_valid_index() and DataFrame.first_valid_index() on empty frames (GH12800)
• Bug in CategoricalIndex.get_loc returns different result from regular Index (GH12531)
• Bug in PeriodIndex.resample where name not propagated (GH12769)
• Bug in date_range closed keyword and timezones (GH12684).
• Bug in pd.concat raises AttributeError when input data contains tz-aware datetime and timedelta (GH12620)
• Bug in pd.concat did not handle empty Series properly (GH11082)
• Bug in .plot.bar alignment when width is specified with int (GH12979)
• Bug in fill_value is ignored if the argument to a binary operator is a constant (GH12723)
• Bug in pd.read_html() when using bs4 flavor and parsing table with a header and only one column (GH1917)
• Bug in .pivot_table when margins=True and dropna=True where nulls still contributed to margin count (GH12407)
• Bug in .pivot_table when dropna=False where table index/column names disappear (GH12133)
• Bug in pd.crosstab() when margins=True and dropna=False which raised (GH12642)
• Bug in Series.name when name attribute can be a hashable type (GH12610)
• Bug in .describe() resets categorical columns information (GH11558)
• Bug where loffset argument was not applied when calling resample().count() on a timeseries (GH12725)
• pd.read_excel() now accepts column names associated with keyword argument names (GH12870)
• Bug in pd.to_numeric() with Index returns np.ndarray, rather than Index (GH12777)
• Bug in pd.to_numeric() with datetime-like may raise TypeError (GH12777)
• Bug in pd.to_numeric() with scalar raises ValueError (GH12777)
Contributors

A total of 60 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Andrew Fiore-Gartland +
- Bastiaan +
- Benoît Vinot +
- Brandon Rhodes +
- DaCoEx +
- Drew Fustin +
- Ernesto Freitas +
- Filip Ter +
- Gregory Livschitz +
- Gábor Lipták
- Hassan Kibirige +
- Iblis Lin
- Israel Saeta Pérez +
- Jason Wolosonovich +
- Jeff Reback
- Joe Jevnik
- Joris Van den Bossche
- Joshua Storck +
- Ka Wo Chen
- Kerby Shedden
- Kieran O’Mahony
- Leif Walsh +
- Mahmoud Lababidi +
- Maoyuan Liu +
- Mark Roth +
- Matt Wittmann
- MaxU +
- Maximilian Roos
- Michael Droettboom +
- Nick Eubank
- Nicolas Bonnotte
- OXPHOS +
- Pauli Virtanen +
5.10.2 Version 0.18.0 (March 13, 2016)

This is a major release from 0.17.1 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Warning: pandas 0.18.0 no longer supports compatibility with Python version 2.6 and 3.3 (GH7718, GH11273)
Warning: numexpr version 2.4.4 will now show a warning and not be used as a computation back-end for pandas because of some buggy behavior. This does not affect other versions (>= 2.1 and >= 2.4.6). (GH12489)

Highlights include:

- Moving and expanding window functions are now methods on Series and DataFrame, similar to .groupby, see here.
- Adding support for a RangeIndex as a specialized form of the Int64Index for memory savings, see here.
- API breaking change to the .resample method to make it more .groupby like, see here.
- Removal of support for positional indexing with floats, which was deprecated since 0.14.0. This will now raise a TypeError, see here.
- The .to_xarray() function has been added for compatibility with the xarray package, see here.
- The read_sas function has been enhanced to read sas7bdat files, see here.
- Addition of the .str.extractall() method, and API changes to the .str.extract() method and .str.cat() method.
- pd.test() top-level nose test runner is available (GH4327).

Check the API Changes and deprecations before updating.

What's new in v0.18.0

- New features
  - Window functions are now methods
  - Changes to rename
  - Range Index
  - Changes to str.extract
  - Addition of str.extractall
  - Changes to str.cat
  - Datetimelike rounding
  - Formatting of integers in FloatIndex
  - Changes to dtype assignment behaviors
  - Method to_xarray
  - Latex representation
  - pd.read_sas() changes
  - Other enhancements

- Backwards incompatible API changes
  - NaT and Timedelta operations
  - Changes to msgpack
  - Signature change for .rank
  - Bug in QuarterBegin with n=0
New features

Window functions are now methods

Window functions have been refactored to be methods on Series/DataFrame objects, rather than top-level functions, which are now deprecated. This allows these window-type functions, to have a similar API to that of .groupby. See the full documentation here (GH11603, GH12373)

```
In [1]: np.random.seed(1234)
In [2]: df = pd.DataFrame({'A': range(10), 'B': np.random.randn(10)})
In [3]: df
Out[3]:
     A      B
0   0  0.471435
1   1 -1.190976
2   2  1.432707
3   3 -0.312652
4   4 -0.720589
5   5  0.887163
6   6  0.859588
7   7 -0.636524
8   8  0.015696
9   9 -2.242685

[10 rows x 2 columns]
```

Previous behavior:

```
In [8]: pd.rolling_mean(df, window=3)
  FutureWarning: pd.rolling_mean is deprecated for DataFrame and will be removed in a future version, replace with
                  DataFrame.rolling(window=3, center=False).mean()
Out[8]:
```

(continues on next page)
A B
0 NaN NaN
1 NaN NaN
2 1 0.237722
3 2 -0.023640
4 3 0.133155
5 4 -0.048693
6 5 0.342054
7 6 0.370076
8 7 0.079587
9 8 -0.954504

New behavior:

In [4]: r = df.rolling(window=3)

These show a descriptive repr

In [5]: r
Out[5]: Rolling [window=3, center=False, axis=0]

with tab-completion of available methods and properties.

In [9]: r.<TAB>  # noQA E225, E999
r.A     r.agg  r.apply  r.count  r.exclusions  r.max  r.
    └─median  r.name  r.skew  r.sum
r.B     r.aggregate  r.corr  r.cov  r.kurt  r.mean  r.
    └─min  r.quantile  r.std  r.var

The methods operate on the Rolling object itself

In [6]: r.mean()
Out[6]:
A   B
0 NaN NaN
1 NaN NaN
2 1.0 0.237722
3 2.0 -0.023640
4 3.0 0.133155
5 4.0 -0.048693
6 5.0 0.342054
7 6.0 0.370076
8 7.0 0.079587
9 8.0 -0.954504
[10 rows x 2 columns]

They provide getitem accessors

In [7]: r['A'].mean()
Out[7]:
0 NaN
1 NaN
2 1.0
3 2.0
4 3.0

(continues on next page)
And multiple aggregations

```python
In [8]: r.agg({'A': ['mean', 'std'],
       ...: 'B': ['mean', 'std']})
```

```text
Out[8]:
A  B
mean std  mean  std
0  NaN  NaN  NaN  NaN
1  NaN  NaN  NaN  NaN
2  1.0 1.0  0.237722 1.327364
3  2.0 1.0 -0.023640 1.335505
4  3.0 1.0  0.133155 1.143778
5  4.0 1.0 -0.048693 0.835747
6  5.0 1.0  0.342054 0.920379
7  6.0 1.0  0.370076 0.871850
8  7.0 1.0  0.079587 0.750099
9  8.0 1.0 -0.954504 1.162285

[10 rows x 4 columns]
```

Changes to rename

Series.rename and NDFrame.rename_axis can now take a scalar or list-like argument for altering the Series or axis name, in addition to their old behaviors of altering labels. (GH9494, GH11965)

```python
In [9]: s = pd.Series(np.random.randn(5))
In [10]: s.rename('newname')
```

```text
Out[10]:
0  1.150036
1  0.991946
2  0.953324
3 -2.021255
4 -0.334077
Name: newname, Length: 5, dtype: float64
```

```python
In [12]: df = pd.DataFrame(np.random.randn(5, 2))
In [12]: (df.rename_axis("indexname")
    ....: .rename_axis("columns_name", axis="columns")
    ....:)
```

```text
Out[12]:
columns_name   0   1
indexname      
0  0.002118  0.405453
1  0.289092  1.321158
```

(continues on next page)
The new functionality works well in method chains. Previously these methods only accepted functions or dicts mapping a *label* to a new label. This continues to work as before for function or dict-like values.

### Range Index

A `RangeIndex` has been added to the `Int64Index` sub-classes to support a memory saving alternative for common use cases. This has a similar implementation to the python `range` object (`xrange` in python 2), in that it only stores the start, stop, and step values for the index. It will transparently interact with the user API, converting to `Int64Index` if needed.

This will now be the default constructed index for `NDFrame` objects, rather than previous an `Int64Index`. (GH939, GH12070, GH12071, GH12109, GH12888)

Previous behavior:

```python
In [3]: s = pd.Series(range(1000))
In [4]: s.index
Out[4]: Int64Index([ 0, 1, 2, 3, 4, 5, 6, 7, 8, 9,
                   ... 990, 991, 992, 993, 994, 995, 996, 997, 998, 999],
                   dtype='int64',
                   length=1000)
In [6]: s.index.nbytes
Out[6]: 8000
```

New behavior:

```python
In [13]: s = pd.Series(range(1000))
In [14]: s.index
Out[14]: RangeIndex(start=0, stop=1000, step=1)
In [15]: s.index.nbytes
Out[15]: 128
```

### Changes to `str.extract`

The `.str.extract` method takes a regular expression with capture groups, finds the first match in each subject string, and returns the contents of the capture groups (GH11386).

In v0.18.0, the `expand` argument was added to `extract`.

- `expand=False`: it returns a `Series`, `Index`, or `DataFrame`, depending on the subject and regular expression pattern (same behavior as pre-0.18.0).
- `expand=True`: it always returns a `DataFrame`, which is more consistent and less confusing from the perspective of a user.
Currently the default is `expand=None` which gives a `FutureWarning` and uses `expand=False`. To avoid this warning, please explicitly specify `expand`.

```python
In [1]: pd.Series(['a1', 'b2', 'c3']).str.extract(r'\[ab\](\d)', expand=None)
```
```
FutureWarning: currently extract(expand=None) means expand=False (return Index/Series/ →DataFrame)
but in a future version of pandas this will be changed to expand=True (return →DataFrame)
```

```python
Out[1]:
0 1
1 2
2 NaN
dtype: object
```

Extracting a regular expression with one group returns a Series if `expand=False`.

```python
In [16]: pd.Series(['a1', 'b2', 'c3']).str.extract(r'\[ab\](\d)', expand=False)
```
```
Out[16]:
0 1
1 2
2 NaN
Length: 3, dtype: object
```

It returns a DataFrame with one column if `expand=True`.

```python
In [17]: pd.Series(['a1', 'b2', 'c3']).str.extract(r'\[ab\](\d)', expand=True)
```
```
Out[17]:
0 1
1 2
2 NaN
[3 rows x 1 columns]
```

Calling on an Index with a regex with exactly one capture group returns an Index if `expand=False`.

```python
In [18]: s = pd.Series(['a1', 'b2', 'c3'], ['A11', 'B22', 'C33'])
In [19]: s.index
```
```
Out[19]: Index(['A11', 'B22', 'C33'], dtype='object')
```

```python
In [20]: s.index.str.extract("(?P<letter>[a-zA-Z])", expand=False)
```
```
Out[20]: Index(['A', 'B', 'C'], dtype='object', name='letter')
```

It returns a DataFrame with one column if `expand=True`.

```python
In [21]: s.index.str.extract("(?P<letter>[a-zA-Z])", expand=True)
```
```
Out[21]:
letter
0 A
1 B
2 C
[3 rows x 1 columns]
```

Calling on an Index with a regex with more than one capture group raises `ValueError` if `expand=False`.
>>> s.index.str.extract("(?P<letter>[a-zA-Z])([0-9]+)", expand=False)
ValueError: only one regex group is supported with Index

It returns a DataFrame if expand=True.

In [22]: s.index.str.extract("(?P<letter>[a-zA-Z])([0-9]+)", expand=True)
Out[22]:
   letter 1
0    A 11
1    B 22
2    C 33
[3 rows x 2 columns]

In summary, extract (expand=True) always returns a DataFrame with a row for every subject string, and a column for every capture group.

Addition of str.extractall

The .str.extractall method was added (GH1386). Unlike extract, which returns only the first match.

In [23]: s = pd.Series(["a1a2", "b1", "c1"], ["A", "B", "C"])
In [24]: s
Out[24]:
A    a1a2
B     b1
C     c1
Length: 3, dtype: object
In [25]: s.str.extract(r"(?P<letter>[ab])(?P<digit>[0-9])", expand=False)
Out[25]:
   letter digit
A    a   1
B    b   1
C  NaN  NaN
[3 rows x 2 columns]

The extractall method returns all matches.

In [26]: s.str.extractall(r"(?P<letter>[ab])(?P<digit>[0-9])")
Out[26]:
   letter digit
     match
A  0    a   1
   1    a   2
B  0    b   1
[3 rows x 2 columns]
Changes to str.cat

The method `.str.cat()` concatenates the members of a Series. Before, if NaN values were present in the Series, calling `.str.cat()` on it would return NaN, unlike the rest of the Series.str.* API. This behavior has been amended to ignore NaN values by default. (GH11435).

A new, friendlier `ValueError` is added to protect against the mistake of supplying the `sep` as an arg, rather than as a kwarg. (GH11334).

```python
In [27]: pd.Series(['a', 'b', np.nan, 'c']).str.cat(sep=' ')
Out[27]: 'a b c'

In [28]: pd.Series(['a', 'b', np.nan, 'c']).str.cat(sep=' ', na_rep='?')
Out[28]: 'a b ? c'

In [2]: pd.Series(['a', 'b', np.nan, 'c']).str.cat(' ')
ValueError: Did you mean to supply a `sep` keyword?
```

Datetimelike rounding

`DatetimeIndex`, `Timestamp`, `TimedeltaIndex`, `Timedelta` have gained the `.round()`, `.floor()` and `.ceil()` method for datetimelike rounding, flooring and ceiling. (GH4314, GH11963)

Naive datetimes

```python
In [29]: dr = pd.date_range('20130101 09:12:56.1234', periods=3)
In [30]: dr
Out[30]: DatetimeIndex(['2013-01-01 09:12:56.123400', '2013-01-02 09:12:56.123400',
                    '2013-01-03 09:12:56.123400'],
                   dtype='datetime64[ns]', freq='D')

In [31]: dr.round('s')
Out[31]: DatetimeIndex(['2013-01-01 09:12:56', '2013-01-02 09:12:56',
                   '2013-01-03 09:12:56'],
                   dtype='datetime64[ns]', freq=None)

# Timestamp scalar
In [32]: dr[0]
Out[32]: Timestamp('2013-01-01 09:12:56.123400', freq='D')

In [33]: dr[0].round('10s')
Out[33]: Timestamp('2013-01-01 09:13:00')
```

Tz-aware are rounded, floored and ceiled in local times

```python
In [34]: dr = dr.tz_localize('US/Eastern')
In [35]: dr
Out[35]: DatetimeIndex(['2013-01-01 09:12:56.123400-05:00',
                    '2013-01-02 09:12:56.123400-05:00',
                    '2013-01-03 09:12:56.123400-05:00'],
                   dtype='datetime64[ns, US/Eastern]', freq=None)
```
In [36]: dr.round('s')
Out[36]:
DatetimeIndex(['2013-01-01 09:12:56-05:00', '2013-01-02 09:12:56-05:00',
                 '2013-01-03 09:12:56-05:00'],
dtype='datetime64[ns, US/Eastern]', freq=None)

Timedeltas

In [37]: t = pd.timedelta_range('1 days 2 hr 13 min 45 us', periods=3, freq='d')
In [38]: t
Out[38]:
TimedeltaIndex(['1 days 02:13:00.000045', '2 days 02:13:00.000045',
                 '3 days 02:13:00.000045'],
dtype='timedelta64[ns]', freq='D')
In [39]: t.round('10min')
Out[39]: TimedeltaIndex(['1 days 02:10:00', '2 days 02:10:00', '3 days 02:10:00'],
                         dtype='timedelta64[ns]', freq=None)

# Timedelta scalar
In [40]: t[0]
Out[40]: Timedelta('1 days 02:13:00.000045')
In [41]: t[0].round('2h')
Out[41]: Timedelta('1 days 02:00:00')

In addition, .round(), .floor() and .ceil() will be available through the .dt accessor of Series.

In [42]: s = pd.Series(dr)
In [43]: s
Out[43]:
0  2013-01-01 09:12:56.123400-05:00
1  2013-01-02 09:12:56.123400-05:00
2  2013-01-03 09:12:56.123400-05:00
Length: 3, dtype: datetime64[ns, US/Eastern]
In [44]: s.dt.round('D')
Out[44]:
0  2013-01-01 00:00:00-05:00
1  2013-01-02 00:00:00-05:00
2  2013-01-03 00:00:00-05:00
Length: 3, dtype: datetime64[ns, US/Eastern]
Formatting of integers in FloatIndex

Integers in FloatIndex, e.g. 1., are now formatted with a decimal point and a 0 digit, e.g. 1.0 (GH11713) This change not only affects the display to the console, but also the output of IO methods like .to_csv or .to_html.

Previous behavior:

```
In [2]: s = pd.Series([1, 2, 3], index=np.arange(3.))
In [3]: s
Out[3]:
0    1
1    2
2    3
dtype: int64
In [4]: s.index
Out[4]: Float64Index([0.0, 1.0, 2.0], dtype='float64')
In [5]: print(s.to_csv(path=None))
0,1
1,2
2,3
```

New behavior:

```
In [45]: s = pd.Series([1, 2, 3], index=np.arange(3.))
In [46]: s
Out[46]:
0.0    1
1.0    2
2.0    3
Length: 3, dtype: int64
In [47]: s.index
Out[47]: Float64Index([0.0, 1.0, 2.0], dtype='float64')
In [48]: print(s.to_csv(path_or_buf=None, header=False))
0.0,1
1.0,2
2.0,3
```

Changes to dtype assignment behaviors

When a DataFrame’s slice is updated with a new slice of the same dtype, the dtype of the DataFrame will now remain the same. (GH10503)

Previous behavior:

```
In [5]: df = pd.DataFrame({'a': [0, 1, 1],
                      'b': pd.Series([100, 200, 300], dtype='uint32')})
In [7]: df.dtypes
Out[7]:
a    int64
b    uint32
```

(continues on next page)
### New behavior:

```python
In [49]: df = pd.DataFrame({
    ...:     'a': [0, 1, 1],
    ...:     'b': pd.Series([100, 200, 300], dtype='uint32')})
    ...

In [50]: df.dtypes
Out[50]:
   a   int64
   b  uint32
Length: 2, dtype: object

In [51]: ix = df['a'] == 1

In [52]: df.loc[ix, 'b'] = df.loc[ix, 'b']

In [53]: df.dtypes
Out[53]:
   a   int64
   b  uint32
Length: 2, dtype: object
```

When a DataFrame’s integer slice is partially updated with a new slice of floats that could potentially be down-casted
to integer without losing precision, the dtype of the slice will be set to float instead of integer.

### Previous behavior:

```python
In [4]: df = pd.DataFrame(np.array(range(1,10)).reshape(3,3),
                     columns=list('abc'),
                     index=[[4,4,8], [8,10,12]])

In [5]: df
Out[5]:
   a  b  c
4  8  1  2  3
10  4  5  6
8  12  7  8  9

In [7]: df.ix[4, 'c'] = np.array([0., 1.])

In [8]: df
Out[8]:
   a  b  c
4  8  1  2  0
```

(continues on next page)
New behavior:

```python
In [54]: df = pd.DataFrame(np.array(range(1,10)).reshape(3,3),
..:          columns=list('abc'),
..:          index=[[4,4,8], [8,10,12]])

In [55]: df
Out[55]:
   a  b  c
4  8  1  2  3
10 4  5  6
8 12  7  8  9
[3 rows x 3 columns]
```

```python
In [56]: df.loc[4, 'c'] = np.array([0., 1.])

In [57]: df
Out[57]:
   a  b  c
4  8  1  2  0.0
10 4  5  1.0
8 12  7  8  9.0
[3 rows x 3 columns]
```

**Method to_xarray**

In a future version of pandas, we will be deprecating Panel and other > 2 ndim objects. In order to provide for continuity, all NDFrame objects have gained the `.to_xarray()` method in order to convert to xarray objects, which has a pandas-like interface for > 2 ndim. (GH11972)

See the xarray full-documentation here.

```python
In [1]: p = Panel(np.arange(2*3*4).reshape(2,3,4))

In [2]: p.to_xarray()
Out[2]:
<xarray.DataArray (items: 2, major_axis: 3, minor_axis: 4)>
array([[[ 0, 1, 2, 3],
        [ 4, 5, 6, 7],
        [ 8, 9,10,11]],
       [[12,13,14,15],
        [16,17,18,19],
        [20,21,22,23]]])
Coordinates:
* items     (items) int64 0 1
* major_axis (major_axis) int64 0 1 2
* minor_axis (minor_axis) int64 0 1 2 3
```
Latex representation

DataFrame has gained a \_repr\_latex\_() method in order to allow for conversion to latex in an ipython/jupyter notebook using nbconvert. (GH11778)

Note that this must be activated by setting the option pd.display.latex.repr=True (GH12182)

For example, if you have a jupyter notebook you plan to convert to latex using nbconvert, place the statement pd.display.latex.repr=True in the first cell to have the contained DataFrame output also stored as latex.

The options display.latex.escape and display.latex.longtable have also been added to the configuration and are used automatically by the to_latex method. See the available options docs for more info.

**pd.read_sas() changes**

read_sas has gained the ability to read SAS7BDAT files, including compressed files. The files can be read in entirety, or incrementally. For full details see here. (GH4052)

**Other enhancements**

- Handle truncated floats in SAS xport files (GH11713)
- Added option to hide index in Series.to_string (GH11729)
- read_excel now supports s3 urls of the format s3://bucketname/filename (GH11447)
- add support for AWS_S3_HOST env variable when reading from s3 (GH12198)
- A simple version of Panel.round() is now implemented (GH11763)
- For Python 3.x, round(DataFrame), round(Series), round(Panel) will work (GH11763)
- sys.getsizeof(obj) returns the memory usage of a pandas object, including the values it contains (GH11597)
- Series gained an is_unique attribute (GH11946)
- DataFrame.quantile and Series.quantile now accept interpolation keyword (GH10174).
- Added DataFrame.style.format for more flexible formatting of cell values (GH11692)
- DataFrame.select_dtypes now allows the np.float16 type code (GH11990)
- pivot_table() now accepts most iterables for the values parameter (GH12017)
- Added Google BigQuery service account authentication support, which enables authentication on remote servers. (GH11881, GH12572). For further details see here
- HDFStore is now iterable: for k in store is equivalent to for k in store.keys() (GH12221).
- Add missing methods/fields to .dt for Period (GH8848)
- The entire code base has been PEP-ified (GH12096)
Backwards incompatible API changes

- the leading white spaces have been removed from the output of `.to_string(index=False)` method (GH11833)
- the `out` parameter has been removed from the `Series.round()` method. (GH11763)
- `DataFrame.round()` leaves non-numeric columns unchanged in its return, rather than raises. (GH11885)
- `DataFrame.head(0)` and `DataFrame.tail(0)` return empty frames, rather than `self`. (GH11937)
- `Series.head(0)` and `Series.tail(0)` return empty series, rather than `self`. (GH11937)
- `to_msgpack` and `read_msgpack` encoding now defaults to 'utf-8'. (GH12170)
- the order of keyword arguments to text file parsing functions (.read_csv(), .read_table(), .read_fwf()) changed to group related arguments. (GH11555)
- `NaTType.isoformat` now returns the string 'NaT' to allow the result to be passed to the constructor of `Timestamp`. (GH12300)

NaT and Timedelta operations

NaT and Timedelta have expanded arithmetic operations, which are extended to `Series` arithmetic where applicable. Operations defined for `datetime64[ns]` or `timedelta64[ns]` are now also defined for `NaT` (GH11564).

NaT now supports arithmetic operations with integers and floats.

```python
In [58]: pd.NaT * 1
Out[58]: NaT

In [59]: pd.NaT * 1.5
Out[59]: NaT

In [60]: pd.NaT / 2
Out[60]: NaT

In [61]: pd.NaT * np.nan
Out[61]: NaT
```

NaT defines more arithmetic operations with `datetime64[ns]` and `timedelta64[ns]`.

```python
In [62]: pd.NaT / pd.NaT
Out[62]: nan

In [63]: pd.Timedelta('1s') / pd.NaT
Out[63]: nan
```

NaT may represent either a `datetime64[ns]` null or a `timedelta64[ns]` null. Given the ambiguity, it is treated as a `timedelta64[ns]`, which allows more operations to succeed.

```python
In [64]: pd.NaT + pd.NaT
Out[64]: NaT

# same as
In [65]: pd.Timedelta('1s') + pd.Timedelta('1s')
Out[65]: Timedelta('0 days 00:00:02')
```

as opposed to
In [3]: pd.Timestamp('19900315') + pd.Timestamp('19900315')
TypeError: unsupported operand type(s) for +: 'Timestamp' and 'Timestamp'

However, when wrapped in a `Series` whose `dtype` is `datetime64[ns]` or `timedelta64[ns]`, the `dtype` information is respected.

In [1]: pd.Series([pd.NaT], dtype='<M8[ns]') + pd.Series([pd.NaT], dtype='<M8[ns]')
TypeError: can only operate on a datetimes for subtraction, but the operator `__add__` was passed

Out[66]:
0    NaT
Length: 1, dtype: timedelta64[ns]

Timedelta division by floats now works.

In [67]: pd.Timedelta('1s') / 2.0
Out[67]: Timedelta('0 days 00:00:00.500000')

Subtraction by `Timedelta` in a `Series` by a `Timestamp` works (GH11925)

In [68]: ser = pd.Series(pd.timedelta_range('1 day', periods=3))

In [69]: ser
Out[69]:
0  1 days
1  2 days
2  3 days
Length: 3, dtype: timedelta64[ns]

In [70]: pd.Timestamp('2012-01-01') - ser
Out[70]:
0  2011-12-31
1  2011-12-30
2  2011-12-29
Length: 3, dtype: datetime64[ns]

NaT.isoformat() now returns 'NaT'. This change allows allows `pd.Timestamp` to rehydrate any timestamp like object from its isoformat (GH12300).

Changes to msgpack

Forward incompatible changes in `msgpack` writing format were made over 0.17.0 and 0.18.0; older versions of pandas cannot read files packed by newer versions (GH12129, GH10527).

Bugs in `to_msgpack` and `read_msgpack` introduced in 0.17.0 and fixed in 0.18.0, caused files packed in Python 2 unreadable by Python 3 (GH12142). The following table describes the backward and forward compat of msgpacks.

<table>
<thead>
<tr>
<th>Packed with</th>
<th>Can be unpacked with</th>
</tr>
</thead>
<tbody>
<tr>
<td>pre-0.17 / Python 2</td>
<td>any</td>
</tr>
<tr>
<td>pre-0.17 / Python 3</td>
<td>any</td>
</tr>
<tr>
<td>0.17 / Python 2</td>
<td>• ==0.17 / Python 2</td>
</tr>
<tr>
<td></td>
<td>• &gt;=0.18 / any Python</td>
</tr>
<tr>
<td>0.17 / Python 3</td>
<td>&gt;=0.18 / any Python</td>
</tr>
<tr>
<td>0.18</td>
<td>&gt;= 0.18</td>
</tr>
</tbody>
</table>

5.10. Version 0.18
0.18.0 is backward-compatible for reading files packed by older versions, except for files packed with 0.17 in Python 2, in which case only they can only be unpacked in Python 2.

### Signature change for .rank

Series.rank and DataFrame.rank now have the same signature (GH11759)

**Previous signature**

```python
In [3]: pd.Series([0,1]).rank(method='average', na_option='keep',
                   ascending=True, pct=False)
```

```
Out[3]:
   0 1
  1 2
dtype: float64
```

```python
In [4]: pd.DataFrame([0,1]).rank(axis=0, numeric_only=None,
                            method='average', na_option='keep',
                            ascending=True, pct=False)
```

```
Out[4]:
   0
  0 1
  1 2
```

**New signature**

```python
In [71]: pd.Series([0,1]).rank(axis=0, method='average', numeric_only=None,
                             na_option='keep', ascending=True, pct=False)
```

```
Out[71]:
   0 1.0
  1 2.0
Length: 2, dtype: float64
```

```python
In [72]: pd.DataFrame([0,1]).rank(axis=0, method='average', numeric_only=None,
                             na_option='keep', ascending=True, pct=False)
```

```
Out[72]:
   0
  0 1.0
  1 2.0
[2 rows x 1 columns]
```

### Bug in QuarterBegin with n=0

In previous versions, the behavior of the QuarterBegin offset was inconsistent depending on the date when the n parameter was 0. (GH11406)

The general semantics of anchored offsets for n=0 is to not move the date when it is an anchor point (e.g., a quarter start date), and otherwise roll forward to the next anchor point.
For the QuarterBegin offset in previous versions, the date would be rolled backwards if date was in the same month as the quarter start date.

This behavior has been corrected in version 0.18.0, which is consistent with other anchored offsets like MonthBegin and YearBegin.

**Resample API**

Like the change in the window functions API above, .resample(...) is changing to have a more groupby-like API. (GH11732, GH12702, GH12202, GH12332, GH12334, GH12348, GH12448).
pandas: powerful Python data analysis toolkit, Release 1.1.1

Previous API:

You would write a resampling operation that immediately evaluates. If a how parameter was not provided, it would default to how='mean'.

```
In [6]: df.resample('2s')
Out[6]:
    A     B     C     D
2010-01-01 09:00:00 0.485748 0.447351 0.357096 0.793615
2010-01-01 09:00:02 0.820801 0.794317 0.364034 0.531096
2010-01-01 09:00:04 0.433985 0.314582 0.424104 0.625733
2010-01-01 09:00:06 0.624988 0.609738 0.631665 0.612452
2010-01-01 09:00:08 0.510470 0.534317 0.573201 0.806949
```

You could also specify a how directly

```
In [7]: df.resample('2s', how='sum')
Out[7]:
    A     B     C     D
2010-01-01 09:00:00 0.971495 0.894701 0.714192 1.587231
2010-01-01 09:00:02 1.641602 1.588635 0.728068 1.062191
2010-01-01 09:00:04 0.867969 0.629165 0.848208 1.251465
2010-01-01 09:00:06 1.249976 1.219477 1.266330 1.224904
2010-01-01 09:00:08 1.020940 1.068634 1.146402 1.613897
```

New API:

Now, you can write `.resample(..)` as a 2-stage operation like `.groupby(..)`, which yields a Resampler.

```
In [82]: r = df.resample('2s')

In [83]: r
Out[83]: <pandas.core.resample.DatetimeIndexResampler object at 0x7fe2797b0b50>
```

**Downsampling**

You can then use this object to perform operations. These are downsampling operations (going from a higher frequency to a lower one).

```
In [84]: r.mean()
Out[84]:
    A     B     C     D
2010-01-01 09:00:00 0.485748 0.447351 0.357096 0.793615
2010-01-01 09:00:02 0.820801 0.794317 0.364034 0.531096
2010-01-01 09:00:04 0.433985 0.314582 0.424104 0.625733
2010-01-01 09:00:06 0.624988 0.609738 0.631665 0.612452
2010-01-01 09:00:08 0.510470 0.534317 0.573201 0.806949
[5 rows x 4 columns]
```

```
In [85]: r.sum()
Out[85]:
    A     B     C     D
2010-01-01 09:00:00 0.971495 0.894701 0.714192 1.587231
2010-01-01 09:00:02 1.641602 1.588635 0.728068 1.062191
2010-01-01 09:00:04 0.867969 0.629165 0.848208 1.251465
2010-01-01 09:00:06 1.249976 1.219477 1.266330 1.224904
2010-01-01 09:00:08 1.020940 1.068634 1.146402 1.613897
```

(continues on next page)
Furthermore, resample now supports `getitem` operations to perform the resample on specific columns.

```python
In [86]: r[['A','C']].mean()
Out[86]:
         A     C
2010-01-01 09:00:00 0.485748 0.357096
2010-01-01 09:00:02 0.820801 0.364034
2010-01-01 09:00:04 0.433985 0.424104
2010-01-01 09:00:06 0.624988 0.633165
2010-01-01 09:00:08 0.510470 0.573201
```

and `.aggregate` type operations.

```python
In [87]: r.agg({'A' : 'mean', 'B' : 'sum'})
Out[87]:
        A     B
2010-01-01 09:00:00 0.485748 0.894701
2010-01-01 09:00:02 0.820801 1.588635
2010-01-01 09:00:04 0.433985 0.629165
2010-01-01 09:00:06 0.624988 1.219477
2010-01-01 09:00:08 0.510470 1.068634
```

These accessors can of course, be combined

```python
In [88]: r[['A','B']].agg(['mean','sum'])
Out[88]:
          A    B
mean  sum  mean  sum
2010-01-01 09:00:00 0.485748 0.971495 0.447351 0.894701
2010-01-01 09:00:02 0.820801 1.641602 0.794317 1.588635
2010-01-01 09:00:04 0.433985 0.867969 0.314582 0.629165
2010-01-01 09:00:06 0.624988 1.249976 0.609738 1.219477
2010-01-01 09:00:08 0.510470 1.020940 0.534317 1.068634
```

**Upsampling**

Upsampling operations take you from a lower frequency to a higher frequency. These are now performed with the `Resampler` objects with `backfill()`, `ffill()`, `fillna()` and `asfreq()` methods.

```python
In [89]: s = pd.Series(np.arange(5, dtype='int64'),
                   index=pd.date_range('2010-01-01', periods=5, freq='Q'))
```

(continues on next page)
Out[90]:
2010-03-31  0
2010-06-30  1
2010-09-30  2
2010-12-31  3
2011-03-31  4
Freq: Q-DEC, Length: 5, dtype: int64

Previously

In [6]: s.resample('M', fill_method='ffill')
Out[6]:
2010-03-31  0
2010-04-30  0
2010-05-31  0
2010-06-30  1
2010-07-31  1
2010-08-31  1
2010-09-30  2
2010-10-31  2
2010-11-30  2
2010-12-31  3
2011-01-31  3
2011-02-28  3
2011-03-31  4
Freq: M, dtype: int64

New API

In [91]: s.resample('M').ffill()
Out[91]:
2010-03-31  0
2010-04-30  0
2010-05-31  0
2010-06-30  1
2010-07-31  1
2010-08-31  1
2010-09-30  2
2010-10-31  2
2010-11-30  2
2010-12-31  3
2011-01-31  3
2011-02-28  3
2011-03-31  4
Freq: M, Length: 13, dtype: int64

Note: In the new API, you can either downsample OR upsample. The prior implementation would allow you to pass an aggregator function (like mean) even though you were upsampling, providing a bit of confusion.
**Warning**: This new API for resample includes some internal changes for the prior-to-0.18.0 API, to work with a deprecation warning in most cases, as the resample operation returns a deferred object. We can intercept operations and just do what the (pre 0.18.0) API did (with a warning). Here is a typical use case:

```
In [4]: r = df.resample('2s')
```

```
In [6]: r*10
```

```
pandas/tseries/resample.py:80: FutureWarning: .resample() is now a deferred
˓→operation
use .resample(...).mean() instead of .resample(...)
```

```
Out[6]:
   A      B      C      D
2010-01-01 09:00:00  4.857476  4.473507  3.570960  7.936154
2010-01-01 09:00:02  8.208011  7.943173  3.640340  5.310957
2010-01-01 09:00:04  4.339846  3.145823  4.241039  6.257326
2010-01-01 09:00:06  6.249881  6.097384  6.331650  6.124518
2010-01-01 09:00:08  5.104699  5.343172  5.732009  8.069486
```

However, getting and assignment operations directly on a Resampler will raise a `ValueError`:

```
In [7]: r.iloc[0] = 5
```

```
ValueError: .resample() is now a deferred operation
use .resample(...).mean() instead of .resample(...)
```

There is a situation where the new API can not perform all the operations when using original code. This code is intending to resample every 2s, take the mean AND then take the min of those results.

```
In [4]: df.resample('2s').min()
```

```
Out[4]:
   A  0.433985  
   B  0.314582  
   C  0.357096  
   D  0.531096  
dtype: float64
```

The new API will:

```
In [92]: df.resample('2s').min()
```

```
Out[92]:
   0.191519  0.272593  0.276464  0.785359
   0.683463  0.712702  0.357817  0.500995
   0.364886  0.013768  0.075381  0.368824
   0.316836  0.568099  0.397203  0.436173
   0.218792  0.143767  0.442141  0.704581
```

The good news is the return dimensions will differ between the new API and the old API, so this should loudly raise an exception.

To replicate the original operation

```
In [93]: df.resample('2s').mean().min()
```

```
Out[93]:
   0.433985  
   0.314582  
   0.357096  
   0.531096  
dtype: float64
```
Changes to eval

In prior versions, new columns assignments in an eval expression resulted in an inplace change to the DataFrame. (GH9297, GH8664, GH10486)

In [94]: df = pd.DataFrame({'a': np.linspace(0, 10, 5), 'b': range(5)})

In [95]: df
Out[95]:
   a  b
0 0.0 0
1 2.5 1
2 5.0 2
3 7.5 3
4 10.0 4

[5 rows x 2 columns]

In [12]: df.eval('c = a + b')

FutureWarning: eval expressions containing an assignment currently default to operating inplace.
This will change in a future version of pandas, use inplace=True to avoid this warning.

In [13]: df
Out[13]:
   a  b  c
0 0.0 0 0.0
1 2.5 1 3.5
2 5.0 2 7.0
3 7.5 3 10.5
4 10.0 4 14.0

In version 0.18.0, a new inplace keyword was added to choose whether the assignment should be done inplace or return a copy.

In [96]: df
Out[96]:
   a  b  c
0 0.0 0 0.0
1 2.5 1 3.5
2 5.0 2 7.0
3 7.5 3 10.5
4 10.0 4 14.0

[5 rows x 3 columns]

In [97]: df.eval('d = c - b', inplace=False)
Out[97]:
   a  b  c  d
0 0.0 0 0.0 0.0
1 2.5 1 3.5 2.5
2 5.0 2 7.0 5.0

(continues on next page)
In [98]: df
Out[98]:
   a   b   c
0  0.0 0.0 0.0
1  2.5 1.0 3.5
2  5.0 2.0 7.0
3  7.5 3.0 10.5
4 10.0 4.0 14.0

[5 rows x 3 columns]

In [99]: df.eval('d = c - b', inplace=True)

In [100]: df
Out[100]:
   a   b   c   d
0  0.0 0.0 0.0  0.0
1  2.5 1.0 3.5  2.5
2  5.0 2.0 7.0  5.0
3  7.5 3.0 10.5 7.5
4 10.0 4.0 14.0 10.0

[5 rows x 4 columns]

Warning: For backwards compatibility, inplace defaults to True if not specified. This will change in a future version of pandas. If your code depends on an inplace assignment you should update to explicitly set inplace=True.

The inplace keyword parameter was also added the query method.

In [101]: df.query('a > 5')
Out[101]:
   a   b   c   d
0  0.0 0.0 0.0  0.0
1  2.5 1.0 3.5  2.5
2  5.0 2.0 7.0  5.0
3  7.5 3.0 10.5 7.5
4 10.0 4.0 14.0 10.0

[2 rows x 4 columns]

In [102]: df.query('a > 5', inplace=True)

In [103]: df
Out[103]:
   a   b   c   d
0  0.0 0.0 0.0  0.0
1  2.5 1.0 3.5  2.5
2  5.0 2.0 7.0  5.0
3  7.5 3.0 10.5 7.5
4 10.0 4.0 14.0 10.0

[2 rows x 4 columns]
**Warning:** Note that the default value for `inplace` in a query is `False`, which is consistent with prior versions.

eval has also been updated to allow multi-line expressions for multiple assignments. These expressions will be evaluated one at a time in order. Only assignments are valid for multi-line expressions.

```
In [104]: df
Out [104]:
   a  b  c  d  
3  7.5 3 10.5 7.5
4 10.0 4 14.0 10.0
[2 rows x 4 columns]
```

```
In [105]: df.eval(""
.......
.......
.......
"", inplace=True)
```

```
In [106]: df
Out [106]:
   a  b  c  d  e  f  g
3  7.5 3 10.5 15.0 -7.0 -3.5
4 10.0 4 14.0 20.0 -2.0 -1.0
[2 rows x 7 columns]
```

**Other API changes**

- `DataFrame.between_time` and `Series.between_time` now only parse a fixed set of time strings. Parsing of date strings is no longer supported and raises a `ValueError`. (GH11818)

```
In [107]: s = pd.Series(range(10), pd.date_range('2015-01-01', freq='H', periods=10))
```

```
In [108]: s.between_time("7:00am", "9:00am")
Out [108]:
2015-01-01 07:00:00 7
2015-01-01 08:00:00 8
2015-01-01 09:00:00 9
Freq: H, Length: 3, dtype: int64
```

This will now raise.

```
In [2]: s.between_time('20150101 07:00:00','20150101 09:00:00')
ValueError: Cannot convert arg ['20150101 07:00:00'] to a time.
```

- `.memory_usage()` now includes values in the index, as does memory_usage in `.info()` (GH11597)
- `DataFrame.to_latex()` now supports non-ascii encodings (e.g. `utf-8`) in Python 2 with the parameter `encoding` (GH7061)
- `pandas.merge()` and `DataFrame.merge()` will show a specific error message when trying to merge with an object that is not of type `DataFrame` or a subclass (GH12081)
• **DataFrame.unstack** and **Series.unstack** now take **fill_value** keyword to allow direct replacement of missing values when an unstack results in missing values in the resulting **DataFrame**. As an added benefit, specifying **fill_value** will preserve the data type of the original stacked data. (GH9746)

• As part of the new API for **window functions** and **resampling**, aggregation functions have been clarified, raising more informative error messages on invalid aggregations. (GH9052). A full set of examples are presented in **groupby**.

• Statistical functions for **NDFrame** objects (like **sum()**, **mean()**, **min()**) will now raise if non-numpy-compatible arguments are passed in for **kwargs** (GH12301)

• **.to_latex** and **.to_html** gain a decimal parameter like **.to_csv**; the default is '. ' (GH12031)

• More helpful error message when constructing a **DataFrame** with empty data but with indices (GH8020)

• **.describe()** will now properly handle bool dtype as a categorical (GH6625)

• More helpful error message with an invalid **.transform** with user defined input (GH10165)

• Exponentially weighted functions now allow specifying alpha directly (GH10789) and raise **ValueError** if parameters violate 0 < alpha <= 1 (GH12492)

## Deprecations

• The functions **pd.rolling_***, **pd.expanding_***, and **pd.ewm* are deprecated and replaced by the corresponding method call. Note that the new suggested syntax includes all of the arguments (even if default) (GH11603)

```python
In [1]: s = pd.Series(range(3))
In [2]: pd.rolling_mean(s,window=2,min_periods=1)
   FutureWarning: pd.rolling_mean is deprecated for Series and will be removed in a future version, replace with Series.rolling(min_periods=1,window=2,center=False).mean()
Out[2]:
   0   0.0
   1   0.5
   2   1.5
dtype: float64
In [3]: pd.rolling_cov(s, s, window=2)
   FutureWarning: pd.rolling_cov is deprecated for Series and will be removed in a future version, replace with Series.rolling(window=2).cov(other=<Series>)
Out[3]:
   0  NaN
   1   0.5
   2   0.5
dtype: float64
```

• The **freq** and **how** arguments to the **.rolling**, **.expanding**, and **.ewm** (new) functions are deprecated, and will be removed in a future version. You can simply resample the input prior to creating a window function. (GH11603).

For example, instead of **s.rolling(window=5,freq='D').max()** to get the max value on a rolling 5 Day window, one could use **s.resample('D').mean().rolling(window=5).max()**, which first resamples the data to daily data, then provides a rolling 5 day window.
• `pd.tseries.frequencies.get_offset_name` function is deprecated. Use offset’s `.freqstr` property as alternative (GH11192)

• `pandas.stats.fama_macbeth` routines are deprecated and will be removed in a future version (GH6077)

• `pandas.stats.ols`, `pandas.stats.plm` and `pandas.stats.var` routines are deprecated and will be removed in a future version (GH6077)

• show a `FutureWarning` rather than a `DeprecationWarning` on using long-time deprecated syntax in `HDFStore.select`, where the `where` clause is not a string-like (GH12027)

• The `pandas.options.display.mpl_style` configuration has been deprecated and will be removed in a future version of pandas. This functionality is better handled by matplotlib’s style sheets (GH11783).

**Removal of deprecated float indexers**

In GH4892 indexing with floating point numbers on a non-`Float64Index` was deprecated (in version 0.14.0). In 0.18.0, this deprecation warning is removed and these will now raise a `TypeError` (GH12165, GH12333)

```
In [109]: s = pd.Series([1, 2, 3], index=[4, 5, 6])

In [110]: s
Out[110]:
     4  1
     5  2
     6  3
Length: 3, dtype: int64

In [111]: s2 = pd.Series([1, 2, 3], index=list('abc'))

In [112]: s2
Out[112]:
a 1
b 2
c 3
Length: 3, dtype: int64
```

Previous behavior:

```
# this is label indexing
In [2]: s[5.0]
FutureWarning: scalar indexers for index type Int64Index should be integers and not floating point
Out[2]: 2

# this is positional indexing
In [3]: s.iloc[1.0]
FutureWarning: scalar indexers for index type Int64Index should be integers and not floating point
Out[3]: 2

# this is label indexing
In [4]: s.loc[5.0]
FutureWarning: scalar indexers for index type Int64Index should be integers and not floating point
Out[4]: 2

# .ix would coerce 1.0 to the positional 1, and index
```
In [5]: s2.ix[1.0] = 10
FutureWarning: scalar indexers for index type Index should be integers and not floating point

In [6]: s2
Out[6]:
   a  1
   b 10
   c  3
   dtype: int64

New behavior:
For iloc, getting & setting via a float scalar will always raise.

In [3]: s.iloc[2.0]
TypeError: cannot do label indexing on <class 'pandas.indexes.numeric.Int64Index'> with these indexers [2.0] of <type 'float'>

Other indexers will coerce to a like integer for both getting and setting. The FutureWarning has been dropped for .loc, .ix and [].

and setting

In [115]: s_copy = s.copy()
In [116]: s_copy[5.0] = 10
In [117]: s_copy
Out[117]:
      4   1
      5  10
      6   3
Length: 3, dtype: int64
In [118]: s_copy = s.copy()
In [119]: s_copy.loc[5.0] = 10
In [120]: s_copy
Out[120]:
      4   1
      5  10
      6   3
Length: 3, dtype: int64

Positional setting with .ix and a float indexer will ADD this value to the index, rather than previously setting the value by position.

In [3]: s2.ix[1.0] = 10
In [4]: s2
}(continues on next page)
Slicing will also coerce integer-like floats to integers for a non-Float64Index.

```
In [121]: s.loc[5.0:6]
Out[121]:
5  2
6  3
Length: 2, dtype: int64
```

Note that for floats that are NOT coercible to ints, the label based bounds will be excluded

```
In [122]: s.loc[5.1:6]
Out[122]:
6  3
Length: 1, dtype: int64
```

Float indexing on a Float64Index is unchanged.

```
In [123]: s = pd.Series([1, 2, 3], index=np.arange(3.))
In [124]: s[1.0]
Out[124]: 2
In [125]: s[1.0:2.5]
Out[125]:
1.0  2
2.0  3
Length: 2, dtype: int64
```

**Removal of prior version deprecations/changes**

- **Removal of** `rolling_corr_pairwise` **in favor of** `.rolling().corr(pairwise=True)` **(GH4950)**
- **Removal of** `expanding_corr_pairwise` **in favor of** `expanding().corr(pairwise=True)` **(GH4950)**
- **Removal of** `DataMatrix` **module. This was not imported into the pandas namespace in any event (GH12111)**
- **Removal of** `cols` **keyword in favor of** `subset` **in** `DataFrame.duplicated()` **and** `DataFrame.drop_duplicates()` **(GH6680)**
- **Removal of** the `read_frame` and `frame_query` (both aliases for `pd.read_sql`) **and** `write_frame` (alias of `to_sql`) **functions in the** `pd.io.sql` **namespace, deprecated since 0.14.0 (GH6292).**
- **Removal of the** `order` **keyword from** `factorize()` **(GH6930)**
Performance improvements

- Improved performance of `andrews_curves` (GH11534)
- Improved huge `DatetimeIndex`, `PeriodIndex` and `TimedeltaIndex`'s ops performance including `NaT` (GH10277)
- Improved performance of `pandas.concat` (GH11958)
- Improved performance of `StataReader` (GH11591)
- Improved performance in construction of `Categoricals` with `Series` of datetimes containing `NaT` (GH12077)
- Improved performance of ISO 8601 date parsing for dates without separators (GH11899), leading zeros (GH11871) and with white space preceding the time zone (GH9714)

Bug fixes

- Bug in `GroupBy.size` when data-frame is empty. (GH11699)
- Bug in `Period.end_time` when a multiple of time period is requested (GH11738)
- Regression in `.clip` with tz-aware datetimes (GH11838)
- Bug in `date_range` when the boundaries fell on the frequency (GH11804, GH12409)
- Bug in consistency of passing nested dicts to `.groupby(...).agg(...)` (GH9052)
- Accept unicode in `Timedelta` constructor (GH11995)
- Bug in value label reading for `StataReader` when reading incrementally (GH12014)
- Bug in vectorized `DateOffset` when `n` parameter is 0 (GH11370)
- Compat for numpy 1.11 w.r.t. `NaT` comparison changes (GH12049)
- Bug in `read_csv` when reading from a `StringIO` in threads (GH11790)
- Bug in not treating `NaT` as a missing value in datetimelikes when factorizing & with `Categoricals` (GH12077)
- Bug in `getitem` when the values of a `Series` were tz-aware (GH12089)
- Bug in `Series.str.get_dummies` when one of the variables was ‘name’ (GH12180)
- Bug in `pd.concat` while concatenating tz-aware `NaT` series. (GH11693, GH11755, GH12217)
- Bug in `pd.read_stata` with version <= 108 files (GH12232)
- Bug in `Series.resample` using a frequency of Nano when the index is a `DatetimeIndex` and contains non-zero nanosecond parts (GH12037)
- Bug in resampling with `.nunique` and a sparse index (GH12352)
- Removed some compiler warnings (GH12471)
- Work around compat issues with `boto` in python 3.5 (GH11915)
- Bug in `NaT` subtraction from `Timestamp` or `DatetimeIndex` with timezones (GH11718)
- Bug in subtraction of `Series` of a single tz-aware `Timestamp` (GH12290)
- Use compat iterators in PY2 to support `.next()` (GH12299)
- Bug in `Timedelta.round` with negative values (GH11690)
- Bug in `.loc` against `CategoricalIndex` may result in normal `Index` (GH11586)
- Bug in `DataFrame.info` when duplicated column names exist (GH11761)
- Bug in `.copy` of datetime tz-aware objects (GH11794)
- Bug in `Series.apply` and `Series.map` where `timedelta64` was not boxed (GH11349)
- Bug in `DataFrame.set_index()` with tz-aware `Series` (GH12358)
- Bug in subclasses of `DataFrame` where `AttributeError` did not propagate (GH11808)
- Bug in `DataFrame.set_index()` with tz-aware `Series` (GH12358)
- Bug in `Series.apply` and `Series.map` where `timedelta64` was not boxed (GH11349)
- Bug in `DataFrame.query` containing an assignment (GH8664)
- Bug in `from_msgpack` where `__contains__()` fails for columns of the unpacked `DataFrame`, if the `DataFrame` has object columns. (GH11880)
- Bug in `.resample` on categorical data with `TimedeltaIndex` (GH12169)
- Bug in timezone info lost when broadcasting scalar datetime to `DataFrame` (GH11682)
- Bug in `Index` creation from `Timestamp` with mixed tz coerces to UTC (GH11488)
- Bug in `DataFrame.groupby` using keyword arguments (GH11614)
- Bug in `DataFrame.duplicated` and `drop_duplicates` causing spurious matches when setting `keep=False` (GH11864)
- Bug in `.loc` result with duplicated key may have `Index` with incorrect dtype (GH11497)
- Bug in `pd.rolling_median` where memory allocation failed even with sufficient memory (GH11696)
- Bug in `DataFrame.style` with spurious zeros (GH12134)
- Bug in `DataFrame.style` with integer columns not starting at 0 (GH12125)
- Bug in `.style.bar` may not render properly using specific browser (GH11678)
- Bug in rich comparison of `Timedelta` with a `numpy.array` of `Timedelta` that caused an infinite recursion (GH11835)
- Bug in `DataFrame.round` dropping column index name (GH11986)
- Bug in `df.replace` while replacing value in mixed dtype `DataFrame` (GH11698)
- Bug in `Index` prevents copying name of passed `Index`, when a new name is not provided (GH11933)
- Bug in `read_excel` failing to read any non-empty sheets when empty sheets exist and `sheetname=None` (GH11711)
- Bug in `read_excel` failing to raise `NotImplemented` error when keywords `parse_dates` and `date_parser` are provided (GH11544)
- Bug in `read_sql` with `pymysql` connections failing to return chunked data (GH11522)
- Bug in `.to_csv` ignoring formatting parameters `decimal`, `na_rep`, `float_format` for float indexes (GH11553)
• Bug in Int64Index and Float64Index preventing the use of the modulo operator (GH9244)
• Bug in MultiIndex.drop for not lexsorted MultiIndexes (GH12078)
• Bug in DataFrame when masking an empty DataFrame (GH11859)
• Bug in .plot potentially modifying the colors input when the number of columns didn’t match the number of series provided (GH12039).
• Bug in Series.plot failing when index has a CustomBusinessDay frequency (GH7222).
• Bug in .to_sql for datetime.time values with sqlite fallback (GH8341)
• Bug in read_excel failing to read data with one column when squeeze=True (GH12157)
• Bug in read_excel failing to read one empty column (GH12292, GH9002)
• Bug in .groupby where a KeyError was not raised for a wrong column if there was only one row in the dataframe (GH11741)
• Bug in .read_csv with dtype specified on empty data producing an error (GH12048)
• Bug in .read_csv where strings like ‘2E’ are treated as valid floats (GH12237)
• Bug in building pandas with debugging symbols (GH12123)
• Removed millisecond property of DatetimeIndex. This would always raise a ValueError (GH12019).
• Bug in Series constructor with read-only data (GH11502)
• Removed pandas._testing.choice(). Should use np.random.choice(), instead. (GH12386)
• Bug in .loc setitem indexer preventing the use of a TZ-aware DatetimeIndex (GH12050)
• Bug in .style indexes and MultiIndexes not appearing (GH11655)
• Bug in to_msgpack and from_msgpack which did not correctly serialize or deserialize NaT (GH12307).
• Bug in .skew and .kurt due to roundoff error for highly similar values (GH11974)
• Bug in Timestamp constructor where microsecond resolution was lost if HHMMSS were not separated with ‘:’ (GH10041)
• Bug in buffer_rd_bytes src->buffer could be freed more than once if reading failed, causing a segfault (GH12098)
• Bug in crosstab where arguments with non-overlapping indexes would return a KeyError (GH10291)
• Bug in DataFrame.apply in which reduction was not being prevented for cases in which dtype was not a numpy dttype (GH12244)
• Bug when initializing categorical series with a scalar value. (GH12336)
• Bug when specifying a UTC DatetimeIndex by setting utc=True in .to_datetime (GH11934)
• Bug when increasing the buffer size of CSV reader in read_csv (GH12494)
• Bug when setting columns of a DataFrame with duplicate column names (GH12344)

5.10. Version 0.18
Contributors

A total of 101 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

• ARF +
• Alex Alekseyev +
• Andrew McPherson +
• Andrew Rosenfeld
• Andy Hayden
• Anthonios Partheniou
• Anton I. Sipos
• Ben +
• Ben North +
• Bran Yang +
• Chris
• Chris Carroux +
• Christopher C. Aycock +
• Christopher Scanlin +
• Cody +
• Da Wang +
• Daniel Grady +
• Dorozhko Anton +
• Dr-Irv +
• Erik M. Bray +
• Evan Wright
• Francis T. O’Donovan +
• Frank Cleary +
• Gianluca Rossi
• Graham Jeffries +
• Guillaume Horel
• Henry Hammond +
• Isaac Schwabacher +
• Jean-Mathieu Deschenes
• Jeff Reback
• Joe Jevnik +
• John Freeman +
• John Fremlin +
• Jonas Hoersch +
• Joris Van den Bossche
• Joris Vankerschaver
• Justin Lecher
• Justin Lin +
• Ka Wo Chen
• Keming Zhang +
• Kerby Shedden
• Kyle +
• Marco Farrugia +
• MasonGallo +
• MattRijk +
• Matthew Lurie +
• Maximilian Roos
• Mayank Asthana +
• Mortada Mehyar
• Moussa Taifi +
• Navreet Gill +
• Nicolas Bonnotte
• Paul Reiners +
• Philip Gura +
• Pietro Battiston
• RahulHP +
• Randy Carnevale
• Rinoc Johnson
• Rishipuri +
• Sangmin Park +
• Scott E Lasley
• Sereger13 +
• Shannon Wang +
• Skipper Seabold
• Thierry Moisan
• Thomas A Caswell
• Toby Dylan Hocking +
• Tom Augspurger
• Travis +
5.11 Version 0.17

5.11.1 Version 0.17.1 (November 21, 2015)

Note: We are proud to announce that pandas has become a sponsored project of the (NumFOCUS organization). This will help ensure the success of development of pandas as a world-class open-source project.

This is a minor bug-fix release from 0.17.0 and includes a large number of bug fixes along several new features, enhancements, and performance improvements. We recommend that all users upgrade to this version.

Highlights include:

- Support for Conditional HTML Formatting, see here
- Releasing the GIL on the csv reader & other ops, see here
- Fixed regression in DataFrame.drop_duplicates from 0.16.2, causing incorrect results on integer values (GH11376)

What’s new in v0.17.1

- New features
  - Conditional HTML formatting
- Enhancements
- API changes
  - Deprecations
- Performance improvements
- Bug fixes
- Contributors

New features

Conditional HTML formatting

Warning: This is a new feature and is under active development. We’ll be adding features an possibly making breaking changes in future releases. Feedback is welcome.

We’ve added experimental support for conditional HTML formatting: the visual styling of a DataFrame based on the data. The styling is accomplished with HTML and CSS. Accesses the styler class with the pandas.DataFrame.style, attribute, an instance of Styler with your data attached.

Here’s a quick example:

```python
In [1]: np.random.seed(123)
In [2]: df = pd.DataFrame(np.random.randn(10, 5), columns=list('abcde'))
```
In [3]: html = df.style.background_gradient(cmap='viridis', low=.5)

We can render the HTML to get the following table.
Styler interacts nicely with the Jupyter Notebook. See the documentation for more.

Enhancements

- DatetimeIndex now supports conversion to strings with astype(str) (GH10442)
- Support for compression (gzip/bz2) in pandas.DataFrame.to_csv() (GH7615)
- pd.read_* functions can now also accept pathlib.Path, or py._path.local.LocalPath objects for the filepath_or_buffer argument. (GH11033) - The DataFrame and Series functions .to_csv(), .to_html() and .to_latex() can now handle paths beginning with tildes (e.g. ~/Documents/) (GH11438)
- DataFrame now uses the fields of a namedtuple as columns, if columns are not supplied (GH11181)
- DataFrame.itertuples() now returns namedtuple objects, when possible. (GH11269, GH11625)
- Added axvlines_kwds to parallel coordinates plot (GH10709)
- Option to .info() and .memory_usage() to provide for deep introspection of memory consumption. Note that this can be expensive to compute and therefore is an optional parameter. (GH11595)

In [4]: df = pd.DataFrame({'A': ['foo'] * 1000}) # noqa: F821

In [5]: df['B'] = df['A'].astype('category')

# shows the '+' as we have object dtypes
In [6]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 2 columns):
   # Column Non-Null Count  Dtype
---  ------ -------------- -----  
   0   A     1000 non-null object
   1   B     1000 non-null  category
dtypes: category(1), object(1)
memory usage: 9.0+ KB

# we have an accurate memory assessment (but can be expensive to compute this)
In [7]: df.info(memory_usage='deep')
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 2 columns):
   # Column Non-Null Count  Dtype
---  ------ -------------- -----  
   0   A     1000 non-null object
   1   B     1000 non-null  category
dtypes: category(1), object(1)
memory usage: 75.5 KB

- Index now has a fillna method (GH10089)
pandas: powerful Python data analysis toolkit, Release 1.1.1

In [8]: pd.Index([1, np.nan, 3]).fillna(2)
Out[8]: Float64Index([1.0, 2.0, 3.0], dtype='float64')

• Series of type category now make .str.<...> and .dt.<...> accessor methods / properties available, if the categories are of that type. (GH10661)

In [9]: s = pd.Series(list('aabb')).astype('category')

In [10]: s
Out[10]:    0   a
      1   a
      2   b
      3   b
Length: 4, dtype: category
Categories (2, object): ['a', 'b']

In [11]: s.str.contains("a")
Out[11]:
0   True
1   True
2  False
3  False
Length: 4, dtype: bool

In [12]: date = pd.Series(pd.date_range('1/1/2015', periods=5)).astype('category')

In [13]: date
Out[13]:
0  2015-01-01
1  2015-01-02
2  2015-01-03
3  2015-01-04
4  2015-01-05
Length: 5, dtype: category

In [14]: date.dt.day
Out[14]:
0   1
1   2
2   3
3   4
4   5
Length: 5, dtype: int64

• pivot_table now has a margins_name argument so you can use something other than the default of ‘All’ (GH3335)

• Implement export of datetime64[ns, tz] dtypes with a fixed HDF5 store (GH11411)

• Pretty printing sets (e.g. in DataFrame cells) now uses set literal syntax (\{x, y\}) instead of Legacy Python syntax (set([x, y])) (GH11215)

• Improve the error message in pandas.io.gbq.to_gbq() when a streaming insert fails (GH11285) and when the DataFrame does not match the schema of the destination table (GH11359)
pandas: powerful Python data analysis toolkit, Release 1.1.1

API changes

- raise NotImplementedError in Index.shift for non-supported index types (GH8038)
- min and max reductions on datetime64 and timedelta64 dtyped series now result in NaT and not nan (GH11245).
- Indexing with a null key will raise a TypeError, instead of a ValueError (GH11356)
- Series.ptp will now ignore missing values by default (GH11163)

Deprecations

- The pandas.io.ga module which implements google-analytics support is deprecated and will be removed in a future version (GH11308)
- Deprecate the engine keyword in .to_csv(), which will be removed in a future version (GH11274)

Performance improvements

- Checking monotonic-ness before sorting on an index (GH11080)
- Series.dropna performance improvement when its dtype can’t contain NaN (GH11159)
- Release the GIL on most datetime field operations (e.g. DatetimeIndex.year, Series.dt.year), normalization, and conversion to and from Period, DatetimeIndex.to_period and PeriodIndex.to_timestamp (GH11263)
- Release the GIL on some rolling algs: rolling_median, rolling_mean, rolling_max, rolling_min, rolling_var, rolling_kurt, rolling_skew (GH11450)
- Release the GIL when reading and parsing text files in read_csv, read_table (GH11272)
- Improved performance of rolling_median (GH11450)
- Improved performance of to_excel (GH11352)
- Performance bug in repr of Categorical categories, which was rendering the strings before chopping them for display (GH11305)
- Performance improvement in Categorical.remove_unused_categories, (GH11643).
- Improved performance of Series constructor with no data and DatetimeIndex (GH11433)
- Improved performance of shift, cumprod, and cumsum with groupby (GH4095)

Bug fixes

- SparseArray.__iter__() now does not cause PendingDeprecationWarning in Python 3.5 (GH11622)
- Regression from 0.16.2 for output formatting of long floats/nan, restored in (GH11302)
- Series.sort_index() now correctly handles the inplace option (GH11402)
- Incorrectly distributed .c file in the build on PyPi when reading a csv of floats and passing na_values=<a scalar> would show an exception (GH11374)
- Bug in .to_latex() output broken when the index has a name (GH10660)
- Bug in `HDFStore.append` with strings whose encoded length exceeded the max unencoded length (GH11234)
- Bug in merging `datetime64[ns, tz]` dtypes (GH11405)
- Bug in `HDFStore.select` when comparing with a numpy scalar in a where clause (GH11283)
- Bug in using `DataFrame.ix` with a MultiIndex indexer (GH11372)
- Bug in `date_range` with ambiguous endpoints (GH11626)
- Prevent adding new attributes to the accessors `.str`, `.dt` and `.cat`. Retrieving such a value was not possible, so error out on setting it. (GH10673)
- Bug in `tz-conversions` with an ambiguous time and `.dt` accessors (GH11295)
- Bug in output formatting when using an index of ambiguous times (GH11619)
- Bug in comparisons of Series vs list-likes (GH11339)
- Bug in `DataFrame.replace` with a `datetime64[ns, tz]` and a non-compat to_replace (GH11326, GH11153)
- Bug in `isnull` where `numpy.datetime64('NaT')` in a `numpy.array` was not determined to be null(GH11206)
- Bug in list-like indexing with a mixed-integer Index (GH11320)
- Bug in `pivot_table` with `margins=True` when indexes are of `Categorical` dtype (GH10993)
- Bug in `DataFrame.plot` cannot use hex strings colors (GH10299)
- Regression in `DataFrame.drop_duplicates` from 0.16.2, causing incorrect results on integer values (GH11376)
- Bug in `pd.eval` where unary ops in a list error (GH11235)
- Bug in `squeeze()` with zero length arrays (GH11230, GH8999)
- Bug in `describe()` dropping column names for hierarchical indexes (GH11517)
- Bug in `DataFrame.pct_change()` not propagating `axis` keyword on `.fillna` method (GH11550)
- Bug in `.to_csv()` when a mix of integer and string column names are passed as the `columns` parameter (GH11637)
- Bug in indexing with a range, (GH11652)
- Bug in inference of numpy scalars and preserving `dtype` when setting columns (GH11638)
- Bug in `to_sql` using unicode column names giving `UnicodeEncodeError` with (GH11431).
- Fix regression in setting of `xticks` in `plot` (GH11529).
- Bug in `holiday.dates` where observance rules could not be applied to holiday and doc enhancement (GH11477, GH11533)
- Fix plotting issues when having plain `Axes` instances instead of `SubplotAxes` (GH11520, GH11556).
- Bug in `DataFrame.to_latex()` produces an extra rule when `header=False` (GH7124)
- Bug in `df.groupby(...).apply(func)` when a `func` returns a `Series` containing a new datetimelike column (GH11324)
- Bug in `pandas.json` when file to load is big (GH11344)
- Bugs in `to_excel` with duplicate columns (GH11007, GH10982, GH10970)
- Fixed a bug that prevented the construction of an empty series of `dtype` `datetime64[ns, tz]` (GH11245).
• Bug in `read_excel` with MultiIndex containing integers (GH11317)
• Bug in `to_excel` with openpyxl 2.2+ and merging (GH11408)
• Bug in `DataFrame.to_dict()` produces a `np.datetime64` object instead of `Timestamp` when only datetime is present in data (GH11327)
• Bug in `DataFrame.corr()` raises exception when computes Kendall correlation for DataFrames with boolean and not boolean columns (GH11560)
• Bug in the link-time error caused by C inline functions on FreeBSD 10+ (with clang) (GH10510)
• Bug in `DataFrame.to_csv` in passing through arguments for formatting MultiIndexes, including `date_format` (GH7791)
• Bug in `DataFrame.join()` with `how='right'` producing a TypeError (GH11519)
• Bug in `Series.quantile` with empty list results has `Index` with object dtype (GH11588)
• Bug in `pd.merge` results in empty `Int64Index` rather than `Index(dtype=object)` when the merge result is empty (GH11588)
• Bug in `Categorical.remove_unused_categories` when having NaN values (GH11599)
• Bug in `DataFrame.to_sparse()` loses column names for MultiIndexes (GH11600)
• Bug in `DataFrame.round()` with non-unique column index producing a Fatal Python error (GH11611)
• Bug in `DataFrame.round()` with `decimals` being a non-unique indexed Series producing extra columns (GH11618)

Contributors
A total of 63 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

• Aleksandr Drozd +
• Alex Chase +
• Anthonios Partheniou
• BrenBarn +
• Brian J. McGuirk +
• Chris
• Christian Berendt +
• Christian Perez +
• Cody Piersall +
• Data & Code Expert Experimenting with Code on Data
• DrIrv +
• Evan Wright
• Guillaume Gay
• Hamed Saljooghinejad +
• Iblis Lin +
• Jake VanderPlas
• Jan Schulz
• Jean-Mathieu Deschenes +
• Jeff Reback
• Jimmy Callin +
• Joris Van den Bossche
• K.-Michael Aye
• Ka Wo Chen
• Loïc Séguin-C +
• Luo Yicheng +
• Magnus Jöud +
• Manuel Leonhardt +
• Matthew Gilbert
• Maximilian Roos
• Michael +
• Nicholas Stahl +
• Nicolas Bonnotte +
• Pastafarianist +
• Petra Chong +
• Phil Schaf +
• Philipp A +
• Rob deCarvalho +
• Roman Khomenko +
• Rémy Léone +
• Sebastian Bank +
• Sinhrks
• Stephan Hoyer
• Thierry Moisan
• Tom Augspurger
• Tux1 +
• Varun +
• Wieland Hoffmann +
• Winterflower
• Yoav Ram +
• Younggun Kim
• Zeke +
• ajcr
5.11.2 Version 0.17.0 (October 9, 2015)

This is a major release from 0.16.2 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

**Warning:** pandas >= 0.17.0 will no longer support compatibility with Python version 3.2 (GH9118)

**Warning:** The pandas.io.data package is deprecated and will be replaced by the pandas-datareader package. This will allow the data modules to be independently updated to your pandas installation. The API for pandas-datareader v0.1.1 is exactly the same as in pandas v0.17.0 (GH8961, GH10861).

After installing pandas-datareader, you can easily change your imports:

```python
from pandas.io import data, wb
```

becomes

```python
from pandas_datareader import data, wb
```

Highlights include:

- Release the Global Interpreter Lock (GIL) on some cython operations, see [here](#)
- Plotting methods are now available as attributes of the `.plot` accessor, see [here](#)
- The sorting API has been revamped to remove some long-time inconsistencies, see [here](#)
- Support for a `datetime64[ns]` with timezones as a first-class dtype, see [here](#)
- The default for `to_datetime` will now be to `raise` when presented with unparseable formats, previously this would return the original input. Also, date parse functions now return consistent results. See [here](#)
- The default for dropna in HDFStore has changed to False, to store by default all rows even if they are all NaN, see [here](#)
- Datetime accessor (dt) now supports `Series.dt.strftime` to generate formatted strings for datetime-likes, and `Series.dt.total_seconds` to generate each duration of the timedelta in seconds. See [here](#)
Period and PeriodIndex can handle multiplied freq like 3D, which corresponding to 3 days span. See here

Development installed versions of pandas will now have PEP440 compliant version strings (GH9518)

Development support for benchmarking with the Air Speed Velocity library (GH8361)

Support for reading SAS xport files, see here

Documentation comparing SAS to pandas, see here

Removal of the automatic TimeSeries broadcasting, deprecated since 0.8.0, see here

Display format with plain text can optionally align with Unicode East Asian Width, see here

Compatibility with Python 3.5 (GH11097)

Compatibility with matplotlib 1.5.0 (GH11111)

Check the API Changes and deprecations before updating.

What’s new in v0.17.0

- New features
  - Datetime with TZ
  - Releasing the GIL
  - Plot submethods
  - Additional methods for dt accessor
    - Series.dt.strftime
    - Series.dt.total_seconds
  - Period frequency enhancement
  - Support for SAS XPORT files
  - Support for math functions in .eval()
  - Changes to Excel with MultiIndex
  - Google BigQuery enhancements
  - Display alignment with Unicode East Asian width
  - Other enhancements

- Backwards incompatible API changes
  - Changes to sorting API
  - Changes to to_datetime and to_timedelta
    - Error handling
    - Consistent parsing
  - Changes to Index comparisons
  - Changes to boolean comparisons vs. None
  - HDFStore dropna behavior
  - Changes to display.precision option
  - Changes to Categorical.unique
New features

Datetime with TZ

We are adding an implementation that natively supports datetime with timezones. A Series or a DataFrame column previously could be assigned a datetime with timezones, and would work as an object dtype. This had performance issues with a large number rows. See the docs for more details. (GH8260, GH10763, GH11034).

The new implementation allows for having a single-timezone across all rows, with operations in a performant manner.

```python
In [1]: df = pd.DataFrame({'A': pd.date_range('20130101', periods=3),
                      'B': pd.date_range('20130101', periods=3, tz='US/Eastern'),
                      'C': pd.date_range('20130101', periods=3, tz='CET')})

In [2]: df
Out[2]:
     A          B          C
0 2013-01-01 2013-01-01 00:00:00-05:00 2013-01-01 00:00:00+01:00
1 2013-01-02 2013-01-02 00:00:00-05:00 2013-01-02 00:00:00+01:00
2 2013-01-03 2013-01-03 00:00:00-05:00 2013-01-03 00:00:00+01:00

[3 rows x 3 columns]

In [3]: df.dtypes
Out[3]:
A    datetime64[ns]
B  datetime64[ns, US/Eastern]
C  datetime64[ns, CET]
Length: 3, dtype: object

In [4]: df.B
Out[4]:
0 2013-01-01 00:00:00-05:00
1 2013-01-02 00:00:00-05:00
2 2013-01-03 00:00:00-05:00
Name: B, Length: 3, dtype: datetime64[ns, US/Eastern]

In [5]: df.B.dt.tz_localize(None)
Out[5]:
0 2013-01-01
1 2013-01-02
2 2013-01-03
Name: B, Length: 3, dtype: datetime64[ns]
This uses a new-dtype representation as well, that is very similar in look-and-feel to its numpy cousin `datetime64[ns]`

```
In [6]: df['B'].dtype
Out[6]: datetime64[ns, US/Eastern]
In [7]: type(df['B'].dtype)
Out[7]: pandas.core.dtypes.dtypes.DatetimeTZDtype
```

**Note:** There is a slightly different string repr for the underlying `DatetimeIndex` as a result of the dtype changes, but functionally these are the same.

Previous behavior:

```
In [1]: pd.date_range('20130101', periods=3, tz='US/Eastern')
Out[1]: DatetimeIndex(['2013-01-01 00:00:00-05:00', '2013-01-02 00:00:00-05:00',
  '2013-01-03 00:00:00-05:00'],
  dtype='datetime64[ns]', freq='D', tz='US/Eastern')
In [2]: pd.date_range('20130101', periods=3, tz='US/Eastern').dtype
Out[2]: dtype('<M8[ns]')
```

New behavior:

```
In [8]: pd.date_range('20130101', periods=3, tz='US/Eastern')
Out[8]: DatetimeIndex(['2013-01-01 00:00:00-05:00', '2013-01-02 00:00:00-05:00',
  '2013-01-03 00:00:00-05:00'],
  dtype='datetime64[ns, US/Eastern]', freq='D')
In [9]: pd.date_range('20130101', periods=3, tz='US/Eastern').dtype
Out[9]: datetime64[ns, US/Eastern]
```

### Releasing the GIL

We are releasing the global-interpreter-lock (GIL) on some cython operations. This will allow other threads to run simultaneously during computation, potentially allowing performance improvements from multi-threading. Notably `groupby`, `nsmallest`, `value_counts` and some indexing operations benefit from this. (GH8882)

For example the groupby expression in the following code will have the GIL released during the factorization step, e.g. `df.groupby('key').sum()` as well as the `.sum()` operation.

```
N = 1000000
ngroups = 10
df = DataFrame({'key': np.random.randint(0, ngroups, size=N),
              'data': np.random.randn(N)})
df.groupby('key')['data'].sum()
```

Releasing of the GIL could benefit an application that uses threads for user interactions (e.g. QT), or performing multi-threaded computations. A nice example of a library that can handle these types of computation-in-parallel is the `dask` library.
Plot submethods

The Series and DataFrame .plot() method allows for customizing plot types by supplying the kind keyword arguments. Unfortunately, many of these kinds of plots use different required and optional keyword arguments, which makes it difficult to discover what any given plot kind uses out of the dozens of possible arguments.

To alleviate this issue, we have added a new, optional plotting interface, which exposes each kind of plot as a method of the .plot attribute. Instead of writing series.plot(kind=<kind>, ...), you can now also use series.plot.<kind>(...):

```python
In [10]: df = pd.DataFrame(np.random.rand(10, 2), columns=['a', 'b'])
In [11]: df.plot.bar()
```

As a result of this change, these methods are now all discoverable via tab-completion:

```python
In [12]: df.plot.<TAB>  # noqa: E225, E999
    df.plot.area  df.plot.barh  df.plot.density  df.plot.hist  df.plot.line
    df.plot.scatter
    df.plot.bar  df.plot.box  df.plot.hexbin  df.plot.kde  df.plot.pie
```

Each method signature only includes relevant arguments. Currently, these are limited to required arguments, but in the future these will include optional arguments, as well. For an overview, see the new Plotting API documentation.

Additional methods for dt accessor

Series.dt.strftime

We are now supporting a Series.dt.strftime method for datetime-likes to generate a formatted string (GH10110). Examples:

```python
# DatetimeIndex
In [13]: s = pd.Series(pd.date_range('20130101', periods=4))

In [14]: s
Out[14]:
0    2013-01-01
```

(continues on next page)
In [15]: s.dt.strftime('%Y/%m/%d')

Out[15]:
0  2013/01/01
1  2013/01/02
2  2013/01/03
3  2013/01/04
Length: 4, dtype: object

# PeriodIndex
In [16]: s = pd.Series(pd.period_range('20130101', periods=4))

In [17]: s
Out[17]:
0  2013-01-01
1  2013-01-02
2  2013-01-03
3  2013-01-04
Length: 4, dtype: period[D]

In [18]: s.dt.strftime('%Y/%m/%d')
Out[18]:
0  2013/01/01
1  2013/01/02
2  2013/01/03
3  2013/01/04
Length: 4, dtype: object

The string format is as the python standard library and details can be found here

**Series.dt.total_seconds**

pd.Series of type timedelta64 has new method .dt.total_seconds() returning the duration of the timedelta in seconds (GH10817)

# TimedeltaIndex
In [19]: s = pd.Series(pd.timedelta_range('1 minutes', periods=4))

In [20]: s
Out[20]:
0  0 days 00:01:00
1  1 days 00:01:00
2  2 days 00:01:00
3  3 days 00:01:00
Length: 4, dtype: timedelta64[ns]

In [21]: s.dt.total_seconds()
Out[21]:
0   60.0
1  86460.0
2 172860.0

Period frequency enhancement

Period, PeriodIndex and period_range can now accept multiplied freq. Also, Period.freq and PeriodIndex.freq are now stored as a DateOffset instance like DatetimeIndex, and not as str (GH7811)

A multiplied freq represents a span of corresponding length. The example below creates a period of 3 days. Addition and subtraction will shift the period by its span.

```
In [22]: p = pd.Period('2015-08-01', freq='3D')
In [23]: p
Out[23]: Period('2015-08-01', '3D')
In [24]: p + 1
Out[24]: Period('2015-08-04', '3D')
In [25]: p - 2
Out[25]: Period('2015-07-26', '3D')
In [26]: p.to_timestamp()
Out[26]: Timestamp('2015-08-01 00:00:00')
In [27]: p.to_timestamp(how='E')
Out[27]: Timestamp('2015-08-03 23:59:59.999999999')
```

You can use the multiplied freq in PeriodIndex and period_range.

```
In [28]: idx = pd.period_range('2015-08-01', periods=4, freq='2D')
In [29]: idx
Out[29]: PeriodIndex(['2015-08-01', '2015-08-03', '2015-08-05', '2015-08-07'], dtype='period[2D]', freq='2D')
In [30]: idx + 1
Out[30]: PeriodIndex(['2015-08-03', '2015-08-05', '2015-08-07', '2015-08-09'], dtype='period[2D]', freq='2D')
```

Support for SAS XPORT files

`read_sas()` provides support for reading SAS XPORT format files. (GH4052).

```
df = pd.read_sas('sas_xport.xpt')
```

It is also possible to obtain an iterator and read an XPORT file incrementally.

```
for df in pd.read_sas('sas_xport.xpt', chunksize=10000):
    do_something(df)
```

See the docs for more details.
Support for math functions in .eval()

.eval() now supports calling math functions (GH4893)

```python
df = pd.DataFrame({'a': np.random.randn(10)})
df.eval("b = sin(a)")
```

The support math functions are \( \sin, \cos, \exp, \log, \expm1, \log1p, \sqrt, \sinh, \cosh, \tanh, \arcsin, \arccos, \arctan, \arccosh, \arcsinh, \arctanh, \text{abs} \) and \( \arctan2 \).

These functions map to the intrinsics for the NumExpr engine. For the Python engine, they are mapped to NumPy calls.

Changes to Excel with MultiIndex

In version 0.16.2 a DataFrame with MultiIndex columns could not be written to Excel via `to_excel`. That functionality has been added (GH10564), along with updating `read_excel` so that the data can be read back with, no loss of information, by specifying which columns/rows make up the MultiIndex in the `header` and `index_col` parameters (GH4679)

See the documentation for more details.

```python
In [31]: df = pd.DataFrame([[1, 2, 3, 4], [5, 6, 7, 8]],
                        columns=pd.MultiIndex.from_product(
                        [[['foo', 'bar'], ['a', 'b']], names=['col1', 'col2']]),
                        index=pd.MultiIndex.from_product([[1], ['j', 'k']],
                        names=['i1', 'i2']))

In [32]: df
Out[32]:
     col1  foo  bar
   col2  a  b  a  b
     i1  j  k
j  1  1  2  3  4
k  5  6  7  8
[2 rows x 4 columns]

In [33]: df.to_excel('test.xlsx')

In [34]: df = pd.read_excel('test.xlsx', header=[0, 1], index_col=[0, 1])

In [35]: df
Out[35]:
     col1  foo  bar
   col2  a  b  a  b
     i1  j  k
j  1  1  2  3  4
k  5  6  7  8
[2 rows x 4 columns]
```

Previously, it was necessary to specify the `has_index_names` argument in `read_excel`, if the serialized data had index names. For version 0.17.0 the output format of `to_excel` has been changed to make this keyword unnecessary - the change is shown below.
Old

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>idx_name</td>
<td>A</td>
<td>B</td>
<td>C</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td>2000-01-07 00:00:00</td>
<td>0.968129</td>
<td>0.906529</td>
<td>0.05343</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>2000-01-10 00:00:00</td>
<td>-0.16632</td>
<td>1.981993</td>
<td>1.833093</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>2000-01-11 00:00:00</td>
<td>0.121057</td>
<td>0.36946</td>
<td>-0.02888</td>
</tr>
<tr>
<td>6</td>
<td></td>
<td>2000-01-12 00:00:00</td>
<td>-1.70456</td>
<td>-0.73098</td>
<td>-0.38088</td>
</tr>
<tr>
<td>7</td>
<td></td>
<td>2000-01-13 00:00:00</td>
<td>-1.20024</td>
<td>1.907733</td>
<td>0.629318</td>
</tr>
<tr>
<td>8</td>
<td></td>
<td>2000-01-14 00:00:00</td>
<td>-0.66344</td>
<td>0.073188</td>
<td>1.583482</td>
</tr>
<tr>
<td>9</td>
<td></td>
<td>2000-01-17 00:00:00</td>
<td>0.716635</td>
<td>-2.07952</td>
<td>1.760536</td>
</tr>
</tbody>
</table>

New

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>idx_name</td>
<td>A</td>
<td>B</td>
<td>C</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td>2000-01-07 00:00:00</td>
<td>0.968129</td>
<td>0.906529</td>
<td>0.05343</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>2000-01-10 00:00:00</td>
<td>-0.16632</td>
<td>1.981993</td>
<td>1.833093</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td>2000-01-11 00:00:00</td>
<td>0.121057</td>
<td>0.36946</td>
<td>-0.02888</td>
</tr>
<tr>
<td>6</td>
<td></td>
<td>2000-01-12 00:00:00</td>
<td>-1.70456</td>
<td>-0.73098</td>
<td>-0.38088</td>
</tr>
<tr>
<td>7</td>
<td></td>
<td>2000-01-13 00:00:00</td>
<td>-1.20024</td>
<td>1.907733</td>
<td>0.629318</td>
</tr>
<tr>
<td>8</td>
<td></td>
<td>2000-01-14 00:00:00</td>
<td>-0.66344</td>
<td>0.073188</td>
<td>1.583482</td>
</tr>
<tr>
<td>9</td>
<td></td>
<td>2000-01-17 00:00:00</td>
<td>0.716635</td>
<td>-2.07952</td>
<td>1.760536</td>
</tr>
</tbody>
</table>

**Warning:** Excel files saved in version 0.16.2 or prior that had index names will still able to be read in, but the `has_index_names` argument must specified to `True`.

**Google BigQuery enhancements**

- Added ability to automatically create a table/dataset using the `pandas.io.gbq.to_gbq()` function if the destination table/dataset does not exist. *(GH8325, GH11121).*
- Added ability to replace an existing table and schema when calling the `pandas.io.gbq.to_gbq()` function via the `if_exists` argument. See the docs for more details *(GH8325).*
- `InvalidColumnOrder` and `InvalidPageToken` in the `gbq` module will raise `ValueError` instead of `IOError`.
- The `generate_bq_schema()` function is now deprecated and will be removed in a future version *(GH11121)*
- The `gbq` module will now support Python 3 *(GH11094).*
Display alignment with Unicode East Asian width

**Warning:** Enabling this option will affect the performance for printing of DataFrame and Series (about 2 times slower). Use only when it is actually required.

Some East Asian countries use Unicode characters its width is corresponding to 2 alphabets. If a DataFrame or Series contains these characters, the default output cannot be aligned properly. The following options are added to enable precise handling for these characters.

- `display.unicode.east_asian_width`: Whether to use the Unicode East Asian Width to calculate the display text width. (GH2612)
- `display.unicode.ambiguous_as_wide`: Whether to handle Unicode characters belong to Ambiguous as Wide. (GH11102)

```python
In [36]: df = pd.DataFrame({'UK': ['UK', ''], 'Alice': ['Alice', '']})
In [37]: df
```

<table>
<thead>
<tr>
<th>0</th>
<th>Alice</th>
<th>UK</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

```python
In [38]: pd.set_option('display.unicode.east_asian_width', True)
In [39]: df
```

<table>
<thead>
<tr>
<th>0</th>
<th>Alice</th>
<th>UK</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

For further details, see [here](#)

**Other enhancements**

- Support for openpyxl >= 2.2. The API for style support is now stable (GH10125)
- `merge` now accepts the argument `indicator` which adds a Categorical-type column (by default called `_merge`) to the output object that takes on the values (GH8790)

<table>
<thead>
<tr>
<th>Observation Origin</th>
<th>_merge value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Merge key only in 'left' frame</td>
<td>left_only</td>
</tr>
<tr>
<td>Merge key only in 'right' frame</td>
<td>right_only</td>
</tr>
<tr>
<td>Merge key in both frames</td>
<td>both</td>
</tr>
</tbody>
</table>

```python
In [40]: df1 = pd.DataFrame({'col1':[0,1], 'col_left': ['a','b']})
In [41]: df2 = pd.DataFrame({'col1':[1,2,2],'col_right': [2,2,2]})
```

(continues on next page)
In [42]: pd.merge(df1, df2, on='col1', how='outer', indicator=True)
Out[42]:
   col1 col_left col_right  _merge
0    0      a       NaN   left_only
1    1      b       2.0    both
2    2     NaN       2.0  right_only
3    2     NaN       2.0  right_only
[4 rows x 4 columns]

For more, see the updated docs
• `pd.to_numeric` is a new function to coerce strings to numbers (possibly with coercion) (GH11133)
• `pd.merge` will now allow duplicate column names if they are not merged upon (GH10639).
• `pd.pivot` will now allow passing index as None (GH3962).
• `pd.concat` will now use existing Series names if provided (GH10698).

In [43]: foo = pd.Series([1, 2], name='foo')
In [44]: bar = pd.Series([1, 2])
In [45]: baz = pd.Series([4, 5])

Previous behavior:
In [1]: pd.concat([foo, bar, baz], 1)
Out[1]:
   0 1 2
0  1 1 4
1  2 2 5

New behavior:
In [46]: pd.concat([foo, bar, baz], 1)
Out[46]:
   foo  0 1
   0   1 1 4
   1   2 2 5
[2 rows x 3 columns]

• DataFrame has gained the `nlargest` and `nsmallest` methods (GH10393)
• Add a `limit_direction` keyword argument that works with `limit` to enable `interpolate` to fill NaN values forward, backward, or both (GH9218, GH10420, GH11115)

In [47]: ser = pd.Series([np.nan, np.nan, 5, np.nan, np.nan, np.nan, 13])
In [48]: ser.interpolate(limit=1, limit_direction='both')
Out[48]:
0   NaN
1   5.0
2   5.0
3   7.0
4   NaN
(continues on next page)
- Added a `DataFrame.round` method to round the values to a variable number of decimal places (GH10568).

```python
In [49]: df = pd.DataFrame(np.random.random([3, 3]),
                   ....:     columns=['A', 'B', 'C'],
                   ....:     index=['first', 'second', 'third'])

In [50]: df
Out[50]:
   A    B    C
first  0.126970  0.966718  0.260476
second  0.897237  0.376750  0.336222
third  0.451376  0.840255  0.123102
[3 rows x 3 columns]
In [51]: df.round(2)
Out[51]:
   A    B    C
first  0.13  0.97  0.26
second  0.90  0.38  0.34
third  0.45  0.84  0.12
[3 rows x 3 columns]
In [52]: df.round({'A': 0, 'C': 2})
Out[52]:
   A    B    C
first  0.0  0.966718  0.26
second  1.0  0.376750  0.34
third  0.0  0.840255  0.12
[3 rows x 3 columns]
```

- `drop_duplicates` and `duplicated` now accept a `keep` keyword to target first, last, and all duplicates. The `take_last` keyword is deprecated, see here (GH6511, GH8505)

```python
In [53]: s = pd.Series(['A', 'B', 'C', 'A', 'B', 'D'])
In [54]: s.drop_duplicates()
Out[54]:
   0  A
   1  B
   2  C
   5  D
Length: 4, dtype: object
In [55]: s.drop_duplicates(keep='last')
Out[55]:
   2  C
   3  A
   4  B
(continues on next page)
Reindex now has a `tolerance` argument that allows for finer control of *Limits on filling while reindexing* (GH10411):

```python
In [57]: df = pd.DataFrame({'x': range(5),
                      ....:           't': pd.date_range('2000-01-01', periods=5)})

In [58]: df.reindex([0.1, 1.9, 3.5],
                ....:       method='nearest',
                ....:       tolerance=0.2)

Out[58]:
          x  t
0.1  0.0 2000-01-01
1.9  2.0 2000-01-03
3.5  NaN NaT

[3 rows x 2 columns]
```

When used on a DatetimeIndex, TimedeltaIndex or PeriodIndex, `tolerance` will coerced into a Timedelta if possible. This allows you to specify tolerance with a string:

```python
In [59]: df = df.set_index('t')

In [60]: df.reindex(pd.to_datetime(['1999-12-31']),
                 ....:       method='nearest',
                 ....:       tolerance='1 day')

Out[60]:
          x
1999-12-31  0

[1 rows x 1 columns]
```

tolerance is also exposed by the lower level `Index.get_indexer` and `Index.get_loc` methods.

- Added functionality to use the `base` argument when resampling a TimeDeltaIndex (GH10530)
- DatetimeIndex can be instantiated using strings contains NaT (GH7599)
- `to_datetime` can now accept the `yearfirst` keyword (GH7599)
- `pandas.tseries.offsets` larger than the Day offset can now be used with a Series for addition/subtraction (GH10699). See the docs for more details.
- `pd.Timedelta.total_seconds()` now returns Timedelta duration to ns precision (previously microsecond precision) (GH10939)
- `PeriodIndex` now supports arithmetic with np.ndarray (GH10638)
• Support pickling of Period objects (GH10439)
• .as_blocks will now take a copy optional argument to return a copy of the data, default is to copy (no change in behavior from prior versions), (GH9607)
• regex argument to DataFrame.filter now handles numeric column names instead of raising ValueError (GH10384).
• Enable reading gzip compressed files via URL, either by explicitly setting the compression parameter or by inferring from the presence of the HTTP Content-Encoding header in the response (GH8685)
• Enable writing Excel files in memory using StringIO/BytesIO (GH7074)
• Enable serialization of lists and dicts to strings in ExcelWriter (GH8188)
• SQL io functions now accept a SQLAlchemy connectable. (GH7877)
• pd.read_sql and to_sql can accept database URI as con parameter (GH10214)
• read_sql_table will now allow reading from views (GH10750).
• Enable writing complex values to HDFStores when using the table format (GH10447)
• Enable pd.read_hdf to be used without specifying a key when the HDF file contains a single dataset (GH10443)
• pd.read stata will now read Stata 118 type files. (GH9882)
• msgpack submodule has been updated to 0.4.6 with backward compatibility (GH10581)
• DataFrame.to_dict now accepts orient='index' keyword argument (GH10844).
• DataFrame.apply will return a Series of dicts if the passed function returns a dict and reduce=True (GH8735).
• Allow passing kwargs to the interpolation methods (GH10378).
• Improved error message when concatenating an empty iterable of Dataframe objects (GH9157)
• pd.read_csv can now read bz2-compressed files incrementally, and the C parser can read bz2-compressed files from AWS S3 (GH11070, GH11072).
  • In pd.read_csv, recognize s3n:// and s3a:// URLs as designating S3 file storage (GH11070, GH11071).
  • Read CSV files from AWS S3 incrementally, instead of first downloading the entire file. (Full file download still required for compressed files in Python 2.) (GH11070, GH11073)
  • pd.read_csv is now able to infer compression type for files read from AWS S3 storage (GH11070, GH11074).

Backwards incompatible API changes

Changes to sorting API

The sorting API has had some longtime inconsistencies. (GH9816, GH8239).
Here is a summary of the API PRIOR to 0.17.0:
• Series.sort is INPLACE while DataFrame.sort returns a new object.
• Series.order returns a new object
• It was possible to use Series/DataFrame.sort_index to sort by values by passing the by keyword.
Series/DataFrame.sortlevel worked only on a MultiIndex for sorting by index.

To address these issues, we have revamped the API:

- We have introduced a new method, `DataFrame.sort_values()`, which is the merger of `DataFrame.sort()`, `Series.sort()`, and `Series.order()`, to handle sorting of values.
- The existing methods `Series.sort()`, `Series.order()`, and `DataFrame.sort()` have been deprecated and will be removed in a future version.
- The `by` argument of `DataFrame.sort_index()` has been deprecated and will be removed in a future version.
- The existing method `.sort_index()` will gain the `level` keyword to enable level sorting.

We now have two distinct and non-overlapping methods of sorting. A * marks items that will show a `FutureWarning`.

To sort by the values:

<table>
<thead>
<tr>
<th>Previous</th>
<th>Replacement</th>
</tr>
</thead>
<tbody>
<tr>
<td>*Series.order()</td>
<td>Series.sort_values()</td>
</tr>
<tr>
<td>*Series.sort()</td>
<td>Series.sort_values(inplace=True)</td>
</tr>
<tr>
<td>*DataFrame.sort(columns=...)</td>
<td>DataFrame.sort_values(by=...)</td>
</tr>
</tbody>
</table>

To sort by the index:

<table>
<thead>
<tr>
<th>Previous</th>
<th>Replacement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.sort_index()</td>
<td>Series.sort_index()</td>
</tr>
<tr>
<td>Series.sortlevel(level=...)</td>
<td>Series.sort_index(level=...)</td>
</tr>
<tr>
<td>DataFrame.sort_index()</td>
<td>DataFrame.sort_index()</td>
</tr>
<tr>
<td>DataFrame.sortlevel(level=...)</td>
<td>DataFrame.sort_index(level=...)</td>
</tr>
<tr>
<td>*DataFrame.sort()</td>
<td>DataFrame.sort_index()</td>
</tr>
</tbody>
</table>

We have also deprecated and changed similar methods in two Series-like classes, Index and Categorical.

<table>
<thead>
<tr>
<th>Previous</th>
<th>Replacement</th>
</tr>
</thead>
<tbody>
<tr>
<td>*Index.order()</td>
<td>Index.sort_values()</td>
</tr>
<tr>
<td>*Categorical.order()</td>
<td>Categorical.sort_values()</td>
</tr>
</tbody>
</table>

### Changes to `to_datetime` and `to_timedelta`

#### Error handling

The default for `pd.to_datetime` error handling has changed to `errors='raise'`. In prior versions it was `errors='ignore'`. Furthermore, the `coerce` argument has been deprecated in favor of `errors='coerce'`. This means that invalid parsing will raise rather that return the original input as in previous versions. (GH10636)

Previous behavior:

```
In [2]: pd.to_datetime(['2009-07-31', 'asd'])
Out[2]: array(['2009-07-31', 'asd'], dtype=object)
```

New behavior:

```
In [2]: pd.to_datetime(['2009-07-31', 'asd'], errors='raise')
```
In [3]: pd.to_datetime(['2009-07-31', 'asd'])
ValueError: Unknown string format

Of course you can coerce this as well.

In [61]: pd.to_datetime(['2009-07-31', 'asd'], errors='coerce')
Out[61]: DatetimeIndex(['2009-07-31', 'NaT'], dtype='datetime64[ns]', freq=None)

To keep the previous behavior, you can use errors='ignore':

In [62]: pd.to_datetime(['2009-07-31', 'asd'], errors='ignore')
Out[62]: Index(['2009-07-31', 'asd'], dtype='object')

Furthermore, pd.to_timedelta has gained a similar API, of errors='raise'|'ignore'|'coerce', and the coerce keyword has been deprecated in favor of errors='coerce'.

Consistent parsing

The string parsing of to_datetime, Timestamp and DatetimeIndex has been made consistent. (GH7599)

Prior to v0.17.0, Timestamp and to_datetime may parse year-only datetime-string incorrectly using today's date, otherwise DatetimeIndex uses the beginning of the year. Timestamp and to_datetime may raise ValueError in some types of datetime-string which DatetimeIndex can parse, such as a quarterly string.

Previous behavior:

In [1]: pd.Timestamp('2012Q2')
ValueError: Unable to parse 2012Q2
...
# Results in today's date.
In [2]: pd.Timestamp('2014')
Out [2]: 2014-08-12 00:00:00

v0.17.0 can parse them as below. It works on DatetimeIndex also.

New behavior:

In [63]: pd.Timestamp('2012Q2')
Out[63]: Timestamp('2012-04-01 00:00:00')

In [64]: pd.Timestamp('2014')
Out[64]: Timestamp('2014-01-01 00:00:00')

In [65]: pd.DatetimeIndex(['2012Q2', '2014'])
Out[65]: DatetimeIndex(['2012-04-01', '2014-01-01'], dtype='datetime64[ns]',
˓ freq=None)

Note: If you want to perform calculations based on today’s date, use Timestamp.now() and pandas.tseries.offsets.

In [66]: import pandas.tseries.offsets as offsets

In [67]: pd.Timestamp.now()
Changes to Index comparisons

Operator equal on Index should behavior similarly to Series (GH9947, GH10637)

Starting in v0.17.0, comparing Index objects of different lengths will raise a ValueError. This is to be consistent with the behavior of Series.

Previous behavior:

```python
In [2]: pd.Index([1, 2, 3]) == pd.Index([1, 4, 5])
Out[2]: array([ True, False, False], dtype=bool)

In [3]: pd.Index([1, 2, 3]) == pd.Index([2])
Out[3]: array([False, True, False], dtype=bool)

In [4]: pd.Index([1, 2, 3]) == pd.Index([1, 2])
Out[4]: False
```

New behavior:

```python
In [8]: pd.Index([1, 2, 3]) == pd.Index([1, 4, 5])
Out[8]: array([ True, False, False], dtype=bool)

In [9]: pd.Index([1, 2, 3]) == pd.Index([2])
ValueError: Lengths must match to compare

In [10]: pd.Index([1, 2, 3]) == pd.Index([1, 2])
ValueError: Lengths must match to compare
```

Note that this is different from the numpy behavior where a comparison can be broadcast:

```python
In [69]: np.array([1, 2, 3]) == np.array([1])
Out[69]: array([ True, False, False])
```

or it can return False if broadcasting can not be done:

```python
In [70]: np.array([1, 2, 3]) == np.array([1, 2])
Out[70]: False
```
Changes to boolean comparisons vs. None

Boolean comparisons of a Series vs None will now be equivalent to comparing with np.nan, rather than raise TypeError. (GH1079).

```python
In [71]: s = pd.Series(range(3))
In [72]: s.iloc[1] = None
In [73]: s
Out[73]:
0  0.0
1  NaN
2  2.0
Length: 3, dtype: float64
```

Previous behavior:

```python
In [5]: s == None
TypeError: Could not compare <type 'NoneType'> type with Series
```

New behavior:

```python
In [74]: s == None
Out[74]:
0  False
1  False
2  False
Length: 3, dtype: bool
```

Usually you simply want to know which values are null.

```python
In [75]: s.isnull()
Out[75]:
0  False
1  True
2  False
Length: 3, dtype: bool
```

**Warning:** You generally will want to use isnull/notnull for these types of comparisons, as isnull/notnull tells you which elements are null. One has to be mindful that nan's don’t compare equal, but None's do. Note that Pandas/numpy uses the fact that np.nan != np.nan, and treats None like np.nan.

```python
In [76]: None == None
Out[76]: True
In [77]: np.nan == np.nan
Out[77]: False
```
HDFStore dropna behavior

The default behavior for HDFStore write functions with `format='table'` is now to keep rows that are all missing. Previously, the behavior was to drop rows that were all missing save the index. The previous behavior can be replicated using the `dropna=True` option. (GH9382)

Previous behavior:

```
In [78]: df_with_missing = pd.DataFrame({'col1': [0, np.nan, 2],
       ....:       'col2': [1, np.nan, np.nan]})

In [79]: df_with_missing
Out[79]:
   col1  col2
0   0.0  1.0
1   NaN  NaN
2   2.0  NaN

[3 rows x 2 columns]
```

```
In [27]:
    df_with_missing.to_hdf('file.h5',
                        'df_with_missing',
                        format='table',
                        mode='w')

In [28]:
    pd.read_hdf('file.h5', 'df_with_missing')
Out[28]:
   col1  col2
0    0   1.0
2    2   NaN
```

New behavior:

```
In [80]:
    df_with_missing.to_hdf('file.h5',
                        'df_with_missing',
                        format='table',
                        mode='w')

In [81]:
    pd.read_hdf('file.h5', 'df_with_missing')
Out[81]:
   col1  col2
0    0   1.0
1   NaN  NaN
2    2   NaN

[3 rows x 2 columns]
```

See the docs for more details.
Changes to display.precision option

The display.precision option has been clarified to refer to decimal places (GH10451).

Earlier versions of pandas would format floating point numbers to have one less decimal place than the value in display.precision.

In [1]: pd.set_option('display.precision', 2)
In [2]: pd.DataFrame({'x': [123.456789]})
Out[2]:
    x
0  123.5

If interpreting precision as “significant figures” this did work for scientific notation but that same interpretation did not work for values with standard formatting. It was also out of step with how numpy handles formatting.

Going forward the value of display.precision will directly control the number of places after the decimal, for regular formatting as well as scientific notation, similar to how numpy’s precision print option works.

In [82]: pd.set_option('display.precision', 2)
In [83]: pd.DataFrame({'x': [123.456789]})
Out[83]:
    x
0  123.46

To preserve output behavior with prior versions the default value of display.precision has been reduced to 6 from 7.

Changes to Categorical.unique

Categorical.unique now returns new Categoricals with categories and codes that are unique, rather than returning np.array (GH10508)

- unordered category: values and categories are sorted by appearance order.
- ordered category: values are sorted by appearance order, categories keep existing order.

In [84]: cat = pd.Categorical(['C', 'A', 'B', 'C'],
                    categories=['A', 'B', 'C'],
                    ordered=True)
In [85]: cat
Out[85]:
['C', 'A', 'B', 'C']
Categories (3, object): ['A' < 'B' < 'C']

In [86]: cat.unique()
Out[86]:
['C', 'A', 'B']
Categories (3, object): ['A' < 'B' < 'C']

In [87]: cat = pd.Categorical(['C', 'A', 'B', 'C'],
                    categories=['A', 'B', 'C'],
                    ordered=True)
Changes to bool passed as header in parsers

In earlier versions of pandas, if a bool was passed the header argument of read_csv, read_excel, or read_html it was implicitly converted to an integer, resulting in header=0 for False and header=1 for True (GH6113)

A bool input to header will now raise a TypeError

Other API changes

- Line and kde plot with subplots=True now uses default colors, not all black. Specify color='k' to draw all lines in black (GH9894)
- Calling the .value_counts() method on a Series with a categorical dtype now returns a Series with a CategoricalIndex (GH10704)
- The metadata properties of subclasses of pandas objects will now be serialized (GH10553).
- groupby using Categorical follows the same rule as Categorical.unique described above (GH10508)
- When constructing DataFrame with an array of complex64 dtype previously meant the corresponding column was automatically promoted to the complex128 dtype. Pandas will now preserve the itemsize of the input for complex data (GH10952)
- some numeric reduction operators would return ValueError, rather than TypeError on object types that includes strings and numbers (GH11131)
- Passing currently unsupported chunksize argument to read_excel or ExcelFile.parse will now raise NotImplementedError (GH8011)
- Allow an ExcelFile object to be passed into read_excel (GH11198)
- DatetimeIndex.union does not infer freq if self and the input have None as freq (GH11086)
- NaT’s methods now either raise ValueError, or return np.nan or NaT (GH9513)
## Deprecations

- For **Series** the following indexing functions are deprecated (GH10177).

<table>
<thead>
<tr>
<th>Deprecated Function</th>
<th>Replacement</th>
</tr>
</thead>
<tbody>
<tr>
<td>.irow(i)</td>
<td>.iloc[i] or .iat[i]</td>
</tr>
<tr>
<td>.iget(i)</td>
<td>.iloc[i] or .iat[i]</td>
</tr>
<tr>
<td>.iget_value(i)</td>
<td>.iloc[i] or .iat[i]</td>
</tr>
</tbody>
</table>

- For **DataFrame** the following indexing functions are deprecated (GH10177).

<table>
<thead>
<tr>
<th>Deprecated Function</th>
<th>Replacement</th>
</tr>
</thead>
<tbody>
<tr>
<td>.irow(i)</td>
<td>.iloc[i]</td>
</tr>
<tr>
<td>.iget_value(i, j)</td>
<td>.iloc[i, j] or .iat[i, j]</td>
</tr>
<tr>
<td>.icol(j)</td>
<td>.iloc[:, j]</td>
</tr>
</tbody>
</table>

**Note:** These indexing function have been deprecated in the documentation since 0.11.0.

- **Categorical.name** was deprecated to make **Categorical** more **numpy.ndarray** like. Use `Series(cat, name="whatever")` instead (GH10482).

- Setting missing values (NaN) in a **Categorical**'s categories will issue a warning (GH10748). You can still have missing values in the values.

- **drop_duplicates** and **duplicated**'s *take_last* keyword was deprecated in favor of **keep**. (GH6511, GH8505)

- **Series.nsmallest** and **nlargest**'s *take_last* keyword was deprecated in favor of **keep**. (GH10792)

- **DataFrame.combineAdd** and **DataFrame.combineMult** are deprecated. They can easily be replaced by using the add and mul methods: `DataFrame.add(other, fill_value=0)` and `DataFrame.mul(other, fill_value=1.)` (GH10735).

- **TimeSeries** deprecated in favor of **Series** (note that this has been an alias since 0.13.0), (GH10890)

- **SparsePanel** deprecated and will be removed in a future version (GH11157).

- **Series.is_time_series** deprecated in favor of **Series.index.is_all_dates** (GH11135)

- **Legacy offsets** (like 'A@JAN') are deprecated (note that this has been alias since 0.8.0) (GH10878)

- **WidePanel** deprecated in favor of **Panel**, **LongPanel** in favor of **DataFrame** (note these have been aliases since < 0.11.0), (GH10892)

- **DataFrame.convert_objects** has been deprecated in favor of type-specific functions `pd.to_datetime`, `pd.to_timestamp` and `pd.to_numeric` (new in 0.17.0) (GH11133).
Removal of prior version deprecations/changes

- Removal of `na_last` parameters from `Series.order()` and `Series.sort()`, in favor of `na_position`. (GH5231)
- Remove of `percentile_width` from `.describe()`, in favor of `percentiles`. (GH7088)
- Removal of `colSpace` parameter from `DataFrame.to_string()`, in favor of `col_space`, circa 0.8.0 version.
- Removal of automatic time-series broadcasting (GH2304)

```python
In [90]: np.random.seed(1234)
In [91]: df = pd.DataFrame(np.random.randn(5, 2),
                columns=list('AB'),
                index=pd.date_range('2013-01-01', periods=5))

In [92]: df
Out[92]:
     A          B
2013-01-01  0.471435 -1.190976
2013-01-02  1.432707 -0.312652
2013-01-03 -0.720589  0.887163
2013-01-04  0.859588 -0.636524
2013-01-05  0.015696 -2.242685
[5 rows x 2 columns]

Previously

```python
In [3]: df + df.A
FutureWarning: TimeSeries broadcasting along DataFrame index by default is deprecated.
Please use DataFrame.<op> to explicitly broadcast arithmetic operations along the index
Out[3]:
     A          B
2013-01-01  0.942870 -0.719541
2013-01-02  2.865414  1.120055
2013-01-03 -1.441177  0.166574
2013-01-04  1.719177  0.223065
2013-01-05  0.031393 -2.226989

Current

```python
In [93]: df.add(df.A, axis='index')
Out[93]:
     A          B
2013-01-01  0.942870 -0.719541
2013-01-02  2.865414  1.120055
2013-01-03 -1.441177  0.166574
2013-01-04  1.719177  0.223065
2013-01-05  0.031393 -2.226989
[5 rows x 2 columns]
• Remove table keyword in HDFStore.put/append, in favor of using format= (GH4645)
• Remove kind in read_excel/ExcelFile as its unused (GH4712)
• Remove infer_type keyword from pd.read_html as its unused (GH4770, GH7032)
• Remove offset and timeRule keywords from Series.tshift/shift, in favor of freq (GH4853, GH4864)
• Remove pd.load/pd.save aliases in favor of pd.to_pickle/pd.read_pickle (GH3787)

**Performance improvements**

• Development support for benchmarking with the Air Speed Velocity library (GH8361)
• Added vbench benchmarks for alternative ExcelWriter engines and reading Excel files (GH7171)
• Performance improvements in Categorical.value_counts (GH10804)
• Performance improvements in SeriesGroupBy.nunique and SeriesGroupBy.value_counts and SeriesGroupby.transform (GH10820, GH11077)
• Performance improvements in DataFrame.drop_duplicates with integer dtypes (GH10917)
• Performance improvements in DataFrame.duplicated with wide frames. (GH10161, GH11180)
• 4x improvement in timedelta string parsing (GH6755, GH10426)
• 8x improvement in timedelta64 and datetime64 ops (GH6755)
• Significantly improved performance of indexing MultiIndex with slicers (GH10287)
• 8x improvement in iloc using list-like input (GH10791)
• Improved performance of Series.isin for datetimelike/integer Series (GH10287)
• 20x improvement in concat of Categoricals when categories are identical (GH10587)
• Improved performance of to_datetime when specified format string is ISO8601 (GH10178)
• 2x improvement of Series.value_counts for float dtype (GH10821)
• Enable infer_datetime_format in to_datetime when date components do not have 0 padding (GH11142)
• Regression from 0.16.1 in constructing DataFrame from nested dictionary (GH11084)
• Performance improvements in addition/subtraction operations for DateOffset with Series or DatetimeIndex (GH10744, GH11205)

**Bug fixes**

• Bug in incorrect computation of .mean() on timedelta64[ns] because of overflow (GH9442)
• Bug in .isin on older numpies (GH11232)
• Bug in DataFrame.to_html(index=False) renders unnecessary name row (GH10344)
• Bug in DataFrame.to_latex() the column_format argument could not be passed (GH9402)
• Bug in DatetimeIndex when localizing with NaT (GH10477)
• Bug in Series.dt ops in preserving meta-data (GH10477)
• Bug in preserving NaT when passed in an otherwise invalid to_datetime construction (GH10477)
• Bug in `DataFrame.apply` when function returns categorical series. (GH9573)
• Bug in `to_datetime` with invalid dates and formats supplied (GH10154)
• Bug in `Index.drop_duplicates` dropping name(s) (GH10115)
• Bug in `Series.quantile` dropping name (GH10881)
• Bug in `pd.Series` when setting a value on an empty `Series` whose index has a frequency. (GH10193)
• Bug in `pd.Series.interpolate` with invalid order keyword values. (GH10633)
• Bug in `DataFrame.plot` raises `ValueError` when color name is specified by multiple characters (GH10387)
• Bug in `Index` construction with a mixed list of tuples (GH10697)
• Bug in `DataFrame.reset_index` when index contains `NaT`. (GH10388)
• Bug in `ExcelReader` when worksheet is empty (GH6403)
• Bug in `BinGrouper.group_info` where returned values are not compatible with base class (GH10914)
• Bug in clearing the cache on `DataFrame.pop` and a subsequent inplace op (GH10912)
• Bug in indexing with a mixed-integer `Index` causing an `ImportError` (GH10610)
• Bug in `Series.count` when index has nulls (GH10946)
• Bug in picking of a non-regular freq `DatetimeIndex` (GH11002)
• Bug causing `DataFrame.where` to not respect the `axis` parameter when the frame has a symmetric shape. (GH9736)
• Bug in `Table.select_column` where name is not preserved (GH10392)
• Bug in `offsets.generate_range` where start and end have finer precision than offset (GH9907)
• Bug in `pd.rolling_*` where `Series.name` would be lost in the output (GH10565)
• Bug in `stack` when index or columns are not unique. (GH10417)
• Bug in setting a `Panel` when an axis has a MultiIndex (GH10360)
• Bug in `USFederalHolidayCalendar` where `USMemorialDay` and `USMartinLutherKingJr` were incorrect (GH10278 and GH9760)
• Bug in `.sample()` where returned object, if set, gives unnecessary `SettingWithCopyWarning` (GH10738)
• Bug in `.sample()` where weights passed as `Series` were not aligned along axis before being treated positionally, potentially causing problems if weight indices were not aligned with sampled object. (GH10738)
• Regression fixed in (GH9311, GH6620, GH9345), where groupby with a datetime-like converting to float with certain aggregators (GH10979)
• Bug in `DataFrame.interpolate` with `axis=1` and `inplace=True` (GH10395)
• Bug in `io.sql.get_schema` when specifying multiple columns as primary key (GH10385).
• Bug in `groupby(sort=False)` with datetime-like `Categorical` raises `ValueError` (GH10505)
• Bug in `groupby(axis=1)` with `filter()` throws `IndexError` (GH11041)
• Bug in `test_categorical` on big-endian builds (GH10425)
• Bug in `Series.shift` and `DataFrame.shift` not supporting categorical data (GH9416)
• Bug in `Series.map` using categorical `Series` raises `AttributeError` (GH10324)
• Bug in MultiIndex.get_level_values including Categorical raises AttributeError (GH10460)
• Bug in pd.get_dummies with sparse=True not returning SparseDataFrame (GH10531)
• Bug in Index subtypes (such as PeriodIndex) not returning their own type for .drop and .insert methods (GH10620)
• Bug in algos.outer_join_indexer when right array is empty (GH10618)
• Bug in filter (regression from 0.16.0) and transform when grouping on multiple keys, one of which is datetime-like (GH10114)
• Bug in to_datetime and to_timedelta causing Index name to be lost (GH10875)
• Bug in len(DataFrame.groupby) causing IndexError when there’s a column containing only NaNs (GH11016)
• Bug that caused segfault when resampling an empty Series (GH10228)
• Bug in DatetimeIndex and PeriodIndex.value_counts resets name from its result, but retains in result's Index. (GH10150)
• Bug in pd.eval using numexpr engine coerces 1 element numpy array to scalar (GH10546)
• Bug in pd.concat with axis=0 when column is of dtype category (GH10177)
• Bug in read_msgpack where input type is not always checked (GH10369, GH10630)
• Bug in pd.read_csv with kwarg index_col=False, index_col=['a', 'b'] or dtype (GH10413, GH10467, GH10577)
• Bug in Series.from_csv with header kwarg not setting the Series.name or the Series.index. name (GH10483)
• Bug in groupby.var which caused variance to be inaccurate for small float values (GH10448)
• Bug in Series.plot(kind='hist') Y Label not informative (GH10485)
• Bug in read_csv when using a converter which generates a uint8 type (GH9266)
• Bug causes memory leak in time-series line and area plot (GH9003)
• Bug when setting a Panel sliced along the major or minor axes when the right-hand side is a DataFrame (GH11014)
• Bug that returns None and does not raise NotImplementedError when operator functions (e.g. .add) of Panel are not implemented (GH7692)
• Bug in line and kde plot cannot accept multiple colors when subplots=True (GH9894)
• Bug in DataFrame.plot raises ValueError when color name is specified by multiple characters (GH10387)
• Bug in left and right align of Series with MultiIndex may be inverted (GH10665)
• Bug in left and right join of with MultiIndex may be inverted (GH10741)
• Bug in read_stata when reading a file with a different order set in columns (GH10757)
• Bug in Categorical may not representing properly when category contains tz or Period (GH10713)
• Bug in Categorical.__iter__ may not returning correct datetime and Period (GH10713)
• Bug in indexing with a PeriodIndex on an object with a PeriodIndex (GH4125)
• Bug in read_csv with engine='c': EOF preceded by a comment, blank line, etc. was not handled correctly (GH10728, GH10548)
• Reading “famafrench” data via `DataReader` results in HTTP 404 error because of the website url is changed (GH10591).

• Bug in `read_msgpack` where DataFrame to decode has duplicate column names (GH9618)

• Bug in `io.common.get_filepath_or_buffer` which caused reading of valid S3 files to fail if the bucket also contained keys for which the user does not have read permission (GH10604)

• Bug in vectorised setting of timestamp columns with python `datetime.date` and numpy `datetime64` (GH10408, GH10412)

• Bug in `Index.take` may add unnecessary `freq` attribute (GH10791)

• Bug in `merge` with empty DataFrame may raise `IndexError` (GH10824)

• Bug in `to_latex` where unexpected keyword argument for some documented arguments (GH10888)

• Bug in indexing of large DataFrame where `IndexError` is uncaught (GH10645 and GH10692)

• Bug in `read_csv` when using the `nrows` or `chunksize` parameters if file contains only a header line (GH9535)

• Bug in serialization of category types in HDF5 in presence of alternate encodings. (GH10366)

• Bug in `pd.DataFrame` when constructing an empty DataFrame with a string dtype (GH9428)

• Bug in `pd.DataFrame.diff` when DataFrame is not consolidated (GH10907)

• Bug in `pd.unique` for arrays with the `datetime64` or `timedelta64` dtype that meant an array with object dtype was returned instead the original dtype (GH9431)

• Bug in `TimedeltaIndex` raising error when slicing from 0s (GH10583)

• Bug in `DatetimeIndex.take` and `TimedeltaIndex.take` may not raise `IndexError` against invalid index (GH10295)

• Bug in `Series([np.nan]).astype('M8[ms]')`, which now returns `Series([pd.NaT])` (GH10747)

• Bug in `PeriodIndex.order` reset freq (GH10295)

• Bug in `date_range` when freq divides end as nanos (GH10885)

• Bug in `iloc` allowing memory outside bounds of a Series to be accessed with negative integers (GH10779)

• Bug in `read_msgpack` where encoding is not respected (GH10581)

• Bug preventing access to the first index when using `iloc` with a list containing the appropriate negative integer (GH10547, GH10779)

• Bug in `TimedeltaIndex` formatter causing error while trying to save DataFrame with `TimedeltaIndex` using `to_csv` (GH10833)

• Bug in `DataFrame.where` when handling Series slicing (GH10218, GH9558)

• Bug where `pd.read_gbq` throws `ValueError` when Bigquery returns zero rows (GH10273)

• Bug in `to_json` which was causing segmentation fault when serializing 0-rank ndarray (GH9576)

• Bug in plotting functions may raise `IndexError` when plotted on `GridSpec` (GH10819)

• Bug in plot result may show unnecessary minor ticklabels (GH10657)

• Bug in `groupby` incorrect computation for aggregation on DataFrame with `NaT` (E.g first, last, min). (GH10590, GH11010)

• Bug when constructing `DataFrame` where passing a dictionary with only scalar values and specifying columns did not raise an error (GH10856)
pandas: powerful Python data analysis toolkit, Release 1.1.1

- Bug in `.var()` causing roundoff errors for highly similar values (GH10242)
- Bug in `DataFrame.plot(subplots=True)` with duplicated columns outputs incorrect result (GH10962)
- Bug in `Index` arithmetic may result in incorrect class (GH10638)
- Bug in `date_range` results in empty if freq is negative annually, quarterly and monthly (GH11018)
- Bug in `DatetimeIndex` cannot infer negative freq (GH11018)
- Remove use of some deprecated numpy comparison operations, mainly in tests. (GH10569)
- Bug in `Index` dtype may not applied properly (GH11017)
- Bug in `io.gbq` when testing for minimum google api client version (GH10652)
- Bug in `DataFrame` construction from nested `dict` with `timedelta` keys (GH11129)
- Bug in `.fillna` against may raise `TypeError` when data contains datetime dtype (GH7095, GH11153)
- Bug in `.groupby` when number of keys to group by is same as length of index (GH11185)
- Bug in `convert_objects` where converted values might not be returned if all null and `coerce` (GH9589)
- Bug in `convert_objects` where `copy` keyword was not respected (GH9589)

Contributors

A total of 112 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Alex Rothberg
- Andrea Bedini +
- Andrew Rosenfeld
- Andy Hayden
- Andy Li +
- Anthonios Partheniou +
- Artemy Kolchinsky
- Bernard Willers
- Charlie Clark +
- Chris +
- Chris Whelan
- Christoph Gohlke +
- Christopher Whelan
- Clark Fitzgerald
- Clearfield Christopher +
- Dan Ringwalt +
- Daniel Ni +
- Data & Code Expert Experimenting with Code on Data +
- David Cottrell
• David John Gagne +
• David Kelly +
• ETF +
• Eduardo Schettino +
• Egor +
• Egor Panfilov +
• Evan Wright
• Frank Pinter +
• Gabriel Araujo +
• Garrett-R
• Gianluca Rossi +
• Guillaume Gay
• Guillaume Poulin
• Harsh Nisar +
• Ian Henriksen +
• Ian Hoegen +
• Jaidev Deshpande +
• Jan Rudolph +
• Jan Schulz
• Jason Swails +
• Jeff Reback
• Jonas Buyl +
• Joris Van den Bossche
• Joris Vankerschaver +
• Josh Levy-Kramer +
• Julien Danjou
• Ka Wo Chen
• Karrie Kehoe +
• Kelsey Jordahl
• Kerby Shedden
• Kevin Sheppard
• Lars Buitinck
• Leif Johnson +
• Luis Ortiz +
• Mac +
• Matt Gambogi +
• Matt Savoie +
• Matthew Gilbert +
• Maximilian Roos +
• Michelangelo D’Agostino +
• Mortada Mehyar
• Nick Eubank
• Nipun Batra
• Ondřej Čertík
• Phillip Cloud
• Pratap Vardhan +
• Rafał Skolasinski +
• Richard Lewis +
• Rinoc Johnson +
• Rob Levy
• Robert Gieseke
• Safia Abdalla +
• Samuel Denny +
• Saumitra Shahapure +
• Sebastian Pölsterl +
• Sebastian Rubbert +
• Sheppard, Kevin +
• Sinhrks
• Siu Kwan Lam +
• Skipper Seabold
• Spencer Carruciu +
• Stephan Hoyer
• Stephen Hoover +
• Stephen Pascoe +
• Terry Santegoeds +
• Thomas Grainger
• Tjerk Santegoeds +
• Tom Augspurger
• Vincent Davis +
• Winterflower +
• Yaroslav Halchenko
• Yuan Tang (Terry) +
5.12 Version 0.16

5.12.1 Version 0.16.2 (June 12, 2015)

This is a minor bug-fix release from 0.16.1 and includes a large number of bug fixes along some new features (\texttt{pipe()} method), enhancements, and performance improvements.

We recommend that all users upgrade to this version.

Highlights include:

- A new \texttt{pipe} method, see \texttt{here}
- Documentation on how to use \texttt{numba} with \texttt{pandas}, see \texttt{here}

What’s new in v0.16.2

- \textit{New features}
  - \textit{Pipe}
  - \textit{Other enhancements}
New features

Pipe

We’ve introduced a new method `DataFrame.pipe()`. As suggested by the name, pipe should be used to pipe data through a chain of function calls. The goal is to avoid confusing nested function calls like

```python
# df is a DataFrame
# f, g, and h are functions that take and return DataFrames
f(g(h(df), arg1=1), arg2=2, arg3=3)  # noqa F821
```

The logic flows from inside out, and function names are separated from their keyword arguments. This can be rewritten as

```python
(df.pipe(h)  # noqa F821
 .pipe(g, arg1=1)  # noqa F821
 .pipe(f, arg2=2, arg3=3)  # noqa F821
)
```

Now both the code and the logic flow from top to bottom. Keyword arguments are next to their functions. Overall the code is much more readable.

In the example above, the functions `f`, `g`, and `h` each expected the DataFrame as the first positional argument. When the function you wish to apply takes its data anywhere other than the first argument, pass a tuple of `(function, keyword)` indicating where the DataFrame should flow. For example:

```
In [1]: import statsmodels.formula.api as sm
In [2]: bb = pd.read_csv('data/baseball.csv', index_col='id')
# sm.ols takes (formula, data)
In [3]: (bb.query('h > 0')
    ...: .assign(ln_h=lambda df: np.log(df.h))
    ...: .pipe((sm.ols, 'data'), 'hr ~ ln_h + year + g + C(lg)')
    ...: .fit()
    ...: .summary()
    ...: )
```

```
Out[3]:<class 'statsmodels.iolib.summary.Summary'>
```

```
""
```

OLS Regression Results

==============================================================================
Dep. Variable: hr R-squared: 0.685
Model: OLS Adj. R-squared: 0.665
Method: Least Squares F-statistic: 34.28
Date: Thu, 20 Aug 2020 Prob (F-statistic): 3.48e-15
```

(continues on next page)
warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.49e+07. This might indicate that there are strong multicollinearity or other numerical problems.

The pipe method is inspired by unix pipes, which stream text through processes. More recently dplyr and magrittr have introduced the popular (%>%) pipe operator for R.

See the documentation for more. (GH10129)

Other enhancements

- Added rsplit to Index/Series StringMethods (GH10303)
- Removed the hard-coded size limits on the DataFrame HTML representation in the IPython notebook, and leave this to IPython itself (only for IPython v3.0 or greater). This eliminates the duplicate scroll bars that appeared in the notebook with large frames (GH10231).

  Note that the notebook has a toggle output scrolling feature to limit the display of very large frames (by clicking left of the output). You can also configure the way DataFrames are displayed using the pandas options, see here.

  axis parameter of DataFrame.quantile now accepts also index and column. (GH9543)

API changes

- Holiday now raises NotImplementedError if both offset and observance are used in the constructor instead of returning an incorrect result (GH10217).
Performance improvements

• Improved Series.resample performance with dtype=datetime64[ns] (GH7754)
• Increase performance of str.split when expand=True (GH10081)

Bug fixes

• Bug in Series.hist raises an error when a one row Series was given (GH10214)
• Bug where HDFStore.select modifies the passed columns list (GH7212)
• Bug in Categorical repr with display.width of None in Python 3 (GH10087)
• Bug in to_json with certain orients and a CategoricalIndex would segfault (GH10317)
• Bug where some of the nan functions do not have consistent return dtypes (GH10251)
• Bug in DataFrame.quantile on checking that a valid axis was passed (GH9543)
• Bug in groupby.apply aggregation for Categorical not preserving categories (GH10138)
• Bug in to_csv where date_format is ignored if the datetime is fractional (GH10209)
• Bug in DataFrame.to_json with mixed data types (GH10289)
• Bug in cache updating when consolidating (GH10264)
• Bug in mean() where integer dtypes can overflow (GH10172)
• Bug where Panel.from_dict does not set dtype when specified (GH10058)
• Bug in Index.union raises AttributeError when passing array-likes. (GH10149)
• Bug in Timestamp’s’ microsecond, quarter, dayofyear, week and daysinmonth properties return np.int type, not built-in int. (GH10050)
• Bug in NaT raises AttributeError when accessing to daysinmonth, dayofweek properties. (GH10096)
• Bug in Index repr when using the max_seq_items=None setting (GH10182).
• Bug in getting timezone data with dateutil on various platforms (GH9059, GH8639, GH9663, GH10121)
• Bug in displaying datetimes with mixed frequencies; display ‘ms’ datetimes to the proper precision. (GH10170)
• Bug in setitem where type promotion is applied to the entire block (GH10280)
• Bug in Series arithmetic methods may incorrectly hold names (GH10068)
• Bug in GroupBy.get_group when grouping on multiple keys, one of which is categorical. (GH10132)
• Bug in DatetimeIndex and TimedeltaIndex names are lost after timedelta arithmetics (GH9926)
• Bug in DataFrame construction from nested dict with datetime64 (GH10160)
• Bug in Series construction from dict with datetime64 keys (GH9456)
• Bug in Series.plot(label="LABEL") not correctly setting the label (GH10119)
• Bug in plot not defaulting to matplotlib axes.grid setting (GH9792)
• Bug causing strings containing an exponent, but no decimal to be parsed as int instead of float in engine='python' for the read_csv parser (GH9565)
• Bug in Series.align resets name when fill_value is specified (GH10067)
• Bug in read_csv causing index name not to be set on an empty DataFrame (GH10184)
• Bug in SparseSeries.abs resets name (GH10241)
• Bug in TimedeltaIndex slicing may reset freq (GH10292)
• Bug in GroupBy.get_group raises ValueError when group key contains NaT (GH6992)
• Bug in SparseSeries constructor ignores input data name (GH10258)
• Bug in Categorical.remove_categories causing a ValueError when removing the NaN category if underlying dtype is floating-point (GH10156)
• Bug where infer_freq infers time rule (WOM-5XXX) unsupported by to_offset (GH9425)
• Bug in DataFrame.to_hdf() where table format would raise a seemingly unrelated error for invalid (non-string) column names. This is now explicitly forbidden. (GH9057)
• Bug to handle masking empty DataFrame (GH10126).
• Bug where MySQL interface could not handle numeric table/column names (GH10255)
• Bug in read_csv with a date_parser that returned a datetime64 array of other time resolution than [ns] (GH10245)
• Bug in Panel.apply when the result has ndim=0 (GH10332)
• Bug in read_hdf where auto_close could not be passed (GH9327).
• Bug in read_hdf where open stores could not be used (GH10330).
• Bug in adding empty DataFrames, now results in a DataFrame that .equals an empty DataFrame (GH10181).
• Bug in to_hdf and HDFStore which did not check that complib choices were valid (GH4582, GH8874).

Contributors

A total of 34 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

• Andrew Rosenfeld
• Artemy Kolchinsky
• Bernard Willers +
• Christer van der Meeren
• Christian Hudon +
• Constantine Glen Evans +
• Daniel Julius Lasiman +
• Evan Wright
• Francesco Brundu +
• Gaëtan de Menten +
• Jake VanderPlas
• James Hiebert +
• Jeff Reback
• Joris Van den Bossche
• Justin Lecher +
5.12.2 Version 0.16.1 (May 11, 2015)

This is a minor bug-fix release from 0.16.0 and includes a large number of bug fixes along several new features, enhancements, and performance improvements. We recommend that all users upgrade to this version.

Highlights include:

- Support for a CategoricalIndex, a category based index, see here
- New section on how-to-contribute to pandas, see here
- Revised “Merge, join, and concatenate” documentation, including graphical examples to make it easier to understand each operations, see here
- New method sample for drawing random samples from Series, DataFrames and Panels. See here
- The default Index printing has changed to a more uniform format, see here
- BusinessHour datetime-offset is now supported, see here
- Further enhancement to the .str accessor to make string operations easier, see here

What’s new in v0.16.1

- Enhancements
  - CategoricalIndex
- Sample
- String methods enhancements
- Other enhancements

- API changes
- Deprecations
- Index representation
- Performance improvements
- Bug fixes
- Contributors

**Warning:** In pandas 0.17.0, the sub-package `pandas.io.data` will be removed in favor of a separately installable package (GH8961).

**Enhancements**

**CategoricalIndex**

We introduce a `CategoricalIndex`, a new type of index object that is useful for supporting indexing with duplicates. This is a container around a `Categorical` (introduced in v0.15.0) and allows efficient indexing and storage of an index with a large number of duplicated elements. Prior to 0.16.1, setting the index of a DataFrame/Series with a category dtype would convert this to regular object-based Index.

```python
In [1]: df = pd.DataFrame({'A': np.arange(6),
                      'B': pd.Series(list('aabbca'))
                      .astype('category', categories=list('cab'))
                      })

In [2]: df
Out[2]:
   A  B
0  0  a
1  1  a
2  2  b
3  3  b
4  4  c
5  5  a

In [3]: df.dtypes
Out[3]:
A    int64
B  category
dtype: object

In [4]: df.B.cat.categories
Out[4]: Index(['c', 'a', 'b'], dtype='object')
```

Setting the index, will create a `CategoricalIndex`
indexing with \_getitem\_/.iloc/.loc/.ix works similarly to an Index with duplicates. The indexers MUST be in the category or the operation will raise.

```python
In [7]: df2.loc['a']
Out[7]:
 A
B
a 0
a 1
a 5
```

and preserves the CategoricalIndex

```python
In [8]: df2.loc['a'].index
Out[8]: CategoricalIndex(['a', 'a', 'a'], categories=['c', 'a', 'b'], ordered=False, name='B', dtype='category')
```

sorting will order by the order of the categories

```python
In [9]: df2.sort_index()
Out[9]:
 A
B
c 4
a 0
a 1
a 5
b 2
b 3
```

groupby operations on the index will preserve the index nature as well

```python
In [10]: df2.groupby(level=0).sum()
Out[10]:
 A
B
 c 4
 a 6
```

```python
In [11]: df2.groupby(level=0).sum().index
Out[11]: CategoricalIndex(['c', 'a', 'b'], categories=['c', 'a', 'b'], ordered=False, name='B', dtype='category')
```

reindexing operations, will return a resulting index based on the type of the passed indexer, meaning that passing a list will return a plain-old-Index; indexing with a Categorical will return a CategoricalIndex, indexed according to the categories of the PASSED Categorical dtype. This allows one to arbitrarily index these even with values NOT in the categories, similarly to how you can reindex ANY pandas index.

```python
In [12]: df2.reindex(['a', 'e'])
Out[12]:
(continues on next page)
A
B
a 0.0
a 1.0
a 5.0
e NaN

In [13]: df2.reindex(['a', 'e']).index
Out[13]: pd.Index(['a', 'a', 'a', 'e'], dtype='object', name='B')

In [14]: df2.reindex(pd.Categorical(['a', 'e'], categories=list('abcde')))
Out[14]:
   A
  B
  a 0.0
  a 1.0
  a 5.0
e NaN

In [15]: df2.reindex(pd.Categorical(['a', 'e'], categories=list('abcde'))).index
Out[15]: pd.CategoricalIndex(['a', 'a', 'a', 'e'],
categories=['a', 'b', 'c', 'd', 'e'],
ordered=False, name='B',
dtype='category')

See the documentation for more. (GH7629, GH10038, GH10039)

Sample

Series, DataFrames, and Panels now have a new method: *sample()*. The method accepts a specific number of rows or columns to return, or a fraction of the total number of rows or columns. It also has options for sampling with or without replacement, for passing in a column for weights for non-uniform sampling, and for setting seed values to facilitate replication. (GH2419)

In [1]: example_series = pd.Series([0, 1, 2, 3, 4, 5])

# When no arguments are passed, returns 1
In [2]: example_series.sample()
Out[2]:
   3  3
Length: 1, dtype: int64

# One may specify either a number of rows:
In [3]: example_series.sample(n=3)
Out[3]:
   2  2
   1  1
   0  0
Length: 3, dtype: int64

# Or a fraction of the rows:
In [4]: example_series.sample(frac=0.5)
Out[4]:
   1  1
   5  5

(continues on next page)
3 3
Length: 3, dtype: int64

# weights are accepted.
In [5]: example_weights = [0, 0, 0.2, 0.2, 0.2, 0.4]

In [6]: example_series.sample(n=3, weights=example_weights)
Out[6]:
2 2
4 4
3 3
Length: 3, dtype: int64

# weights will also be normalized if they do not sum to one, # and missing values will be treated as zeros.
In [7]: example_weights2 = [0.5, 0, 0, 0, None, np.nan]

In [8]: example_series.sample(n=1, weights=example_weights2)
Out[8]:
0 0
Length: 1, dtype: int64

When applied to a DataFrame, one may pass the name of a column to specify sampling weights when sampling from rows.

In [9]: df = pd.DataFrame({'col1': [9, 8, 7, 6], 'weight_column': [0.5, 0.4, 0.1, 0]})

In [10]: df.sample(n=3, weights='weight_column')
Out[10]:
   col1  weight_column
0     9           0.5
1     8           0.4
2     7           0.1

[3 rows x 2 columns]

String methods enhancements

Continuing from v0.16.0, the following enhancements make string operations easier and more consistent with standard python string operations.

- Added StringMethods (.str accessor) to Index (GH9068)

  The .str accessor is now available for both Series and Index.

In [11]: idx = pd.Index(['jack', 'jill', 'jesse', 'frank'])

In [12]: idx.str.strip()
Out[12]: Index(['jack', 'jill', 'jesse', 'frank'], dtype='object')

One special case for the .str accessor on Index is that if a string method returns bool, the .str accessor will return a np.array instead of a boolean Index (GH8875). This enables the following expression to work naturally:
In [13]: idx = pd.Index(['a1', 'a2', 'b1', 'b2'])

In [14]: s = pd.Series(range(4), index=idx)

In [15]: s
Out[15]:
  a1  0
  a2  1
  b1  2
  b2  3
Length: 4, dtype: int64

In [16]: idx.str.startswith('a')
Out[16]:
array([ True, True, False, False])

In [17]: s[s.index.str.startswith('a')]
Out[17]:
  a1  0
  a2  1
Length: 2, dtype: int64

- The following new methods are accessible via .str accessor to apply the function to each values. (GH9766, GH9773, GH10031, GH10045, GH10052)

<table>
<thead>
<tr>
<th>Methods</th>
<th>capitalize()</th>
<th>swapcase()</th>
<th>normalize()</th>
<th>partition()</th>
<th>rpartition()</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>index()</td>
<td>rindex()</td>
<td>translate()</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

- split now takes expand keyword to specify whether to expand dimensionality. return_type is deprecated. (GH9847)

In [18]: s = pd.Series(['a,b', 'a,c', 'b,c'])

# return Series
In [19]: s.str.split(',')
Out[19]:
  0 [a, b]
  1 [a, c]
  2 [b, c]
Length: 3, dtype: object

# return DataFrame
In [20]: s.str.split(',', expand=True)
Out[20]:
     0  1
  0  a  b
  1  a  c
  2  b  c
[3 rows x 2 columns]

In [21]: idx = pd.Index(['a,b', 'a,c', 'b,c'])

# return Index
In [22]: idx.str.split(',')
Out[22]: Index([['a', 'b'], ['a', 'c'], ['b', 'c']], dtype='object')
# return MultiIndex
In [23]: idx.str.split(',', expand=True)
Out[23]:
MultiIndex([('a', 'b'), ('a', 'c'), ('b', 'c')],

• Improved `extract` and `get_dummies` methods for `Index.str` (GH9980)

### Other enhancements

• `BusinessHour` offset is now supported, which represents business hours starting from 09:00 - 17:00 on `BusinessDay` by default. See `Here` for details. (GH7905)

```python
In [24]: pd.Timestamp('2014-08-01 09:00') + pd.tseries.offsets.BusinessHour()
Out[24]: Timestamp('2014-08-01 10:00:00')

In [25]: pd.Timestamp('2014-08-01 07:00') + pd.tseries.offsets.BusinessHour()
Out[25]: Timestamp('2014-08-01 10:00:00')

In [26]: pd.Timestamp('2014-08-01 16:30') + pd.tseries.offsets.BusinessHour()
Out[26]: Timestamp('2014-08-04 09:30:00')
```

• `DataFrame.diff` now takes an `axis` parameter that determines the direction of differencing (GH9727)
• Allow `clip`, `clip_lower`, and `clip_upper` to accept array-like arguments as thresholds (This is a regression from 0.11.0). These methods now have an `axis` parameter which determines how the Series or DataFrame will be aligned with the threshold(s). (GH6966)
• `DataFrame.mask()` and `Series.mask()` now support same keywords as `where` (GH8801)
• `drop` function can now accept `errors` keyword to suppress `ValueError` raised when any of label does not exist in the target data. (GH6736)

```python
In [27]: df = pd.DataFrame(np.random.randn(3, 3), columns=['A', 'B', 'C'])
In [28]: df.drop(['A', 'X'], axis=1, errors='ignore')
Out[28]:
   B    C
0 -0.706771 -1.039575
1 -0.424972  0.567020
2 -1.087401 -0.673690
[3 rows x 2 columns]
```

• Add support for separating years and quarters using dashes, for example 2014-Q1. (GH9688)
• Allow conversion of values with dtype `datetime64` or `timedelta64` to strings using `astype(str)` (GH9757)
• `get_dummies` function now accepts `sparse` keyword. If set to `True`, the return `DataFrame` is sparse, e.g. `SparseDataFrame`. (GH8823)
• `Period` now accepts `datetime64` as value input. (GH9054)
• Allow timedelta string conversion when leading zero is missing from time definition, ie 0:00:00 vs 00:00:00. (GH9570)

• Allow Panel.shift with axis='items' (GH9890)

• Trying to write an excel file now raises NotImplementedError if the DataFrame has a MultiIndex instead of writing a broken Excel file. (GH9794)

• Allow Categorical.add_categories to accept Series or np.array. (GH9927)

• Add/delete str/dt/cat accessors dynamically from __dir__. (GH9910)

• Add normalize as a dt accessor method. (GH10047)

• DataFrame and Series now have _constructor_expanddim property as overridable constructor for one higher dimensionality data. This should be used only when it is really needed, see here

• pd.lib.infer_dtypes now returns 'bytes' in Python 3 where appropriate. (GH10032)

API changes

• When passing in an ax to df.plot(..., ax=ax), the share kwarg will now default to False. The result is that the visibility of xlabels and xticklabels will not anymore be changed. You have to do that by yourself for the right axes in your figure or set share=True explicitly (but this changes the visible for all axes in the figure, not only the one which is passed in!). If pandas creates the subplots itself (e.g. no passed in ax kwarg), then the default is still share=True and the visibility changes are applied.

• assign() now inserts new columns in alphabetical order. Previously the order was arbitrary. (GH9777)

• By default, read_csv and read_table will now try to infer the compression type based on the file extension. Set compression=None to restore the previous behavior (no decompression). (GH9770)

Deprecations

• Series.str.split's return_type keyword was removed in favor of expand (GH9847)

Index representation

The string representation of Index and its sub-classes have now been unified. These will show a single-line display if there are few values; a wrapped multi-line display for a lot of values (but less than display.max_seq_items; if lots of items (>display.max_seq_items) will show a truncated display (the head and tail of the data). The formatting for MultiIndex is unchanged (a multi-line wrapped display). The display width responds to the option display.max_seq_items, which is defaulted to 100. (GH6482)

Previous behavior

```
In [2]: pd.Index(range(4), name='foo')
Out[2]: Int64Index([0, 1, 2, 3], dtype='int64')

In [3]: pd.Index(range(104), name='foo')
Out[3]: Int64Index([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, ...], dtype='int64')
```
**In [4]:**  `pd.date_range('20130101', periods=4, name='foo', tz='US/Eastern')`

```
Out[4]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2013-01-01 00:00:00-05:00, ..., 2013-01-04 00:00:00-05:00]
Length: 4, Freq: D, Timezone: US/Eastern
```

**In [5]:**  `pd.date_range('20130101', periods=104, name='foo', tz='US/Eastern')`

```
Out[5]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2013-01-01 00:00:00-05:00, ..., 2013-04-14 00:00:00-04:00]
Length: 104, Freq: D, Timezone: US/Eastern
```

**New behavior**

**In [29]:**  `pd.set_option('display.width', 80)`

**In [30]:**  `pd.Index(range(4), name='foo')`

```
Out[30]:
RangeIndex(start=0, stop=4, step=1, name='foo')
```

**In [31]:**  `pd.Index(range(104), name='foo')`

```
Out[31]:
RangeIndex(start=0, stop=104, step=1, name='foo')
```

**In [32]:**  `pd.Index(range(104), name='foo')`

```
Out[32]:
RangeIndex(start=0, stop=104, step=1, name='foo')
```

**In [33]:**  `pd.CategoricalIndex(['a', 'bb', 'ccc', 'dddd'],
    ordered=True, name='foobarlo')`

```
Out[33]:
CategoricalIndex(['a', 'bb', 'ccc', 'dddd'], categories=['a', 'bb', 'ccc',
    'dddd'], ordered=True, name='foobarlo', dtype='category')
```

**In [34]:**  `pd.CategoricalIndex(['a', 'bb', 'ccc', 'dddd'] * 10,
    ordered=True, name='foobarlo')`

```
Out[34]:
CategoricalIndex(['a', 'bb', 'ccc', 'dddd', 'a', 'bb', 'ccc', 'dddd', 'a', 'bb',
    'ccc', 'dddd', 'a', 'bb', 'ccc', 'dddd', 'a', 'bb', 'ccc', 'dddd', 'a', 'bb',
    'ccc', 'dddd'], categories=['a', 'bb', 'ccc', 'dddd'], ordered=True, name='foobargo',
    dtype='category')
```

**In [35]:**  `pd.CategoricalIndex(['a', 'bb', 'ccc', 'dddd'] * 100,
    ordered=True, name='foobarlo')`

```
Out[35]:
CategoricalIndex(['a', 'bb', 'ccc', 'dddd', 'a', 'bb', 'ccc', 'dddd', 'a', 'bb',
    'ccc', 'dddd', 'a', 'bb', 'ccc', 'dddd', 'a', 'bb', 'ccc', 'dddd', 'a', 'bb',
    'ccc', 'dddd'], categories=['a', 'bb', 'ccc', 'dddd'], ordered=True, name='foobarlo',
    dtype='category', length=400)
```

**In [36]:**  `pd.date_range('20130101', periods=4, name='foo', tz='US/Eastern')`

```
(continues on next page)
```
Performance improvements

- Improved csv write performance with mixed dtypes, including datetimes by up to 5x (GH9940)
- Improved csv write performance generally by 2x (GH9940)
- Improved the performance of pd.lib.max_len_string_array by 5-7x (GH10024)

Bug fixes

- Bug where labels did not appear properly in the legend of DataFrame.plot(), passing label= arguments works, and Series indices are no longer mutated. (GH9542)
- Bug in json serialization causing a segfault when a frame had zero length. (GH9805)
- Bug in read_csv where missing trailing delimiters would cause segfault. (GH5664)
- Bug in retaining index name on appending (GH9862)
- Bug in scatter_matrix draws unexpected axis ticklabels (GH5662)
- Fixed bug in StataWriter resulting in changes to input DataFrame upon save (GH9795).
- Bug in transform causing length mismatch when null entries were present and a fast aggregator was being used (GH9697)
- Bug in equals causing false negatives when block order differed (GH9330)
- Bug in grouping with multiple `pd.Grouper` where one is non-time based (GH10063)
- Bug in `read_sql_table` error when reading postgres table with timezone (GH7139)
- Bug in `DataFrame` slicing may not retain metadata (GH9776)
- Bug where `TimedeltaIndex` were not properly serialized in fixed HDFStore (GH9635)
- Bug with `TimedeltaIndex` constructor ignoring name when given another `TimedeltaIndex` as data (GH10025).
- Bug in `DataFrameFormatter._get_formatted_index` with not applying `max_colwidth` to the `DataFrame` index (GH7856)
- Bug in `.loc` with a read-only ndarray data source (GH10043)
- Bug in `groupby.apply()` that would raise if a passed user defined function either returned only None (for all input). (GH9685)
- Always use temporary files in pytables tests (GH9992)
- Bug in plotting continuously using `secondary_y` may not show legend properly. (GH9610, GH9779)
- Bug in `DataFrame.plot(kind="hist")` results in TypeError when `DataFrame` contains non-numeric columns (GH9853)
- Bug where repeated plotting of `DataFrame` with a `DatetimeIndex` may raise TypeError (GH9852)
- Bug in `setup.py` that would allow an incompat cython version to build (GH9827)
- Bug in plotting `secondary_y` incorrectly attaches `right_ax` property to secondary axes specifying itself recursively. (GH9861)
- Bug in `Series.quantile` on empty `Series` of type `Datetime` or `Timedelta` (GH9675)
- Bug in `where` causing incorrect results when upcasting was required (GH9731)
- Bug in `FloatArrayFormatter` where decision boundary for displaying “small” floats in decimal format is off by one order of magnitude for a given display.precision (GH9764)
- Fixed bug where `DataFrame.plot()` raised an error when both `color` and `style` keywords were passed and there was no color symbol in the style strings (GH9671)
- Not showing a `DeprecationWarning` on combining list-likes with an `Index` (GH10083)
- Bug in `read_csv` and `read_table` when using `skip_rows` parameter if blank lines are present. (GH9832)
- Bug in `read_csv()` interprets `index_col=True` as 1 (GH9798)
- Bug in index equality comparisons using `==` failing on `Index/MultiIndex` type incompatibility (GH9785)
- Bug in which `SparseDataFrame` could not take `nan` as a column name (GH8822)
- Bug in `to_msgpack` and `read_msgpack` zlib and blosc compression support (GH9783)
- Bug `GroupBy.size` doesn’t attach index name properly if grouped by `TimeGrouper` (GH9925)
- Bug causing an exception in slice assignments because `length_of_indexer` returns wrong results (GH9995)
- Bug in csv parser causing lines with initial white space plus one non-space character to be skipped. (GH9710)
- Bug in C csv parser causing spurious NaNs when data started with newline followed by white space. (GH10022)
- Bug causing elements with a null group to spill into the final group when grouping by a `Categorical` (GH9603)
- Bug where `.iloc` and `.loc` behavior is not consistent on empty dataframes (GH9964)
• Bug in invalid attribute access on a TimedeltaIndex incorrectly raised ValueError instead of AttributeError (GH9680)

• Bug in unequal comparisons between categorical data and a scalar, which was not in the categories (e.g. Series(Categorical(list("abc"), ordered=True)) > "d". This returned False for all elements, but now raises a TypeError. Equality comparisons also now return False for == and True for !=. (GH9848)

• Bug in DataFrame __setitem__ when right hand side is a dictionary (GH9874)

• Bug in where when dtype is datetime64/timedelta64, but dtype of other is not (GH9804)

• Bug in MultiIndex.sortlevel() results in unicode level name breaks (GH9856)

• Bug in which groupby.transform incorrectly enforced output dtypes to match input dtypes. (GH9807)

• Bug in DataFrame constructor when columns parameter is set, and data is an empty list (GH9939)

• Bug in bar plot with log=True raises TypeError if all values are less than 1 (GH9905)

• Bug in horizontal bar plot ignores log=True (GH9905)

• Bug in PyTables queries that did not return proper results using the index (GH8265, GH9676)

• Bug where dividing a dataframe containing values of type Decimal by another Decimal would raise. (GH9787)

• Bug where using DataFrames asfreq would remove the name of the index. (GH9885)

• Bug causing extra index point when resample BM/BQ (GH9756)

• Changed caching in AbstractHolidayCalendar to be at the instance level rather than at the class level as the latter can result in unexpected behaviour. (GH9552)

• Fixed latex output for MultiIndexed dataframes (GH9778)

• Bug causing an exception when setting an empty range using DataFrame.loc (GH9596)

• Bug in hiding ticklabels with subplots and shared axes when adding a new plot to an existing grid of axes (GH9158)

• Bug in transform and filter when grouping on a categorical variable (GH9921)

• Bug in transform when groups are equal in number and dtype to the input index (GH9700)

• Google BigQuery connector now imports dependencies on a per-method basis. (GH9713)

• Updated BigQuery connector to no longer use deprecated oauth2client.tools.run() (GH8327)

• Bug in subclassed DataFrame. It may not return the correct class, when slicing or subsetting it. (GH9632)

• Bug in .median() where non-float null values are not handled correctly (GH10040)

• Bug in Series.fillna() where it raises if a numerically convertible string is given (GH10092)
Contributors

A total of 58 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Alfonso MHC +
- Andy Hayden
- Artemy Kolchinsky
- Chris Gilmer +
- Chris Grinolds +
- Dan Birken
- David BROCHART +
- David Hirschfeld +
- David Stephens
- Dr. Leo +
- Evan Wright +
- Frans van Dunné +
- Hatem Nassrat +
- Henning Sperr +
- Hugo Herter +
- Jan Schulz
- Jeff Blackburne +
- Jeff Reback
- Jim Crist +
- Jonas Abernot +
- Joris Van den Bossche
- Kerby Shedden
- Leo Razoumov +
- Manuel Riel +
- Mortada Mehyar
- Nick Burns +
- Nick Eubank +
- Olivier Grisel
- Phillip Cloud
- Pietro Battiston
- Roy Hyunjin Han
- Sam Zhang +
- Scott Sanderson +
5.12.3 Version 0.16.0 (March 22, 2015)

This is a major release from 0.15.2 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- DataFrame.assign method, see here
- Series.to_coo/from_coo methods to interact with scipy.sparse, see here
- Backwards incompatible change to Timedelta to conform the .seconds attribute with datetime.timedelta, see here
- Changes to the .loc slicing API to conform with the behavior of .ix see here
- Changes to the default for ordering in the Categorical constructor, see here
What's new in v0.16.0

- **New features**
  - DataFrame assign
  - Interaction with scipy.sparse
  - String methods enhancements
  - Other enhancements
- **Backwards incompatible API changes**
  - Changes in timedelta
  - Indexing changes
  - Categorical changes
  - Other API changes
  - Deprecations
  - Removal of prior version deprecations/changes
- **Performance improvements**
- **Bug fixes**
- **Contributors**

New features

**DataFrame assign**

Inspired by dplyr's mutate verb, DataFrame has a new `assign()` method. The function signature for `assign` is simply `**kwargs`. The keys are the column names for the new fields, and the values are either a value to be inserted (for example, a `Series` or `NumPy` array), or a function of one argument to be called on the `DataFrame`. The new values are inserted, and the entire DataFrame (with all original and new columns) is returned.

```python
In [1]: iris = pd.read_csv('data/iris.data')
In [2]: iris.head()
```

```
Out[2]:
          SepalLength  SepalWidth  PetalLength  PetalWidth    Name
0          5.1         3.5         1.4         0.2  Iris-setosa
1          4.9         3.0         1.4         0.2  Iris-setosa
2          4.7         3.2         1.3         0.2  Iris-setosa
3          4.6         3.1         1.5         0.2  Iris-setosa
4          5.0         3.6         1.4         0.2  Iris-setosa
```
Above was an example of inserting a precomputed value. We can also pass in a function to be evaluated.

```python
In [4]: iris.assign(sepal_ratio=lambda x: (x['SepalWidth'] / x['SepalLength'])).head()
```

```
Out[4]:
```

```
```

The power of `assign` comes when used in chains of operations. For example, we can limit the DataFrame to just those with a Sepal Length greater than 5, calculate the ratio, and plot

```python
In [5]: iris = pd.read_csv('data/iris.data')
```

```python
In [6]: (iris.query('SepalLength > 5')
```

```python
```

```python
```

See the documentation for more. (GH9229)
Interaction with scipy.sparse

Added SparseSeries.to_coo() and SparseSeries.from_coo() methods (GH8048) for converting to and from scipy.sparse.coo_matrix instances (see here). For example, given a SparseSeries with MultiIndex we can convert to a scipy.sparse.coo_matrix by specifying the row and column labels as index levels:

```
s = pd.Series([3.0, np.nan, 1.0, 3.0, np.nan, np.nan])
s.index = pd.MultiIndex.from_tuples([(1, 2, 'a', 0),
                                  (1, 2, 'a', 1),
                                  (1, 1, 'b', 0),
                                  (1, 1, 'b', 1),
                                  (2, 1, 'b', 0),
                                  (2, 1, 'b', 1)],
                        names=['A', 'B', 'C', 'D'])
s
# SparseSeries
ss = s.to_sparse()
s
A, rows, columns = ss.to_coo(row_levels=['A', 'B'],
                            column_levels=['C', 'D'],
                            sort_labels=False)
A
A.todense()
rows
columns
```

The from_coo method is a convenience method for creating a SparseSeries from a scipy.sparse.coo_matrix:

```
from scipy import sparse
A = sparse.coo_matrix(([3.0, 1.0, 2.0], ([1, 0, 0], [0, 2, 3])),
                      shape=(3, 4))
A
A.todense()
ss = pd.SparseSeries.from_coo(A)
ss
```

String methods enhancements

- Following new methods are accessible via .str accessor to apply the function to each values. This is intended to make it more consistent with standard methods on strings. (GH9282, GH9352, GH9386, GH9387, GH9439)

<table>
<thead>
<tr>
<th>Methods</th>
<th>isalnum()</th>
<th>isalpha()</th>
<th>isdigit()</th>
<th>isdigit()</th>
<th>isspace()</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

```
In [7]: s = pd.Series(['abcd', '3456', 'EFGH'])
```

(continues on next page)
• Series.str.pad() and Series.str.center() now accept fillchar option to specify filling character (GH9352)

```python
In [10]: s = pd.Series(['12', '300', '25'])
In [11]: s.str.pad(5, fillchar='_')
```

```
Out[11]:
0 ___12
1 __300
2 ___25
Length: 3, dtype: object
```

• Added Series.str.slice_replace(), which previously raised NotImplementedError (GH8888)

```python
In [12]: s = pd.Series(['ABCD', 'EFGH', 'IJK'])
In [13]: s.str.slice_replace(1, 3, 'X')
```

```
Out[13]:
0 AXD
1 EXH
2 IX
Length: 3, dtype: object
```

Other enhancements

• Reindex now supports method='nearest' for frames or series with a monotonic increasing or decreasing index (GH9258):

```python
In [15]: df = pd.DataFrame({'x': range(5)})
In [16]: df.reindex([0.2, 1.8, 3.5], method='nearest')
```

(continues on next page)
This method is also exposed by the lower level `Index.get_indexer` and `Index.get_loc` methods.

- The `read_excel()` function’s `sheetname` argument now accepts a list and `None`, to get multiple or all sheets respectively. If more than one sheet is specified, a dictionary is returned. (GH9450)

```python
# Returns the 1st and 4th sheet, as a dictionary of DataFrames.
pd.read_excel('path_to_file.xls', sheetname=['Sheet1', 3])
```

- Allow Stata files to be read incrementally with an iterator; support for long strings in Stata files. See the docs [here](GH9493:).

- Paths beginning with `~` will now be expanded to begin with the user’s home directory (GH9066)

- Added time interval selection in `get_data_yahoo` (GH9071)

- Added `Timestamp.to_datetime64()` to complement `Timedelta.to_timedelta64()` (GH9255)

- `tseries.frequencies.to_offset()` now accepts `Timedelta` as input (GH9064)

- Lag parameter was added to the autocorrelation method of `Series`, defaults to lag-1 autocorrelation (GH9192)

- `Timedelta` will now accept `nanoseconds` keyword in constructor (GH9273)

- SQL code now safely escapes table and column names (GH8986)

- Added auto-complete for `Series.str.<tab>`, `Series.dt.<tab>` and `Series.cat.<tab>` (GH9322)

- `Index.get_indexer` now supports `method='pad'` and `method='backfill'` even for any target array, not just monotonic targets. These methods also work for monotonic decreasing as well as monotonic increasing indexes (GH9258).

- `Index.asof` now works on all index types (GH9258).

- A verbose argument has been augmented in `io.read_excel()`, defaults to False. Set to True to print sheet names as they are parsed. (GH9450)

- Added `days_in_month` (compatibility alias `daysinmonth`) property to `Timestamp`, `DatetimeIndex`, `Period`, `PeriodIndex`, and `Series.dt` (GH9572)

- Added decimal option in `to_csv` to provide formatting for non-`'.'` decimal separators (GH781)

- Added `normalize` option for `Timestamp` to normalized to midnight (GH8794)

- Added example for `DataFrame` import to R using HDF5 file and `rhdf5` library. See the [documentation](GH9636) for more.
Backwards incompatible API changes

Changes in timedelta

In v0.15.0 a new scalar type `Timedelta` was introduced, that is a sub-class of `datetime.timedelta`. Mentioned here was a notice of an API change w.r.t. the `.seconds` accessor. The intent was to provide a user-friendly set of accessors that give the ‘natural’ value for that unit, e.g. if you had a `Timedelta('1 day, 10:11:12')`, then `.seconds` would return 12. However, this is at odds with the definition of `datetime.timedelta`, which defines `.seconds` as $10 \times 3600 + 11 \times 60 + 12 = 36672$.

So in v0.16.0, we are restoring the API to match that of `datetime.timedelta`. Further, the component values are still available through the `.components` accessor. This affects the `.seconds` and `.microseconds` accessors, and removes the `.hours`, `.minutes`, `.milliseconds` accessors. These changes affect `TimedeltaIndex` and the Series `.dt` accessor as well. (GH9185, GH9139)

```
In [2]: t = pd.Timedelta('1 day, 10:11:12.100123')
In [3]: t.days
Out[3]: 1
In [4]: t.seconds
Out[4]: 12
In [5]: t.microseconds
Out[5]: 123
```

Previous behavior

```
In [17]: t = pd.Timedelta('1 day, 10:11:12.100123')
In [18]: t.days
Out[18]: 1
In [19]: t.seconds
Out[19]: 36672
In [20]: t.microseconds
Out[20]: 100123
```

New behavior

Using `.components` allows the full component access

```
In [21]: t.components
Out[21]: Components(days=1, hours=10, minutes=11, seconds=12, milliseconds=100, microseconds=123, nanoseconds=0)
In [22]: t.components.seconds
Out[22]: 12
```
Indexing changes

The behavior of a small sub-set of edge cases for using `.loc` have changed (GH8613). Furthermore we have improved the content of the error messages that are raised:

- Slicing with `.loc` where the start and/or stop bound is not found in the index is now allowed; this previously would raise a `KeyError`. This makes the behavior the same as `.ix` in this case. This change is only for slicing, not when indexing with a single label.

```python
In [23]: df = pd.DataFrame(np.random.randn(5, 4),
   ....:     columns=list('ABCD'),
   ....:     index=pd.date_range('20130101', periods=5))

In [24]: df
Out[24]:
   A    B    C    D
2013-01-01 0.469112 -0.282863 -1.509059 -1.135632
2013-01-02 1.212112 -0.173215  0.119209 -1.044236
2013-01-03 -0.861849 -2.104569 -0.494929  1.071804
2013-01-04  0.721555 -0.706771 -1.039575  0.271860
2013-01-05 -0.424972  0.567020  0.276232 -1.087401
[5 rows x 4 columns]

In [25]: s = pd.Series(range(5), [-2, -1, 1, 2, 3])

In [26]: s
Out[26]:
   -2  0
   -1  1
    1  2
    2  3
    3  4
Length: 5, dtype: int64
```

Previous behavior

```python
In [4]: df.loc['2013-01-02':'2013-01-10']
KeyError: 'stop bound [2013-01-10] is not in the [index]'

In [6]: s.loc[-10:3]
KeyError: 'start bound [-10] is not the [index]'
```

New behavior

```python
In [27]: df.loc['2013-01-02':'2013-01-10']
Out[27]:
   A    B    C    D
2013-01-02 1.212112 -0.173215  0.119209 -1.044236
2013-01-03 -0.861849 -2.104569 -0.494929  1.071804
2013-01-04  0.721555 -0.706771 -1.039575  0.271860
2013-01-05 -0.424972  0.567020  0.276232 -1.087401
[4 rows x 4 columns]

In [28]: s.loc[-10:3]
Out[28]:
   -2  0
   -1  1
    1  2
    2  3
    3  4
(continues on next page)
```
- Allow slicing with float-like values on an integer index for `.ix`. Previously this was only enabled for `.loc`:

  Previous behavior

  ```python
  In [8]: s.ix[-1.0:2]
  TypeError: the slice start value [-1.0] is not a proper indexer for this index
  →type (Int64Index)
  ```

  New behavior

  ```python
  In [2]: s.ix[-1.0:2]
  Out[2]:
  -1  1
   1  2
   2  3
  dtype: int64
  ```

- Provide a useful exception for indexing with an invalid type for that index when using `.loc`. For example trying to use `.loc` on an index of type `DatetimeIndex` or `PeriodIndex` or `TimedeltaIndex`, with an integer (or a float).

  Previous behavior

  ```python
  In [4]: df.loc[2:3]
  KeyError: 'start bound [2] is not the [index]'
  ```

  New behavior

  ```python
  In [4]: df.loc[2:3]
  TypeError: Cannot do slice indexing on <class 'pandas.tseries.index.DatetimeIndex'> with <type 'int'> keys
  ```

**Categorical changes**

In prior versions, Categoricals that had an unspecified ordering (meaning no ordered keyword was passed) were defaulted as ordered Categoricals. Going forward, the ordered keyword in the Categorical constructor will default to False. Ordering must now be explicit.

Furthermore, previously you could change the ordered attribute of a Categorical by just setting the attribute, e.g. `cat.ordered=True`; This is now deprecated and you should use `cat.as_ordered()` or `cat.as_unordered()`. These will by default return a new object and not modify the existing object. (GH9347, GH9190)

Previous behavior

```python
In [3]: s = pd.Series([0, 1, 2], dtype='category')
In [4]: s
(continues on next page)```
Out[4]:
0 0
1 1
2 2
dtype: category
Categories (3, int64): [0 < 1 < 2]

In [5]: s.cat.ordered
Out[5]: True

In [6]: s.cat.ordered = False

In [7]: s
Out[7]:
0 0
1 1
2 2
dtype: category
Categories (3, int64): [0, 1, 2]

New behavior

In [29]: s = pd.Series([0, 1, 2], dtype='category')

In [30]: s
Out[30]:
0 0
1 1
2 2
Length: 3, dtype: category
Categories (3, int64): [0, 1, 2]

In [31]: s.cat.ordered
Out[31]: False

In [32]: s = s.cat.as_ordered()

In [33]: s
Out[33]:
0 0
1 1
2 2
Length: 3, dtype: category
Categories (3, int64): [0 < 1 < 2]

In [34]: s.cat.ordered
Out[34]: True

# you can set in the constructor of the Categorical
In [35]: s = pd.Series(pd.Categorical([0, 1, 2], ordered=True))

In [36]: s
Out[36]:
0 0
1 1
2 2
Length: 3, dtype: category
For ease of creation of series of categorical data, we have added the ability to pass keywords when calling .
astype(). These are passed directly to the constructor.

```python
In [54]: s = pd.Series(["a", "b", "c", "a"]).astype('category', ordered=True)

In [55]: s
Out[55]:
0   a
1   b
2   c
3   a
dtype: category
Categories (3, object): [a < b < c]
```

```python
In [56]: s = (pd.Series(["a", "b", "c", "a"])
       ....: .astype('category', categories=list('abcdef'), ordered=False))

In [57]: s
Out[57]:
0   a
1   b
2   c
3   a
dtype: category
Categories (6, object): [a, b, c, d, e, f]
```

**Other API changes**

- `Index.duplicated now returns np.array(dtype=bool)` rather than `Index(dtype=object)` containing bool values. (GH8875)

- `DataFrame.to_json now returns accurate type serialisation for each column for frames of mixed dtype` (GH9037)

Previously data was coerced to a common dtype before serialisation, which for example resulted in integers being serialised to floats:

```python
In [2]: pd.DataFrame({'i': [1,2], 'f': [3.0, 4.2]}).to_json()
Out[2]: '{"f":{"0":3.0,"1":4.2},"i":{"0":1.0,"1":2.0}}'
```

Now each column is serialised using its correct dtype:

```python
In [2]: pd.DataFrame({'i': [1,2], 'f': [3.0, 4.2]}).to_json()
Out[2]: '{"f":{"0":3.0,"1":4.2},"i":{"0":1,"1":2}}'
```

- `DatetimeIndex, PeriodIndex and TimedeltaIndex.summary now output the same format.` (GH9116)

- `TimedeltaIndex.freqstr now output the same string format as DatetimeIndex.` (GH9116)
• Bar and horizontal bar plots no longer add a dashed line along the info axis. The prior style can be achieved with matplotlib’s `axhline` or `axvline` methods (GH9088).

• Series accessors `.dt`, `.cat` and `.str` now raise AttributeError instead of TypeError if the series does not contain the appropriate type of data (GH9617). This follows Python’s built-in exception hierarchy more closely and ensures that tests like `hasattr(s, 'cat')` are consistent on both Python 2 and 3.

• Series now supports bitwise operation for integral types (GH9016). Previously even if the input dtypes were integral, the output dtype was coerced to bool.

Previous behavior

```
In [2]: pd.Series([0, 1, 2, 3], list('abcd')) | pd.Series([4, 4, 4, 4], list('abcd'))
Out[2]:
a True
b True
c True
d True
dtype: bool
```

New behavior. If the input dtypes are integral, the output dtype is also integral and the output values are the result of the bitwise operation.

```
In [2]: pd.Series([0, 1, 2, 3], list('abcd')) | pd.Series([4, 4, 4, 4], list('abcd'))
Out[2]:
a  4
b  5
c  6
d  7
dtype: int64
```

• During division involving a Series or DataFrame, `0/0` and `0//0` now give `np.nan` instead of `np.inf` (GH9144, GH8445)

Previous behavior

```
In [2]: p = pd.Series([0, 1])
In [3]: p / 0
Out[3]:
0   inf
1   inf
dtype: float64
```

```
In [4]: p // 0
Out[4]:
0   inf
1   inf
dtype: float64
```

New behavior

```
In [38]: p = pd.Series([0, 1])
In [39]: p / 0
Out[39]:
0   NaN
```
1   inf
Length: 2, dtype: float64

In [40]: p // 0
Out[40]:
0   NaN
1   inf
Length: 2, dtype: float64

- `Series.values_counts` and `Series.describe` for categorical data will now put `NaN` entries at the end. (GH9443)
- `Series.describe` for categorical data will now give counts and frequencies of 0, not `NaN`, for unused categories (GH9443)
- Due to a bug fix, looking up a partial string label with `DatetimeIndex.asof` now includes values that match the string, even if they are after the start of the partial string label (GH9258).

Old behavior:

```python
In [4]: pd.to_datetime(['2000-01-31', '2000-02-28']).asof('2000-02')
Out[4]: Timestamp('2000-01-31 00:00:00')
```

Fixed behavior:

```python
In [41]: pd.to_datetime(['2000-01-31', '2000-02-28']).asof('2000-02')
Out[41]: Timestamp('2000-02-28 00:00:00')
```

To reproduce the old behavior, simply add more precision to the label (e.g., use `2000-02-01` instead of `2000-02`).

**Deprecations**

- The `rplot` trellis plotting interface is deprecated and will be removed in a future version. We refer to external packages like `seaborn` for similar but more refined functionality (GH3445). The documentation includes some examples how to convert your existing code from `rplot` to `seaborn` here.

- The `pandas.sandbox.qtpandas` interface is deprecated and will be removed in a future version. We refer users to the external package `pandas-qt`. (GH9615)

- The `pandas.rpy` interface is deprecated and will be removed in a future version. Similar functionality can be accessed through the `rpy2` project (GH9602)

- Adding `DatetimeIndex/PeriodIndex` to another `DatetimeIndex/PeriodIndex` is being deprecated as a set-operation. This will be changed to a `TypeError` in a future version. `.union()` should be used for the union set operation. (GH9094)

- Subtracting `DatetimeIndex/PeriodIndex` from another `DatetimeIndex/PeriodIndex` is being deprecated as a set-operation. This will be changed to an actual numeric subtraction yielding a `TimeDeltaIndex` in a future version. `.difference()` should be used for the differencing set operation. (GH9094)
Removal of prior version deprecations/changes

- DataFrame.pivot_table and crosstab's rows and cols keyword arguments were removed in favor of index and columns (GH6581)
- DataFrame.to_excel and DataFrame.to_csv cols keyword argument was removed in favor of columns (GH6581)
- Removed convert_dummies in favor of get_dummies (GH6581)
- Removed value_range in favor of describe (GH6581)

Performance improvements

- Fixed a performance regression for .loc indexing with an array or list-like (GH9126).
- DataFrame.to_json 30x performance improvement for mixed dtype frames. (GH9037)
- Performance improvements in MultiIndex.duplicated by working with labels instead of values (GH9125)
- Improved the speed of nunique by calling unique instead of value_counts (GH9129, GH7771)
- Performance improvement of up to 10x in DataFrame.count and DataFrame.dropna by taking advantage of homogeneous/heterogeneous dtypes appropriately (GH9136)
- Performance improvement of up to 20x in DataFrame.count when using a MultiIndex and the level keyword argument (GH9163)
- Performance and memory usage improvements in merge when key space exceeds int64 bounds (GH9151)
- Performance improvements in multi-key groupby (GH9429)
- Performance improvements in MultiIndex.sortlevel (GH9445)
- Performance and memory usage improvements in DataFrame.duplicated (GH9398)
- Cythonized Period (GH9440)
- Decreased memory usage on to_hdf (GH9648)

Bug fixes

- Changed .to_html to remove leading/trailing spaces in table body (GH4987)
- Fixed issue using read_csv on s3 with Python 3 (GH9452)
- Fixed compatibility issue in DatetimeIndex affecting architectures where numpy.int_ defaults to numpy.int32 (GH8943)
- Bug in Panel indexing with an object-like (GH9140)
- Bug in the returned Series.dt.components index was reset to the default index (GH9247)
- Bug in Categorical.__getitem__/__setitem__ with listlike input getting incorrect results from indexer coercion (GH9469)
- Bug in partial setting with a DatetimeIndex (GH9478)
- Bug in groupby for integer and datetime64 columns when applying an aggregator that caused the value to be changed when the number was sufficiently large (GH9311, GH6620)
- Fixed bug in `to_sql` when mapping a `Timestamp` object column (datetime column with timezone info) to the appropriate sqlalchemy type (GH9085).
- Fixed bug in `to_sql` when mapping a `Timestamp` object column to the appropriate sqlalchemy type (GH9083).
- Bug in `.loc` partial setting with `np.datetime64` (GH9516)
- Incorrect dtypes inferred on datetimelike looking `Series` & on `.xs` slices (GH9477)
- Items in `Categorical.unique()` (and `s.unique() if s is of dtype category`) now appear in the order in which they are originally found, not in sorted order (GH9331). This is now consistent with the behavior for other dtypes in pandas.
- Fixed bug on big endian platforms which produced incorrect results in StataReader (GH8688).
- Bug in `MultiIndex.has_duplicates` when having many levels causes an indexer overflow (GH9075, GH5873)
- Bug in `pivot` and `unstack` where `nan` values would break index alignment (GH4862, GH7401, GH7403, GH7405, GH7466, GH9497)
- Bug in `left join` on `MultiIndex` with `sort=True` or null values (GH9210).
- Bug in `MultiIndex` where inserting new keys would fail (GH9250).
- Bug in `groupby` when key space exceeds int64 bounds (GH9096).
- Bug in `unstack` with `TimedeltaIndex` or `DatetimeIndex` and nulls (GH9491).
- Bug in `rank` where comparing floats with tolerance will cause inconsistent behaviour (GH8365).
- Fixed character encoding bug in `read_stata` and StataReader when loading data from a URL (GH9231).
- Bug in `adding offsets.Nano` to other offsets raises `TypeError` (GH9284)
- Bug in `datetime_index.iteration`, related to (GH8890), fixed in (GH9100)
- Bugs in `resample` around DST transitions. This required fixing offset classes so they behave correctly on DST transitions. (GH5172, GH8744, GH8653, GH9173, GH9468).
- Bug in `binary operator method (eg .mul())` alignment with integer levels (GH9463).
- Bug in `boxplot`, scatter and hexbin plot may show an unnecessary warning (GH8877)
- Bug in `subplot` with `layout kw` may show unnecessary warning (GH9464)
- Bug in using grouper functions that need passed through arguments (e.g. axis), when using wrapped function (e.g. `fillna`), (GH9221)
- `DataFrame` now properly supports simultaneous `copy` and `dtype` arguments in constructor (GH9099)
- Bug in `read_csv` when using skiprows on a file with CR line endings with the c engine. (GH9079)
- `isnull` now detects NaT in `PeriodIndex` (GH9129)
- Bug in `groupby .nth()` with a multiple column groupby (GH8979)
- Bug in `DataFrame.where` and `Series.where` coerce numerics to string incorrectly (GH9280)
- Bug in `DataFrame.where` and `Series.where` raise `ValueError` when string list-like is passed. (GH9280)
- Accessing `Series.str` methods on with non-string values now raises `TypeError` instead of producing incorrect results (GH9184)
- Bug in `DatetimeIndex.__contains__` when index has duplicates and is not monotonic increasing (GH9512)
• Fixed division by zero error for `Series.kurt()` when all values are equal (GH9197)
• Fixed issue in the `xlsxwriter` engine where it added a default ‘General’ format to cells if no other format was applied. This prevented other row or column formatting being applied. (GH9167)
• Fixes issue with `index_col=False` when `usecols` is also specified in `read_csv`. (GH9082)
• Bug where `wide_to_long` would modify the input stub names list (GH9204)
• Bug in `to_sql` not storing float64 values using double precision. (GH9009)
• SparseSeries and SparsePanel now accept zero argument constructors (same as their non-sparse counterparts) (GH9272).
• Regression in merging Categorical and object dtypes (GH9426)
• Bug in `read_csv` with buffer overflows with certain malformed input files (GH9205)
• Bug in groupby `MultiIndex` with missing pair (GH9049, GH9344)
• Fixed bug in `Series.groupby` where grouping on MultiIndex levels would ignore the sort argument (GH9444)
• Fix bug in `DataFrame.Groupby` where `sort=False` is ignored in the case of Categorical columns. (GH8868)
• Fixed bug with reading CSV files from Amazon S3 on python 3 raising a TypeError (GH9452)
• Bug in the Google BigQuery reader where the ‘jobComplete’ key may be present but False in the query results (GH8728)
• Bug in `Series.values_counts` with excluding NaN for categorical type `Series` with `dropna=True` (GH9443)
• Fixed missing numeric_only option for `DataFrame.std/var/sem` (GH9201)
• Support constructing `Panel` or `Panel4D` with scalar data (GH8285)
• Series text representation disconnected from `max_rows/max_columns` (GH7508).
• Series number formatting inconsistent when truncated (GH8532).

Previous behavior

```
In [2]: pd.options.display.max_rows = 10
In [3]: s = pd.Series([1,1,1,1,1,1,1,1,1,1,0.9999,1,1]*10)
In [4]: s
Out[4]:
   0    1.0000
   1    1.0000
   2    1.0000
   ...    ...
  127  0.9999
  128   1.0000
  129   1.0000

Length: 130, dtype: float64
```

New behavior

```
0    1.0000
1    1.0000
2    1.0000
3    1.0000
4    1.0000
```
... 125 1.0000 126 1.0000 127 0.9999 128 1.0000 129 1.0000 dtype: float64

- A Spurious `SettingWithCopy` Warning was generated when setting a new item in a frame in some cases (GH8730)

The following would previously report a `SettingWithCopy` Warning.

```python
In [42]: df1 = pd.DataFrame({'x': pd.Series(['a', 'b', 'c']),
                      'y': pd.Series(['d', 'e', 'f'])})

In [43]: df2 = df1["x"]

In [44]: df2['y'] = ['g', 'h', 'i']
```

### Contributors

A total of 60 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Aaron Toth +
- Alan Du +
- Alessandro Amici +
- Artemy Kolchinsky
- Ashwini Chaudhary +
- Ben Schiller
- Bill Letson
- Brandon Bradley +
- Chau Hoang +
- Chris Reynolds
- Chris Whelan +
- Christer van der Meeren +
- David Cottrell +
- David Stephens
- Ehsan Azarnasab +
- Garrett-R +
- Guillaume Gay
- Jake Torcasso +
- Jason Sexauer
• Jeff Reback
• John McNamara
• Joris Van den Bossche
• Joschka zur Jacobsmühen +
• Juarez Bochi +
• Junya Hayashi +
• K.-Michael Aye
• Kerby Shedden +
• Kevin Sheppard
• Kieran O’Mahony
• Kodi Arfer +
• Matti Airas +
• Min RK +
• Mortada Mehyar
• Robert +
• Scott E Lasley
• Scott Lasley +
• Sergio Pascual +
• Skipper Seabold
• Stephan Hoyer
• Thomas Grainger
• Tom Augspurger
• TomAugspurger
• Vladimir Filimonov +
• Vyomkesh Tripathi +
• Will Holmgren
• Yulong Yang +
• behzad nouri
• bertrandhaut +
• bjonen
• cel4 +
• clham
• hsperr +
• ischwabacher
• jnmclarty
• josham +
5.13  Version 0.15

5.13.1  Version 0.15.2 (December 12, 2014)

This is a minor release from 0.15.1 and includes a large number of bug fixes along with several new features, enhancements, and performance improvements. A small number of API changes were necessary to fix existing bugs. We recommend that all users upgrade to this version.

- Enhancements
- API Changes
- Performance Improvements
- Bug Fixes

API changes

- Indexing in MultiIndex beyond lex-sort depth is now supported, though a lexically sorted index will have a better performance. (GH2646)

```python
In [1]: df = pd.DataFrame({
       'jim': [0, 0, 1, 1],
       'joe': ['x', 'x', 'z', 'y'],
       'jolie': np.random.rand(4)
}).set_index(['jim', 'joe'])

In [2]: df
Out[2]:
      jolie
     jim  joe
0    x  0.126970
  x  0.966718
1    z  0.260476
  y  0.897237
[4 rows x 1 columns]

In [3]: df.index.lexsort_depth
Out[3]: 1

# in prior versions this would raise a KeyError
# will now show a PerformanceWarning

In [4]: df.loc[(1, 'z')]
Out[4]:
      jolie
     jim  joe
1    z  0.260476
```

(continues on next page)
### lexically sorting

```python
In [5]: df2 = df.sort_index()

In [6]: df2
Out[6]:
    jolie
   jim   joe
0    x  0.126970
     x  0.966718
1    y  0.897237
     z  0.260476
[4 rows x 1 columns]
```

```python
In [7]: df2.index.lexsort_depth
Out[7]:
[97x678]2

In [8]: df2.loc[(1,'z')]
Out[8]:
    jolie
   jim   joe
1    z  0.260476
[1 rows x 1 columns]
```

• Bug in unique of Series with category dtype, which returned all categories regardless whether they were “used” or not (see GH8559 for the discussion). Previous behaviour was to return all categories:

```python
In [3]: cat = pd.Categorical(['a', 'b', 'a'], categories=['a', 'b', 'c'])

In [4]: cat
Out[4]:
[a, b, a]
Categories (3, object): [a < b < c]

In [5]: cat.unique()
Out[5]: array(['a', 'b', 'c'], dtype=object)
```

Now, only the categories that do effectively occur in the array are returned:

```python
In [9]: cat = pd.Categorical(['a', 'b', 'a'], categories=['a', 'b', 'c'])

In [10]: cat.unique()
Out[10]:
['a', 'b']
Categories (2, object): ['a', 'b']
```

• Series.all and Series.any now support the level and skipna parameters. Series.all, Series.any, Index.all, and Index.any no longer support the out and keepdims parameters, which existed for compatibility with ndarray. Various index types no longer support the all and any aggregation functions and will now raise TypeError. (GH8302).

• Allow equality comparisons of Series with a categorical dtype and object dtype; previously these would raise TypeError (GH8938)
• Bug in NDFrame: conflicting attribute/column names now behave consistently between getting and setting. Previously, when both a column and attribute named y existed, data.y would return the attribute, while data.y = z would update the column (GH8994)

```python
In [11]: data = pd.DataFrame({'x': [1, 2, 3]})
In [12]: data.y = 2
In [13]: data['y'] = [2, 4, 6]

In [14]: data
Out[14]:
   x  y
0 1  2
1 2  4
2 3  6

[3 rows x 2 columns]

# this assignment was inconsistent
In [15]: data.y = 5
```

Old behavior:

```python
In [6]: data.y
Out[6]: 2

In [7]: data['y'].values
Out[7]: array([5, 5, 5])
```

New behavior:

```python
In [16]: data.y
Out[16]: 5

In [17]: data['y'].values
Out[17]: array([2, 4, 6])
```

• Timestamp('now') is now equivalent to Timestamp.now() in that it returns the local time rather than UTC. Also, Timestamp('today') is now equivalent to Timestamp.today() and both have tz as a possible argument. (GH9000)

• Fix negative step support for label-based slices (GH8753)

Old behavior:

```python
In [1]: s = pd.Series(np.arange(3), ['a', 'b', 'c'])
Out[1]:
   a  0
   b  1
   c  2
dtype: int64

In [2]: s.loc['c':'a':-1]
Out[2]:
   c  2
dtype: int64
```

New behavior:
Enhancements

Categorical enhancements:

- Added ability to export Categorical data to Stata (GH8633). See here for limitations of categorical variables exported to Stata data files.

- Added flag `order_categoricals` to StataReader and read_stata to select whether to order imported categorical data (GH8836). See here for more information on importing categorical variables from Stata data files.

- Added ability to export Categorical data to/to from HDF5 (GH7621). Queries work the same as if it was an object array. However, the `category` dtyped data is stored in a more efficient manner. See here for an example and caveats w.r.t. prior versions of pandas.

- Added support for `searchsorted()` on `Categorical` class (GH8420).

Other enhancements:

- Added the ability to specify the SQL type of columns when writing a DataFrame to a database (GH8778). For example, specifying to use the sqlalchemy `String` type instead of the default `Text` type for string columns:

```python
from sqlalchemy.types import String
data.to_sql('data_dtype', engine, dtype={'Col_1': String})  # noqa F821
```

- `Series.all` and `Series.any` now support the `level` and `skipna` parameters (GH8302):

```python
In [20]: s = pd.Series([[False, True, False], index=[0, 0, 1])

In [21]: s.any(level=0)
Out [21]:
0  True
1  False
Length: 2, dtype: bool
```

- Panel now supports the `all` and `any` aggregation functions. (GH8302):

```python
>>> p = pd.Panel(np.random.rand(2, 5, 4) > 0.1)
>>> p.all()
    0 1 2 3
0 True True True True
1 True False True True
2 True True True True
3 False True False True
4 True True True True
```

- Added support for `utcfromtimestamp()`, `fromtimestamp()`, and `combine()` on `Timestamp` class (GH5351).
• Added Google Analytics (pandas.io.ga) basic documentation (GH8835). See here.
• Timedelta arithmetic returns NotImplemented in unknown cases, allowing extensions by custom classes (GH8813).
• Timedelta now supports arithmetic with numpy.ndarray objects of the appropriate dtype (numpy 1.8 or newer only) (GH8884).
• Added Timedelta.to_timedelta64() method to the public API (GH8884).
• Added gbq.generate_bq_schema() function to the gbq module (GH8325).
• Series now works with map objects the same way as generators (GH8909).
• Added context manager to HDFStore for automatic closing (GH8791).
• to_datetime gains an exact keyword to allow for a format to not require an exact match for a provided format string (if its False). exact defaults to True (meaning that exact matching is still the default) (GH8904)
• Added axvlines boolean option to parallel_coordinates plot function, determines whether vertical lines will be printed, default is True
• Added ability to read table footers to read_html (GH8552)
• to_sql now infers data types of non-NA values for columns that contain NA values and have dtype object (GH8778).

Performance

• Reduce memory usage when skiprows is an integer in read_csv (GH8681)
• Performance boost for to_datetime conversions with a passed format=, and the exact=False (GH8904)

Bug fixes

• Bug in concat of Series with category dtype which were coercing to object. (GH8641)
• Bug in Timestamp-Timestamp not returning a Timedelta type and datelike-datelike ops with timezones (GH8865)
• Made consistent a timezone mismatch exception (either tz operated with None or incompatible timezone), will now return TypeError rather than ValueError (a couple of edge cases only), (GH8865)
• Bug in using a pd.Grouper(key=...) with no level/axis or level only (GH8795, GH8866)
• Report a TypeError when invalid/no parameters are passed in a groupby (GH8015)
• Bug in packaging pandas with py2app/cx_Freeze (GH8602, GH8831)
• Bug in groupby signatures that didn’t include *args or **kwargs (GH8733).
• io.data.Options now raises RemoteDataError when no expiry dates are available from Yahoo and when it receives no data from Yahoo (GH8761), (GH8783).
• Unclear error message in csv parsing when passing dtype and names and the parsed data is a different data type (GH8833)
• Bug in slicing a MultiIndex with an empty list and at least one boolean indexer (GH8781)
• io.data.Options now raises RemoteDataError when no expiry dates are available from Yahoo (GH8761).
• Timedelta kwargs may now be numpys ints and floats (GH8757).
- Fixed several outstanding bugs for Timedelta arithmetic and comparisons (GH8813, GH5963, GH5436).
- `sql_schema` now generates dialect appropriate CREATE TABLE statements (GH8697)
- `slice` string method now takes step into account (GH8754)
- **Bug** in `BlockManager` where setting values with different type would break block integrity (GH8850)
- **Bug** in `DatetimeIndex` when using time object as key (GH8667)
- **Bug** in `merge` where how='left' and sort=False would not preserve left frame order (GH7331)
- **Bug** in `MultiIndex.reindex` where reindexing at level would not reorder labels (GH4088)
- **Bug** in certain operations with dateutil timezones, manifesting with dateutil 2.3 (GH8639)
- Regression in DatetimeIndex iteration with a Fixed/Local offset timezone (GH8890)
- **Bug** in `to_datetime` when parsing a nanoseconds using the %f format (GH8989)
- `io.data.Options` now raises RemoteDataError when no expiry dates are available from Yahoo and when it receives no data from Yahoo (GH8761), (GH8783).
- Fix: The font size was only set on x axis if vertical or the y axis if horizontal. (GH8765)
- Fixed division by 0 when reading big csv files in python 3 (GH8621)
- **Bug** in outputting a MultiIndex with to_html, index=False which would add an extra column (GH8452)
- Imported categorical variables from Stata files retain the ordinal information in the underlying data (GH8836).
- Defined `.size` attribute across NDFrame objects to provide compat with numpy >= 1.9.1; buggy with np. array_split (GH8846)
- Skip testing of histogram plots for matplotlib <= 1.2 (GH8648).
- **Bug** where `get_data_google` returned object dtypes (GH3995)
- **Bug** in `DataFrame.stack(..., dropna=False)` when the `DataFrame`'s columns is a MultiIndex whose labels do not reference all its levels. (GH8844)
- **Bug** in that Option context applied on __enter__ (GH8514)
- **Bug** in resample that causes a ValueError when resampling across multiple days and the last offset is not calculated from the start of the range (GH8683)
- **Bug** where `DataFrame.plot(kind='scatter')` fails when checking if an np.array is in the DataFrame (GH8852)
- `in` pd.infer_freq/DataFrame.inferred_freq that prevented proper sub-daily frequency inference when the index contained DST days (GH8772).
- **Bug** where index name was still used when plotting a series with use_index=False (GH8558).
- **Bugs** when trying to stack multiple columns, when some (or all) of the level names are numbers (GH8584).
- **Bug** in `MultiIndex` where __contains__ returns wrong result if index is not lexically sorted or unique (GH7724)
- **BUG CSV:** fix problem with trailing white space in skipped rows, (GH8679), (GH8661), (GH8983)
- **Regression** in `Timestamp` does not parse ‘Z’ zone designator for UTC (GH8777)
- **Bug** in `StataWriter` the produces writes strings with 244 characters irrespective of actual size (GH8969)
- Fixed ValueError raised by cummin/cummax when datetime64 Series contains NaT. (GH8965)
- **Bug** in `DataReader` returns object dtype if there are missing values (GH8980)
Bug in plotting if sharex was enabled and index was a timeseries, would show labels on multiple axes (GH3964).

Bug where passing a unit to the TimedeltaIndex constructor applied the to nano-second conversion twice. (GH9011).

Bug in plotting of a period-like array (GH9012)

Contributors

A total of 49 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Aaron Staple
- Angelos Evripiotis +
- Artemy Kolchinsky
- Benoit Pointet +
- Brian Jacobowski +
- Charalampos Papaloizou +
- Chris Warth +
- David Stephens
- Fabio Zanini +
- Francesc Via +
- Henry Kleynhans +
- Jake VanderPlas +
- Jan Schulz
- Jeff Reback
- Jeff Tratner
- Joris Van den Bossche
- Kevin Sheppard
- Matt Suggit +
- Matthew Brett
- Phillip Cloud
- Rupert Thompson +
- Scott E Lasley +
- Stephan Hoyer
- Stephen Simmons +
- Sylvain Corlay +
- Thomas Grainger +
- Tiago Antao +
- Tom Augspurger
- Trent Hauck
5.13.2 Version 0.15.1 (November 9, 2014)

This is a minor bug-fix release from 0.15.0 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

- Enhancements
- API Changes
- Bug Fixes

API changes

- `s.dt.hour` and other `.dt` accessors will now return `np.nan` for missing values (rather than previously -1), (GH8689)

\begin{verbatim}
In [1]: s = pd.Series(pd.date_range('20130101', periods=5, freq='D'))
In [2]: s.iloc[2] = np.nan
In [3]: s
Out [3]:
\end{verbatim}
previous behavior:

```
In [6]: s.dt.hour
Out[6]:
0   0
1   0
2  -1
3   0
4   0
dtype: int64
```

current behavior:

```
In [4]: s.dt.hour
Out[4]:
0   0.0
1   0.0
2  NaN
3   0.0
4   0.0
Length: 5, dtype: float64
```

- `groupby` with `as_index=False` will not add erroneous extra columns to result (GH8582):

  previous behavior:

  ```
  In [4]: df.groupby(ts, as_index=False).max()
  Out[4]:
   NaN  jim  joe
  0  72  81
  ```

```
• groupby will not erroneously exclude columns if the column name conflicts with the grouper name (GH8112):

```
In [10]: df = pd.DataFrame({'jim': range(5), 'joe': range(5, 10)})
In [11]: df
Out[11]:
   jim  joe
0    0   5
1    1   6
2    2   7
3    3   8
4    4   9
[5 rows x 2 columns]
In [12]: gr = df.groupby(df['jim'] < 2)
```

previous behavior (excludes 1st column from output):

```
In [4]: gr.apply(sum)
Out[4]:
   joe
jim False 24
     True 11
```

current behavior:

```
In [13]: gr.apply(sum)
Out[13]:
   jim  joe
     jim
jim False  9  24
     True  1  11
[2 rows x 2 columns]
```

• Support for slicing with monotonic decreasing indexes, even if start or stop is not found in the index (GH7860):

```
In [14]: s = pd.Series(['a', 'b', 'c', 'd'], [4, 3, 2, 1])
```
previous behavior:

```
In [8]: s.loc[3.5:1.5]
KeyError: 3.5
```

current behavior:

```
In [16]: s.loc[3.5:1.5]
Out[16]:
3   b
2   c
Length: 2, dtype: object
```

- `io.data.Options` has been fixed for a change in the format of the Yahoo Options page (GH8612), (GH8741)

**Note:** As a result of a change in Yahoo’s option page layout, when an expiry date is given, `Options` methods now return data for a single expiry date. Previously, methods returned all data for the selected month.

The `month` and `year` parameters have been undeprecated and can be used to get all options data for a given month.

If an expiry date that is not valid is given, data for the next expiry after the given date is returned.

Option data frames are now saved on the instance as `callsYYMMDD` or `putsYYMMDD`. Previously they were saved as `callsMMYY` and `putsMMYY`. The next expiry is saved as `calls` and `puts`.

New features:
- The expiry parameter can now be a single date or a list-like object containing dates.
- A new property `expiry_dates` was added, which returns all available expiry dates.

Current behavior:

```
In [17]: from pandas.io.data import Options

In [18]: aapl = Options('aapl', 'yahoo')

In [19]: aapl.get_call_data().iloc[0:5, 0:1]
Out[19]:
Last
Strike Expiry Type Symbol      
80 2014-11-14 call AAPL141114C00080000 29.05
84 2014-11-14 call AAPL141114C00084000 24.80
85 2014-11-14 call AAPL141114C00085000 24.05
86 2014-11-14 call AAPL141114C00086000 22.76
87 2014-11-14 call AAPL141114C00087000 21.74
```

(continues on next page)
In [20]: aapl.expiry_dates
Out[20]:
[datetime.date(2014, 11, 14),
datetime.date(2014, 11, 22),
datetime.date(2014, 11, 28),
datetime.date(2014, 12, 5),
datetime.date(2014, 12, 12),
datetime.date(2014, 12, 20),
datetime.date(2015, 1, 17),
datetime.date(2015, 2, 20),
datetime.date(2015, 4, 17),
datetime.date(2015, 7, 17),
datetime.date(2016, 1, 15),
datetime.date(2017, 1, 20)]

In [21]: aapl.get_near_stock_price(expiry=aapl.expiry_dates[0:3]).iloc[0:5, 0:1]
Out[21]:
<table>
<thead>
<tr>
<th>Last</th>
<th>Strike</th>
<th>Expiry</th>
<th>Type</th>
<th>Symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>109</td>
<td>2014-11-22</td>
<td>call</td>
<td>AAPL141122C00109000</td>
</tr>
<tr>
<td></td>
<td>110</td>
<td>2014-11-14</td>
<td>call</td>
<td>AAPL141114C000110000</td>
</tr>
<tr>
<td></td>
<td>110</td>
<td>2014-11-22</td>
<td>call</td>
<td>AAPL141122C00110000</td>
</tr>
</tbody>
</table>

- pandas now also registers the `datetime64` dtype in matplotlib’s units registry to plot such values as datetimes. This is activated once pandas is imported. In previous versions, plotting an array of `datetime64` values will have resulted in plotted integer values. To keep the previous behaviour, you can do `del matplotlib.units.registry[np.datetime64]` (GH8614).

**Enhancements**

- `concat` permits a wider variety of iterables of pandas objects to be passed as the first parameter (GH8645):

  In [17]: from collections import deque
  In [18]: df1 = pd.DataFrame([1, 2, 3])
  In [19]: df2 = pd.DataFrame([4, 5, 6])
  
  previous behavior:
  In [7]: pd.concat(deque((df1, df2)))
  TypeError: first argument must be a list-like of pandas objects, you passed an object of type "deque"
  
  current behavior:
  In [20]: pd.concat(deque((df1, df2)))
  Out[20]:
<table>
<thead>
<tr>
<th>0</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 1</td>
</tr>
<tr>
<td>1 2</td>
</tr>
<tr>
<td>2 3</td>
</tr>
<tr>
<td>0 4</td>
</tr>
</tbody>
</table>
• Represent `MultiIndex` labels with a dtype that utilizes memory based on the level size. In prior versions, the memory usage was a constant 8 bytes per element in each level. In addition, in prior versions, the reported memory usage was incorrect as it didn’t show the usage for the memory occupied by the underlying data array. (GH8456)

```
In [21]: dfi = pd.DataFrame(1, index=pd.MultiIndex.from_product([['a'], range(1000)]), columns=['A'])

previous behavior:
```

```
# this was underreported in prior versions
In [1]: dfi.memory_usage(index=True)
Out[1]:
Index 8000 # took about 24008 bytes in < 0.15.1
A 8000
dtype: int64
```

current behavior:

```
In [22]: dfi.memory_usage(index=True)
Out[22]:
Index 52080
A 8000
Length: 2, dtype: int64
```

• Added Index properties `is_monotonic_increasing` and `is_monotonic_decreasing` (GH8680).

• Added option to select columns when importing Stata files (GH7935)

• Qualify memory usage in `DataFrame.info()` by adding + if it is a lower bound (GH8578)

• Raise errors in certain aggregation cases where an argument such as `numeric_only` is not handled (GH8592).

• Added support for 3-character ISO and non-standard country codes in `io.wb.download()` (GH8482)

• World Bank data requests now will warn/raise based on an `errors` argument, as well as a list of hard-coded country codes and the World Bank’s JSON response. In prior versions, the error messages didn’t look at the World Bank’s JSON response. Problem-inducing input were simply dropped prior to the request. The issue was that many good countries were cropped in the hard-coded approach. All countries will work now, but some bad countries will raise exceptions because some edge cases break the entire response. (GH8482)

• Added option to `Series.str.split()` to return a `DataFrame` rather than a `Series` (GH8428)

• Added option to `df.info(null_counts=None|True|False)` to override the default display options and force showing of the null-counts (GH8701)
Bug fixes

- Bug in unpickling of a CustomBusinessDay object (GH8591)
- Bug in coercing Categorical to a records array, e.g. df.to_records() (GH8626)
- Bug in Categorical not created properly with Series.to_frame() (GH8626)
- Bug in coercing in astype of a Categorical of a passed pd.Categorical (this now raises TypeError correctly), (GH8626)
- Bug in cut/qcut when using Series and retbins=True (GH8589)
- Bug in writing Categorical columns to an SQL database with to_sql (GH8624).
- Bug in comparing Categorical of datetime raising when being compared to a scalar datetime (GH8687)
- Bug in selecting from a Categorical with .iloc (GH8623)
- Bug in groupby-transform with a Categorical (GH8623)
- Bug in duplicated/drop_duplicates with a Categorical (GH8623)
- Bug in Categorical reflected comparison operator raising if the first argument was a numpy array scalar (e.g. np.int64) (GH8658)
- Bug in Panel indexing with a list-like (GH8710)
- Compat issue is DataFrame.dtypes when options.mode.use_inf_as_null is True (GH8722)
- Bug in read_csv, dialect parameter would not take a string (GH8703)
- Bug in slicing a MultiIndex level with an empty-list (GH8737)
- Bug in numeric index operations of add/sub with Float/Index Index with numpy arrays (GH8608)
- Bug in setitem with empty indexer and unwanted coercion of dtypes (GH8669)
- Bug in ix/loc block splitting on setitem (manifests with integer-like dtypes, e.g. datetime64) (GH8607)
- Bug when doing label based indexing with integers not found in the index for non-unique but monotonic indexes (GH8680).
- Bug when indexing a Float64Index with np.nan on numpy 1.7 (GH8980).
- Fix shape attribute for MultiIndex (GH8609)
- Bug in GroupBy where a name conflict between the grouper and columns would break groupby operations (GH7115, GH8112)
- Fixed a bug where plotting a column y and specifying a label would mutate the index name of the original DataFrame (GH8494)
- Fix regression in plotting of a DatetimeIndex directly with matplotlib (GH8614).
- Bug in date_range where partially-specified dates would incorporate current date (GH6961)
- Bug in Setting by indexer to a scalar value with a mixed-dtype Panel4d was failing (GH8702)
- Bug whereDataReader's would fail if one of the symbols passed was invalid. Now returns data for valid symbols and np.nan for invalid (GH8494)
- Bug in get_quote_yahoo that wouldn’t allow non-float return values (GH5229).
Contributors

A total of 23 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

• Aaron Staple +
• Andrew Rosenfeld
• Anton I. Sipos
• Artemy Kolchinsky
• Bill Letson +
• Dave Hughes +
• David Stephens
• Guillaume Horel +
• Jeff Reback
• Joris Van den Bossche
• Kevin Sheppard
• Nick Stahl +
• Sanghee Kim +
• Stephan Hoyer
• Tom Augspurger
• TomAugspurger
• WANG Aiyong +
• behzad nouri
• immerrr
• jnmclarty
• jreback
• pallav-fdsi +
• unutbu

5.13.3 Version 0.15.0 (October 18, 2014)

This is a major release from 0.14.1 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Warning: pandas >= 0.15.0 will no longer support compatibility with NumPy versions < 1.7.0. If you want to use the latest versions of pandas, please upgrade to NumPy >= 1.7.0 (GH7711)

• Highlights include:
  – The Categorical type was integrated as a first-class pandas type, see here
  – New scalar type Timedelta, and a new index type TimedeltaIndex, see here
- New datetimelike properties accessor `.dt` for Series, see *Datetimelike Properties*
- New DataFrame default display for `df.info()` to include memory usage, see *Memory Usage*
- `read_csv` will now by default ignore blank lines when parsing, see *here*
- API change in using Indexes in set operations, see *here*
- Enhancements in the handling of timezones, see *here*
- A lot of improvements to the rolling and expanding moment functions, see *here*
- Internal refactoring of the `Index` class to no longer sub-class `ndarray`, see *Internal Refactoring*
- dropping support for `PyTables` less than version 3.0.0, and `numexpr` less than version 2.1 (GH7990)
- Split indexing documentation into *Indexing and Selecting Data* and *MultiIndex / Advanced Indexing*
- Split out string methods documentation into *Working with Text Data*

• Check the *API Changes* and *deprecations* before updating

• *Other Enhancements*

• *Performance Improvements*

• *Bug Fixes*

---

**Warning:** In 0.15.0 `Index` has internally been refactored to no longer sub-class `ndarray` but instead subclass `PandasObject`, similarly to the rest of the pandas objects. This change allows very easy sub-classing and creation of new index types. This should be a transparent change with only very limited API implications (See the *Internal Refactoring*)

---

**Warning:** The refactoring in `Categorical` changed the two argument constructor from “codes/labels and levels” to “values and levels (now called ‘categories’)”. This can lead to subtle bugs. If you use `Categorical` directly, please audit your code before updating to this pandas version and change it to use the `from_codes()` constructor. See more on `Categorical here`

---

**New features**

**Categoricals in Series/DataFrame**

*Categorical* can now be included in *Series* and *DataFrames* and gained new methods to manipulate. Thanks to Jan Schulz for much of this API/implementation. (GH3943, GH5313, GH5314, GH7444, GH7839, GH7848, GH7864, GH7914, GH7768, GH8006, GH3678, GH8075, GH8076, GH8143, GH8453, GH8518).

For full docs, see the *categorical introduction* and the *API documentation*.

```
In [1]: df = pd.DataFrame({"id": [1, 2, 3, 4, 5, 6],
                    ...
                    "raw_grade": ['a', 'b', 'b', 'a', 'a', 'e']})
    ...

In [2]: df["grade"] = df["raw_grade"].astype("category")

In [3]: df["grade"]
Out[3]:
0    a
```
1 b
2 b
3 a
4 a
5 e
Name: grade, Length: 6, dtype: category
Categories (3, object): ['a', 'b', 'e']

# Rename the categories
In [4]: df['grade'].cat.categories = ['very good', 'good', 'very bad']

# Reorder the categories and simultaneously add the missing categories
In [5]: df['grade'] = df['grade'].cat.set_categories(
    ...: ['very bad', 'bad',
    ...:     'medium', 'good', 'very good'])

In [6]: df['grade']
Out[6]:
0 very good
1 good
2 good
3 very good
4 very good
5 very bad
Name: grade, Length: 6, dtype: category
Categories (5, object): ['very bad', 'bad', 'medium', 'good', 'very good']

In [7]: df.sort_values('grade')
Out[7]:
   id raw_grade  grade
5   6         e  very bad
1   2         b    good
2   3         b    good
0   1         a  very good
3   4         a  very good
4   5         a  very good
[6 rows x 3 columns]

In [8]: df.groupby('grade').size()
Out[8]:
grade
very bad     1
bad          0
medium       0
good         2
very good    3
Length: 5, dtype: int64

- pandas.core.group_agg and pandas.core.factor_agg were removed. As an alternative, construct a dataframe and use df.groupby(<group>).agg(<func>).
- Supplying “codes/labels and levels” to the Categorical constructor is not supported anymore. Supplying two arguments to the constructor is now interpreted as “values and levels (now called ‘categories’)”. Please change your code to use the from_codes() constructor.
- The Categorical.labels attribute was renamed to Categorical.codes and is read only. If you want to manipulate codes, please use one of the API methods on Categoricals.
• The `Categorical.levels` attribute is renamed to `Categorical.categories`.

### TimedeltaIndex/Scalar

We introduce a new scalar type `Timedelta`, which is a subclass of `datetime.timedelta`, and behaves in a similar manner, but allows compatibility with `np.timedelta64` types as well as a host of custom representation, parsing, and attributes. This type is very similar to how `Timestamp` works for `datetimes`. It is a nice-API box for the type. See the [docs](https://pandas.pydata.org/pandas-docs/stable/reference/typing.html) (GH3009, GH4533, GH8209, GH8187, GH8190, GH7869, GH7661, GH8345, GH8471)

**Warning:** `Timedelta` scalars (and `TimedeltaIndex`) component fields are *not the same* as the component fields on a `datetime.timedelta` object. For example, `.seconds` on a `datetime.timedelta` object returns the total number of seconds combined between `hours`, `minutes` and `seconds`. In contrast, the pandas `Timedelta` breaks out hours, minutes, microseconds and nanoseconds separately.

```python
# Timedelta accessor
In [9]: tds = pd.Timedelta('31 days 5 min 3 sec')
In [10]: tds.minutes
Out[10]: 5L
In [11]: tds.seconds
Out[11]: 3L

# datetime.timedelta accessor
# this is 5 minutes * 60 + 3 seconds
In [12]: tds.to_pytimedelta().seconds
Out[12]: 303
```

**Note:** this is no longer true starting from v0.16.0, where full compatibility with `datetime.timedelta` is introduced. See the 0.16.0 [whatsnew entry](https://pandas.pydata.org/pandas-docs/stable/whatsnew/v0.16.0.html)

**Warning:** Prior to 0.15.0 `pd.to_timedelta` would return a `Series` for list-like/`Series` input, and a `np.timedelta64` for scalar input. It will now return a `TimedeltaIndex` for list-like input, `Series` for `Series` input, and `Timedelta` for scalar input.

The arguments to `pd.to_timedelta` are now `(arg,unit='ns',box=True,coerce=False)`, previously were `(arg,box=True,unit='ns')` as these are more logical.

```python
Construct a scalar
In [9]: pd.Timedelta('1 days 06:05:01.00003')
Out[9]: Timedelta('1 days 06:05:01.000030')
In [10]: pd.Timedelta('15.5us')
Out[10]: Timedelta('0 days 00:00:00.000015500')
In [11]: pd.Timedelta('1 hour 15.5us')
Out[11]: Timedelta('0 days 01:00:00.000015500')

# negative Timedeltas have this string repr
# to be more consistent with datetime.timedelta conventions
In [12]: pd.Timedelta('-1us')
Out[12]: Timedelta('-1 days +23:59:59.999999')
```

(continues on next page)
Access fields for a Timedelta

```
In [14]: td = pd.Timedelta('1 hour 3m 15.5us')
In [15]: td.seconds
Out[15]: 3780
In [16]: td.microseconds
Out[16]: 15
In [17]: td.nanoseconds
Out[17]: 500
```

Construct a TimedeltaIndex

```
In [18]: pd.TimedeltaIndex(['1 days', '1 days, 00:00:05', 
                   '2 days 00:00:02'], 
                   np.timedelta64(2, 'D'), 
                   datetime.timedelta(days=2, seconds=2))
```

Constructing a TimedeltaIndex with a regular range

```
In [19]: pd.timedelta_range('1 days', periods=5, freq='D')
Out[19]: TimedeltaIndex(['1 days', '2 days', '3 days', '4 days', '5 days'], 
                       dtype='timedelta64[ns]', freq='D')
```

```
In [20]: pd.timedelta_range(start='1 days', end='2 days', freq='30T')
Out[20]: TimedeltaIndex(['1 days 00:00:00', '1 days 00:30:00', '1 days 01:00:00', 
                       '1 days 01:30:00', '1 days 02:00:00', '1 days 02:30:00', 
                       '1 days 03:00:00', '1 days 03:30:00', '1 days 04:00:00', 
                       '1 days 04:30:00', '1 days 05:00:00', '1 days 05:30:00', 
                       '1 days 06:00:00', '1 days 06:30:00', '1 days 07:00:00', 
                       '1 days 07:30:00', '1 days 08:00:00', '1 days 08:30:00', 
                       '1 days 09:00:00', '1 days 09:30:00', '1 days 10:00:00', 
                       '1 days 10:30:00', '1 days 11:00:00', '1 days 11:30:00', 
                       '1 days 12:00:00', '1 days 12:30:00', '1 days 13:00:00', 
                       '1 days 13:30:00', '1 days 14:00:00', '1 days 14:30:00', 
                       '1 days 15:00:00', '1 days 15:30:00', '1 days 16:00:00', 
                       '1 days 16:30:00', '1 days 17:00:00', '1 days 17:30:00', 
                       '1 days 18:00:00', '1 days 18:30:00', '1 days 19:00:00', 
                       '1 days 19:30:00', '1 days 20:00:00', '1 days 20:30:00', 
                       '1 days 21:00:00', '1 days 21:30:00', '1 days 22:00:00', 
                       '1 days 22:30:00', '1 days 23:00:00', '1 days 23:30:00', 
                       '2 days 00:00:00'], 
                       dtype='timedelta64[ns]', freq='30T')
```

You can now use a TimedeltaIndex as the index of a pandas object
In [21]: s = pd.Series(np.arange(5),
               index=pd.timedelta_range('1 days', periods=5, freq='s'))

In [22]: s
Out[22]:
1 days 00:00:00 0
1 days 00:00:01 1
1 days 00:00:02 2
1 days 00:00:03 3
1 days 00:00:04 4
Freq: S, Length: 5, dtype: int64

You can select with partial string selections

In [23]: s['1 day 00:00:02']
Out[23]: 2

In [24]: s['1 day': '1 day 00:00:02']
Out[24]:
1 days 00:00:00 0
1 days 00:00:01 1
1 days 00:00:02 2
Freq: S, Length: 3, dtype: int64

Finally, the combination of TimedeltaIndex with DatetimeIndex allow certain combination operations that are NaT preserving:

In [25]: tdi = pd.TimedeltaIndex(['1 days', pd.NaT, '2 days'])

In [26]: tdi.tolist()
Out[26]: [Timedelta('1 days 00:00:00'), NaT, Timedelta('2 days 00:00:00')]

In [27]: dti = pd.date_range('20130101', periods=3)

In [28]: dti.tolist()
Out[28]: [Timestamp('2013-01-01 00:00:00', freq='D'),
          Timestamp('2013-01-02 00:00:00', freq='D'),
          Timestamp('2013-01-03 00:00:00', freq='D')]

In [29]: (dti + tdi).tolist()
Out[29]: [Timestamp('2013-01-02 00:00:00'), NaT, Timestamp('2013-01-05 00:00:00')]

In [30]: (dti - tdi).tolist()
Out[30]: [Timestamp('2012-12-31 00:00:00'), NaT, Timestamp('2013-01-01 00:00:00')]

• iteration of a Series e.g. list(Series(...)) of timedelta64[ns] would prior to v0.15.0 return np.timedelta64 for each element. These will now be wrapped in Timedelta.
Memory usage

Implemented methods to find memory usage of a DataFrame. See the FAQ for more. (GH6852).

A new display option display.memory_usage (see Options and settings) sets the default behavior of the memory_usage argument in the df.info() method. By default display.memory_usage is True.

```python
In [31]: dtypes = ['int64', 'float64', 'datetime64[ns]', 'timedelta64[ns]',
    ....: 'complex128', 'object', 'bool']
    ....:

In [32]: n = 5000

In [33]: data = {t: np.random.randint(100, size=n).astype(t) for t in dtypes}

In [34]: df = pd.DataFrame(data)

In [35]: df['categorical'] = df['object'].astype('category')

In [36]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 8 columns):
   # Column     Non-Null Count   Dtype
     ---        --------------   -----  
      0 int64     5000 non-null  int64
      1 float64   5000 non-null  float64
      2 datetime64[ns]  5000 non-null datetime64[ns]
      3 timedelta64[ns]  5000 non-null timedelta64[ns]
      4 complex128  5000 non-null complex128
      5 object     5000 non-null  object
      6 bool       5000 non-null  bool
      7 categorical 5000 non-null  category
dtypes: bool(1), category(1), complex128(1), datetime64[ns](1), float64(1), int64(1),
   object(1), timedelta64[ns](1)
memory usage: 289.1+ KB
```

Additionally memory_usage() is an available method for a dataframe object which returns the memory usage of each column.

```python
In [37]: df.memory_usage(index=True)
```

```
Out[37]:
Index                       128
int64                       40000
float64                     40000
datetime64[ns]              40000
timedelta64[ns]             40000
complex128                  80000
object                       40000
bool                         5000
categorical                 10920
Length: 9, dtype: int64
```
Series.dt accessor

Series has gained an accessor to succinctly return datetime like properties for the values of the Series, if its a datetime/period like Series. (GH7207) This will return a Series, indexed like the existing Series. See the docs

```python
# datetime
In [38]: s = pd.Series(pd.date_range('20130101 09:10:12', periods=4))

In [39]: s
Out[39]:
0  2013-01-01 09:10:12
1  2013-01-02 09:10:12
2  2013-01-03 09:10:12
3  2013-01-04 09:10:12
Length: 4, dtype: datetime64[ns]

In [40]: s.dt.hour
Out[40]:
0    9
1    9
2    9
3    9
Length: 4, dtype: int64

In [41]: s.dt.second
Out[41]:
0   12
1   12
2   12
3   12
Length: 4, dtype: int64

In [42]: s.dt.day
Out[42]:
0    1
1    2
2    3
3    4
Length: 4, dtype: int64

In [43]: s.dt.freq
Out[43]: 'D'
```

This enables nice expressions like this:

```python
In [44]: s[s.dt.day == 2]
Out[44]:
1  2013-01-02 09:10:12
Length: 1, dtype: datetime64[ns]
```

You can easily produce tz aware transformations:

```python
In [45]: stz = s.dt.tz_localize('US/Eastern')

In [46]: stz
Out[46]:
0  2013-01-01 09:10:12-05:00
```

(continues on next page)
pandas: powerful Python data analysis toolkit, Release 1.1.1

1 2013-01-02 09:10:12-05:00
2 2013-01-03 09:10:12-05:00
3 2013-01-04 09:10:12-05:00
Length: 4, dtype: datetime64[ns, US/Eastern]

In [47]: stz.dt.tz
Out[47]: <DstTzInfo 'US/Eastern' LMT-1 day, 19:04:00 STD>

You can also chain these types of operations:

In [48]: s.dt.tz_localize('UTC').dt.tz_convert('US/Eastern')
Out[48]:
0 2013-01-01 04:10:12-05:00
1 2013-01-02 04:10:12-05:00
2 2013-01-03 04:10:12-05:00
3 2013-01-04 04:10:12-05:00
Length: 4, dtype: datetime64[ns, US/Eastern]

The .dt accessor works for period and timedelta dtypes.

# period
In [49]: s = pd.Series(pd.period_range('20130101', periods=4, freq='D'))

In [50]: s
Out[50]:
0 2013-01-01
1 2013-01-02
2 2013-01-03
3 2013-01-04
Length: 4, dtype: period[D]

In [51]: s.dt.year
Out[51]:
0 2013
1 2013
2 2013
3 2013
Length: 4, dtype: int64

In [52]: s.dt.day
Out[52]:
0 1
1 2
2 3
3 4
Length: 4, dtype: int64

# timedelta
In [53]: s = pd.Series(pd.timedelta_range('1 day 00:00:05', periods=4, freq='s'))

In [54]: s
Out[54]:
0 1 days 00:00:05
1 1 days 00:00:06
2 1 days 00:00:07
3 1 days 00:00:08

(continues on next page)
In [55]: s.dt.days
Out[55]:
0 1
1 1
2 1
3 1
Length: 4, dtype: int64

In [56]: s.dt.seconds
Out[56]:
0 5
1 6
2 7
3 8
Length: 4, dtype: int64

In [57]: s.dt.components
Out[57]:
      days  hours  minutes  seconds  milliseconds  microseconds  nanoseconds
0       1       0        0        5              0             0             0
1       1       0        0        6              0             0             0
2       1       0        0        7              0             0             0
3       1       0        0        8              0             0             0

[4 rows x 7 columns]

Timezone handling improvements

• tz_localize(None) for tz-aware Timestamp and DatetimeIndex now removes timezone holding
local time, previously this resulted in Exception or TypeError (GH7812)

In [58]: ts = pd.Timestamp('2014-08-01 09:00', tz='US/Eastern')

In [59]: ts
Out[59]: Timestamp('2014-08-01 09:00:00-04:00', tz='US/Eastern')

In [60]: ts.tz_localize(None)
Out[60]: Timestamp('2014-08-01 09:00:00')

In [61]: didx = pd.date_range(start='2014-08-01 09:00', freq='H',
...:                      periods=10, tz='US/Eastern')

In [62]: didx
Out[62]:
DatetimeIndex(['2014-08-01 09:00:00-04:00', '2014-08-01 10:00:00-04:00',
              '2014-08-01 11:00:00-04:00', '2014-08-01 12:00:00-04:00',
              '2014-08-01 13:00:00-04:00', '2014-08-01 14:00:00-04:00',
              '2014-08-01 15:00:00-04:00', '2014-08-01 16:00:00-04:00',
              '2014-08-01 17:00:00-04:00', '2014-08-01 18:00:00-04:00'],
               dtype='datetime64[ns, US/Eastern]', freq='H')

In [63]: didx.tz_localize(None)
Out[63]:
DatetimeIndex(['2014-08-01 09:00:00', '2014-08-01 10:00:00',
              '2014-08-01 11:00:00', '2014-08-01 12:00:00',
              '2014-08-01 13:00:00', '2014-08-01 14:00:00',
              '2014-08-01 15:00:00', '2014-08-01 16:00:00',
              '2014-08-01 17:00:00', '2014-08-01 18:00:00'],
       dtype='datetime64[ns]', freq=None)

• tz_localize now accepts the ambiguous keyword which allows for passing an array of bools indicating whether the date belongs in DST or not, ‘NaT’ for setting transition times to NaT, ‘infer’ for inferring DST/non-DST, and ‘raise’ (default) for an AmbiguousTimeError to be raised. See the docs for more details (GH7943)

• DataFrame.tz_localize and DataFrame.tz_convert now accepts an optional level argument for localizing a specific level of a MultiIndex (GH7846)

• Timestamp.tz_localize and Timestamp.tz_convert now raise TypeError in error cases, rather than Exception (GH8025)

• a timeseries/index localized to UTC when inserted into a Series/DataFrame will preserve the UTC timezone (rather than being a naive datetime64[ns]) as object dtype (GH8411)

• Timestamp.__repr__ displays dateutil.tz.tzoffset info (GH7907)

Rolling/expanding moments improvements

• rolling_min(), rolling_max(), rolling_cov(), and rolling_corr() now return objects with all NaN when len(arg) < min_periods <= window rather than raising. (This makes all rolling functions consistent in this behavior). (GH7766)

Prior to 0.15.0

In [64]: s = pd.Series([10, 11, 12, 13])

In [15]: pd.rolling_min(s, window=10, min_periods=5)
ValueError: min_periods (5) must be <= window (4)

New behavior

In [4]: pd.rolling_min(s, window=10, min_periods=5)
Out[4]:
0   NaN
1   NaN
2   NaN
3   NaN
dtype: float64

• rolling_max(), rolling_min(), rolling_sum(), rolling_mean(), rolling_median(), rolling_std(), rolling_var(), rolling_skew(), rolling_kurt(), rolling_quantile(), rolling_cov(), rolling_corr(), rolling_corr_pairwise(), rolling_window(), and rolling_apply() with center=True previously would return a result of the same structure as the input arg with NaN in the final (window-1)/2 entries.

Now the final (window-1)/2 entries of the result are calculated as if the input arg were followed by (window-1)/2 NaN values (or with shrinking windows, in the case of rolling_apply()). (GH7925, GH8269)

Prior behavior (note final value is NaN):
In [7]: pd.rolling_sum(Series(range(4)), window=3, min_periods=0, center=True)
Out[7]:
0   1
1   3
2   6
3  NaN
dtype: float64

New behavior (note final value is 5 = sum([2, 3, NaN])):

In [7]: pd.rolling_sum(pd.Series(range(4)), window=3,
....: min_periods=0, center=True)
Out[7]:
0   1
1   3
2   6
3   5
dtype: float64

- rolling_window() now normalizes the weights properly in rolling mean mode (mean=True) so that the
calculated weighted means (e.g. ‘triang’, ‘gaussian’) are distributed about the same means as those calculated
without weighting (i.e. ‘boxcar’). See the note on normalization for further details. (GH7618)

In [65]: s = pd.Series([10.5, 8.8, 11.4, 9.7, 9.3])

Behavior prior to 0.15.0:

In [39]: pd.rolling_window(s, window=3, win_type='triang', center=True)
Out[39]:
0   NaN
1  6.583333
2  6.883333
3  6.683333
4   NaN
dtype: float64

New behavior

In [10]: pd.rolling_window(s, window=3, win_type='triang', center=True)
Out[10]:
0   NaN
1   9.875
2  10.325
3  10.025
4   NaN
dtype: float64

- Removed center argument from all expanding_ functions (see list), as the results produced when
center=True did not make much sense. (GH7925)
- Added optional ddof argument to expanding_cov() and rolling_cov(). The default value of 1 is
backwards-compatible. (GH8279)
- Documented the ddof argument to expanding_var(), expanding_std(), rolling_var(), and
rolling_std(). These functions’ support of a ddof argument (with a default value of 1) was previously
undocumented. (GH8064)
- ewma(), ewmstd(), ewmvol(), ewmvar(), ewmcov(), and ewmcorr() now interpret min_periods
in the same manner that the rolling_*() and expanding_*() functions do: a given result entry will be
NaN if the (expanding, in this case) window does not contain at least min_periods values. The previous behavior was to set to NaN the min_periods entries starting with the first non-NaN value. (GH7977)

Prior behavior (note values start at index 2, which is min_periods after index 0 (the index of the first non-empty value)):

```python
In [66]: s = pd.Series([1, None, None, None, 2, 3])
```

```python
In [51]: ewma(s, com=3., min_periods=2)
Out[51]:
0    NaN
1    NaN
2  1.000000
3  1.000000
4  1.571429
5  2.189189
dtype: float64
```

New behavior (note values start at index 4, the location of the 2nd (since min_periods=2) non-empty value):

```python
In [2]: pd.ewma(s, com=3., min_periods=2)
```

```python
Out[2]:
0    NaN
1    NaN
2    NaN
3    NaN
4  1.759644
5  2.383784
dtype: float64
```

- `ewmstd()`, `ewmvol()`, `ewmvar()`, `ewmcov()`, and `ewmcorr()` now have an optional adjust argument, just like `ewma()` does, affecting how the weights are calculated. The default value of adjust is True, which is backwards-compatible. See Exponentially weighted moment functions for details. (GH7911)

- `ewma()`, `ewmstd()`, `ewmvol()`, `ewmvar()`, `ewmcov()`, and `ewmcorr()` now have an optional ignore_na argument. When ignore_na=False (the default), missing values are taken into account in the weights calculation. When ignore_na=True (which reproduces the pre-0.15.0 behavior), missing values are ignored in the weights calculation. (GH7543)

```python
In [7]: pd.ewma(pd.Series([None, 1., 8.]), com=2.)
```

```python
Out[7]:
0   NaN
1  1.0
2  5.2
dtype: float64
```

```python
In [8]: pd.ewma(pd.Series([1., None, 8.]), com=2.,
   ....: ignore_na=True) # pre-0.15.0 behavior
```

```python
Out[8]:
0  1.0
1  1.0
2  5.2
dtype: float64
```

```python
In [9]: pd.ewma(pd.Series([1., None, 8.]), com=2.,
   ....: ignore_na=False) # new default
```

```python
Out[9]:
0  1.000000
```
Warning: By default (ignore_na=False) the ewm*() functions' weights calculation in the presence of missing values is different than in pre-0.15.0 versions. To reproduce the pre-0.15.0 calculation of weights in the presence of missing values one must specify explicitly ignore_na=True.

• Bug in expanding_cov(), expanding_corr(), rolling_cov(), rolling_cor(), ewmcov(), and ewmcorr() returning results with columns sorted by name and producing an error for non-unique columns: now handles non-unique columns and returns columns in original order (except for the case of two DataFrames with pairwise=False, where behavior is unchanged) (GH7542)
• Bug in rolling_count() and expanding_*() functions unnecessarily producing error message for zero-length data (GH8056)
• Bug in rolling_apply() and expanding_apply() interpreting min_periods=0 as min_periods=1 (GH8080)
• Bug in expanding_std() and expanding_var() for a single value producing a confusing error message (GH7900)
• Bug in rolling_std() and rolling_var() for a single value producing 0 rather than NaN (GH7900)
• Bug in ewmstd(), ewmvol(), ewmvar(), and ewmcov() calculation of de-biasing factors when bias=False (the default). Previously an incorrect constant factor was used, based on adjust=True, ignore_na=True, and an infinite number of observations. Now a different factor is used for each entry, based on the actual weights (analogous to the usual N/(N-1) factor). In particular, for a single point a value of NaN is returned when bias=False, whereas previously a value of (approximately) 0 was returned.

For example, consider the following pre-0.15.0 results for ewmvar(..., bias=False), and the corresponding debiasing factors:

\begin{verbatim}
In [67]: s = pd.Series([1., 2., 0., 4.])
In [89]: ewmvar(s, com=2., bias=False)
Out[89]:
   0   -2.775558e-16
   1      3.000000e-01
   2      9.556787e-01
   3      3.585799e+00
dtype: float64
In [90]: ewmvar(s, com=2., bias=False) / ewmvar(s, com=2., bias=True)
Out[90]:
   0     1.25
   1     1.25
   2     1.25
   3     1.25
dtype: float64
\end{verbatim}

Note that entry 0 is approximately 0, and the debiasing factors are a constant 1.25. By comparison, the following 0.15.0 results have a NaN for entry 0, and the debiasing factors are decreasing (towards 1.25):
In [14]: pd.ewmvar(s, com=2., bias=False)
Out[14]:
0   NaN
1  0.500000
2  1.210526
3  4.089069
dtype: float64

In [15]: pd.ewmvar(s, com=2., bias=False) / pd.ewmvar(s, com=2., bias=True)
Out[15]:
0   NaN
1  2.083333
2  1.583333
3  1.425439
dtype: float64

See Exponentially weighted moment functions for details. (GH7912)

Improvements in the SQL IO module

- Added support for a chunksize parameter to to_sql function. This allows DataFrame to be written in chunks and avoid packet-size overflow errors (GH8062).
- Added support for a chunksize parameter to read_sql function. Specifying this argument will return an iterator through chunks of the query result (GH2908).
- Added support for writing datetime.date and datetime.time object columns with to_sql (GH6932).
- Added support for specifying a schema to read from/write to with read_sql_table and to_sql (GH7441, GH7952). For example:

```python
df.to_sql('table', engine, schema='other_schema')  # noqa F821
pd.read_sql_table('table', engine, schema='other_schema')  # noqa F821
```

- Added support for writing NaN values with to_sql (GH2754).
- Added support for writing datetime64 columns with to_sql for all database flavors (GH7103).

Backwards incompatible API changes

Breaking changes

API changes related to Categorical (see here for more details):

- The Categorical constructor with two arguments changed from “codes/labels and levels” to “values and levels (now called ‘categories’)”. This can lead to subtle bugs. If you use Categorical directly, please audit your code by changing it to use the from_codes() constructor.

An old function call like (prior to 0.15.0):

```python
pd.Categorical([0,1,0,2,1], levels=['a', 'b', 'c'])
```

will have to adapted to the following to keep the same behaviour:
In [2]: pd.Categorical.from_codes([0, 1, 0, 2, 1], categories=['a', 'b', 'c'])
Out[2]:
[a, b, a, c, b]
Categories (3, object): [a, b, c]

API changes related to the introduction of the Timedelta scalar (see above for more details):

- Prior to 0.15.0 to_timedelta() would return a Series for list-like/Series input, and a np.
timedelta64 for scalar input. It will now return a TimedeltaIndex for list-like input, Series for Series input, and Timedelta for scalar input.

For API changes related to the rolling and expanding functions, see detailed overview above.

Other notable API changes:

- Consistency when indexing with .loc and a list-like indexer when no values are found.

In [68]: df = pd.DataFrame([['a'], ['b']], index=[1, 2])
In [69]: df
Out[69]:
0  a
2  b
[2 rows x 1 columns]

In prior versions there was a difference in these two constructs:
- df.loc[[3]] would return a frame reindexed by 3 (with all np.nan values)
- df.loc[[3],:] would raise KeyError.

Both will now raise a KeyError. The rule is that at least 1 indexer must be found when using a list-like and .loc (GH7999)

Furthermore in prior versions these were also different:
- df.loc[[1,3]] would return a frame reindexed by [1,3]
- df.loc[[1,3],:] would raise KeyError.

Both will now return a frame reindex by [1,3]. E.g.

In [3]: df.loc[[1, 3]]
Out[3]:
0  1  a
3  NaN

In [4]: df.loc[[1, 3], :]
Out[4]:
0  1  a
3  NaN

This can also be seen in multi-axis indexing with a Panel.

```python
>>> p = pd.Panel(np.arange(2 * 3 * 4).reshape(2, 3, 4),
...               items=['ItemA', 'ItemB'],
...               major_axis=[1, 2, 3],
```

(continues on next page)
The following would raise `KeyError` prior to 0.15.0:

```python
In [5]:
Out[5]:
   ItemA  ItemD
0     3    NaN
1     7    NaN
2    11    NaN
```

Furthermore, `.loc` will raise if no values are found in a MultiIndex with a list-like indexer:

```python
In [70]: s = pd.Series(np.arange(3, dtype='int64'),
                index=pd.MultiIndex.from_product([['A'],
                                                   ['foo', 'bar', 'baz']],
                                              names=['one', 'two'])).sort_index()
In [71]: s.loc['D']
```

```python
KeyError: "['D'] not in index"
```

- Assigning values to `None` now considers the dtype when choosing an ‘empty’ value (GH7941).

Previously, assigning to `None` in numeric containers changed the dtype to object (or errored, depending on the call). It now uses `NaN`:

```python
In [73]: s = pd.Series([1, 2, 3])
In [74]: s.loc[0] = None
In [75]: s
```

```python
0   NaN
1   2.0
2   3.0
Length: 3, dtype: float64
```

`NaN` is now used similarly for datetime containers.
For object containers, we now preserve None values (previously these were converted to NaN values).

```python
In [76]: s = pd.Series(["a", "b", "c"])
In [77]: s.loc[0] = None
In [78]: s
Out[78]:
0   None
1     b
2     c
Length: 3, dtype: object
```

To insert a NaN, you must explicitly use np.nan. See the docs.

- In prior versions, updating a pandas object inplace would not reflect in other python references to this object. (GH8511, GH5104)

```python
In [79]: s = pd.Series([1, 2, 3])
In [80]: s2 = s
In [81]: s += 1.5

Behavior prior to v0.15.0

# the original object
In [5]: s
Out[5]:
0     2.5
1     3.5
2     4.5
dtype: float64

# a reference to the original object
In [7]: s2
Out[7]:
0     1
1     2
2     3
dtype: int64

This is now the correct behavior

# the original object
In [82]: s
Out[82]:
0     2.5
1     3.5
2     4.5
Length: 3, dtype: float64

# a reference to the original object
In [83]: s2
Out[83]:
0     2.5
1     3.5
```
• Made both the C-based and Python engines for read_csv and read_table ignore empty lines in input as well as white space-filled lines, as long as sep is not white space. This is an API change that can be controlled by the keyword parameter skip_blank_lines. See the docs (GH4466).

• A timeseries/index localized to UTC when inserted into a Series/DataFrame will preserve the UTC timezone and inserted as object dtype rather than being converted to a naive datetime64[ns] (GH8411).

• Bug in passing a DatetimeIndex with a timezone that was not being retained in DataFrame construction from a dict (GH7822).

In prior versions this would drop the timezone, now it retains the timezone, but gives a column of object dtype:

```python
In [84]: i = pd.date_range('1/1/2011', periods=3, freq='10s', tz='US/Eastern')
In [85]: i
Out[85]: DatetimeIndex(['2011-01-01 00:00:00-05:00', '2011-01-01 00:00:10-05:00',
                   '2011-01-01 00:00:20-05:00'],
                  dtype='datetime64[ns, US/Eastern]', freq='10S')
In [86]: df = pd.DataFrame({'a': i})
In [87]: df
Out[87]:
   a
0 2011-01-01 00:00:00-05:00
1 2011-01-01 00:00:10-05:00
2 2011-01-01 00:00:20-05:00

[3 rows x 1 columns]
```

Previously this would have yielded a column of datetime64 dtype, but without timezone info.

The behaviour of assigning a column to an existing dataframe as df['a'] = i remains unchanged (this already returned an object column with a timezone).

• When passing multiple levels to stack(), it will now raise a ValueError when the levels aren’t all level names or all level numbers (GH7660). See Reshaping by stacking and unstacking.

• Raise a ValueError in df.to_hdf with ‘fixed’ format, if df has non-unique columns as the resulting file will be broken (GH7761).

• SettingWithCopy raise/warnings (according to the option mode.chained_assignment) will now be issued when setting a value on a sliced mixed-dtype DataFrame using chained-assignment. (GH7845, GH7950)
• merge, DataFrame.merge, and ordered_merge now return the same type as the left argument (GH7737).

• Previously an enlargement with a mixed-dtype frame would act unlike .append which will preserve dtypes (related GH2578, GH8176):

```python
In [89]: df = pd.DataFrame([[True, 1], [False, 2]],
                      columns=["female", "fitness"])

In [90]: df
Out[90]:
     female  fitness
0      True     1
1     False     2

[2 rows x 2 columns]
```

```python
In [91]: df.dtypes
Out[91]:
female  bool
fitness   int64
Length: 2, dtype: object

# dtypes are now preserved
```

```python
In [93]: df
Out[93]:
     female  fitness
0      True     1
1     False     2
2     False     2

[3 rows x 2 columns]
```

```python
In [94]: df.dtypes
Out[94]:
female  bool
fitness   int64
Length: 2, dtype: object
```

• Series.to_csv() now returns a string when path=None, matching the behaviour of DataFrame.to_csv() (GH8215).

• read_hdf now raises IOError when a file that doesn’t exist is passed in. Previously, a new, empty file was created, and a KeyError raised (GH7715).

• DataFrame.info() now ends its output with a newline character (GH8114).
- Concatenating no objects will now raise a `ValueError` rather than a bare `Exception`.
- Merge errors will now be sub-classes of `ValueError` rather than raw `Exception` (GH8501)
- `DataFrame.plot` and `Series.plot` keywords are now have consistent orders (GH8037)

**Internal refactoring**

In 0.15.0 `Index` has internally been refactored to no longer sub-class `ndarray` but instead subclass `PandasObject`, similarly to the rest of the pandas objects. This change allows very easy sub-classing and creation of new index types. This should be a transparent change with only very limited API implications (GH5080, GH7439, GH7796, GH8024, GH8367, GH7997, GH8522):

- you may need to unpickle pandas version < 0.15.0 pickles using `pd.read_pickle` rather than `pickle.load`. See `pickle docs`
- when plotting with a `PeriodIndex`, the matplotlib internal axes will now be arrays of `Period` rather than a `PeriodIndex` (this is similar to how a `DatetimeIndex` passes arrays of datetimes now)
- MultiIndexes will now raise similarly to other pandas objects w.r.t. truth testing, see here (GH7897).
- When plotting a `DatetimeIndex` directly with matplotlib’s `plot` function, the axis labels will no longer be formatted as dates but as integers (the internal representation of a `datetime64`). UPDATE This is fixed in 0.15.1, see here.

**Deprecations**

- The attributes `Categorical labels` and `levels` attributes are deprecated and renamed to `codes` and `categories`.
- The `outtype` argument to `pd.DataFrame.to_dict` has been deprecated in favor of `orient`. (GH7840)
- The `convert_dummies` method has been deprecated in favor of `get_dummies` (GH8140)
- The `infer_dst` argument in `tz_localize` will be deprecated in favor of `ambiguous` to allow for more flexibility in dealing with DST transitions. Replace `infer_dst=True` with `ambiguous='infer'` for the same behavior (GH7943). See the docs for more details.
- The top-level `pd.value_range` has been deprecated and can be replaced by `.describe()` (GH8481)
- The `Index` set operations `+` and `−` were deprecated in order to provide these for numeric type operations on certain index types. `+` can be replaced by `.union()` or `|`, and `−` by `.difference()`. Further the method name `Index.diff()` is deprecated and can be replaced by `Index.difference()` (GH8226)

```python
# +
pd.Index(['a', 'b', 'c']) + pd.Index(['b', 'c', 'd'])

# should be replaced by
pd.Index(['a', 'b', 'c']).union(pd.Index(['b', 'c', 'd']))

# −
pd.Index(['a', 'b', 'c']) − pd.Index(['b', 'c', 'd'])

# should be replaced by
pd.Index(['a', 'b', 'c']).difference(pd.Index(['b', 'c', 'd']))
```

- The `infer_types` argument to `read_html()` now has no effect and is deprecated (GH7762, GH7032).
Removal of prior version deprecations/changes

- Remove DataFrame.delevel method in favor of DataFrame.reset_index

Enhancements

Enhancements in the importing/exporting of Stata files:

- Added support for bool, uint8, uint16 and uint32 data types in to_stata (GH7097, GH7365)
- Added conversion option when importing Stata files (GH8527)
- DataFrame.to_stata and StataWriter check string length for compatibility with limitations imposed in dta files where fixed-width strings must contain 244 or fewer characters. Attempting to write Stata dta files with strings longer than 244 characters raises a ValueError. (GH7858)
- read_stata and StataReader can import missing data information into a DataFrame by setting the argument convert_missing to True. When using this options, missing values are returned as StataMissingValue objects and columns containing missing values have object data type. (GH8045)

Enhancements in the plotting functions:

- Added layout keyword to DataFrame.plot. You can pass a tuple of (rows, columns), one of which can be -1 to automatically infer (GH6667, GH8071).
- Allow to pass multiple axes to DataFrame.plot, hist and boxplot (GH5353, GH6970, GH7069)
- Added support for c, colormap and colorbar arguments for DataFrame.plot with kind='scatter' (GH7780)
- Histogram from DataFrame.plot with kind='hist' (GH7809), See the docs.
- Boxplot from DataFrame.plot with kind='box' (GH7998), See the docs.

Other:

- read_csv now has a keyword parameter float_precision which specifies which floating-point converter the C engine should use during parsing, see here (GH8002, GH8044)
- Added searchsorted method to Series objects (GH7447)
- describe() on mixed-types DataFrames is more flexible. Type-based column filtering is now possible via the include/exclude arguments. See the docs (GH8164).

```
In [95]: df = pd.DataFrame({'catA': ['foo', 'foo', 'bar'] * 8,
        ....:      'catB': ['a', 'b', 'c', 'd'] * 6,
        ....:      'numC': np.arange(24),
        ....:      'numD': np.arange(24.) + .5})

In [96]: df.describe(include=['object'])
Out[96]:
   catA  catB
count 24  24
unique 2  4
top   foo  b
freq  16  6

[4 rows x 2 columns]
In [97]: df.describe(include=['number', 'object'], exclude=['float'])
```
Out[97]:

catA  catB  numC
count 24 24 24.000000
unique 2 4 NaN
top  foo  b  NaN
freq 16 6 NaN
mean NaN NaN 11.500000
std NaN NaN 7.071068
min NaN NaN 0.000000
25% NaN NaN 5.750000
50% NaN NaN 11.500000
75% NaN NaN 17.250000
max NaN NaN 23.000000
[11 rows x 3 columns]

Requesting all columns is possible with the shorthand ‘all’

In [98]: df.describe(include='all')
Out[98]:
catA  catB  numC  numD
count 24 24 24.000000 24.000000
unique 2 4 NaN  NaN
top  foo  b  NaN  NaN
freq 16 6 NaN  NaN
mean NaN NaN 11.500000 12.000000
std NaN NaN 7.071068 7.071068
min NaN NaN 0.000000  0.500000
25% NaN NaN 5.750000 6.250000
50% NaN NaN 11.500000 12.000000
75% NaN NaN 17.250000 17.750000
max NaN NaN 23.000000 23.500000
[11 rows x 4 columns]

Without those arguments, describe will behave as before, including only numerical columns or, if none are, only categorical columns. See also the docs

• Added split as an option to the orient argument in pd.DataFrame.to_dict. (GH7840)

• The get_dummies method can now be used on DataFrames. By default only categorical columns are encoded as 0’s and 1’s, while other columns are left untouched.

In [99]: df = pd.DataFrame({'A': ['a', 'b', 'a'], 'B': ['c', 'c', 'b'], 'C': [1, 2, 3]})

In [100]: pd.get_dummies(df)
Out[100]:

          A_a  A_b  B_b  B_c
0  1  1  0  0  1
1  2  0  1  0  1
2  3  1  0  1  0
[3 rows x 5 columns]

• PeriodIndex supports resolution as the same as DatetimeIndex (GH7708)
- `pandas.tseries.holiday` has added support for additional holidays and ways to observe holidays (GH7070)
- `pandas.tseries.holiday.Holiday` now supports a list of offsets in Python3 (GH7070)
- `pandas.tseries.holiday.Holiday` now supports a `days_of_week` parameter (GH7070)
- `GroupBy.nth()` now supports selecting multiple `nth` values (GH7910)

```python
In [101]: business_dates = pd.date_range(start='4/1/2014', end='6/30/2014', freq='B')
In [102]: df = pd.DataFrame(1, index=business_dates, columns=['a', 'b'])
# get the first, 4th, and last date index for each month
In [103]: df.groupby([df.index.year, df.index.month]).nth([0, 3, -1])
Out[103]:
         a  b
2014  4  1  1
        4  1  1
        5  1  1
        6  1  1
        6  1  1
[9 rows x 2 columns]
```

- `Period` and `PeriodIndex` supports addition/subtraction with timedelta-likes (GH7966)

  If `Period freq` is D,H,T,S,L,U,N, Timedelta-like can be added if the result can have same freq. Otherwise, only the same offsets can be added.

```python
In [104]: idx = pd.period_range('2014-07-01 09:00', periods=5, freq='H')
In [105]: idx
Out[105]: PeriodIndex(
['2014-07-01 09:00', '2014-07-01 10:00', '2014-07-01 11:00',
 '2014-07-01 12:00', '2014-07-01 13:00'],
dtype='period[H]', freq='H')
In [106]: idx + pd.offsets.Hour(2)
Out[106]: PeriodIndex(
['2014-07-01 11:00', '2014-07-01 12:00', '2014-07-01 13:00',
 '2014-07-01 14:00', '2014-07-01 15:00'],
dtype='period[H]', freq='H')
In [107]: idx + pd.Timedelta('120m')
Out[107]: PeriodIndex(
['2014-07-01 11:00', '2014-07-01 12:00', '2014-07-01 13:00',
 '2014-07-01 14:00', '2014-07-01 15:00'],
dtype='period[H]', freq='H')
In [108]: idx = pd.period_range('2014-07', periods=5, freq='M')
In [109]: idx
Out[109]: PeriodIndex(
dtype='period[M]', freq='M')
```
In [110]: idx = pd.offsets.MonthEnd(3)
                      dtype='period[M]', freq='M')

- Added experimental compatibility with openpyxl for versions >= 2.0. The DataFrame.to_excel method engine keyword now recognizes openpyxl1 and openpyxl2 which will explicitly require openpyxl v1 and v2 respectively, failing if the requested version is not available. The openpyxl engine is a now a meta-engine that automatically uses whichever version of openpyxl is installed. (GH7177)

- DataFrame.fillna can now accept a DataFrame as a fill value (GH8377)

- Passing multiple levels to stack() will now work when multiple level numbers are passed (GH7660). See Reshaping by stacking and unstacking.

- set_names(), set_labels(), and set_levels() methods now take an optional level keyword argument to all modification of specific level(s) of a MultiIndex. Additionally set_names() now accepts a scalar string value when operating on an Index or on a specific level of a MultiIndex (GH7792)

In [111]: idx = pd.MultiIndex.from_product([['a'], range(3), list("pqr")],
                                      names=['foo', 'bar', 'baz'])

In [112]: idx.set_names('qux', level=0)
Out[112]: 
MultiIndex([('a', 0, 'p'),
             ('a', 0, 'q'),
             ('a', 0, 'r'),
             ('a', 1, 'p'),
             ('a', 1, 'q'),
             ('a', 1, 'r'),
             ('a', 2, 'p'),
             ('a', 2, 'q'),
             ('a', 2, 'r')],
           names=['qux', 'bar', 'baz'])

In [113]: idx.set_names(['qux', 'corge'], level=[0, 1])
Out[113]: 
MultiIndex([('a', 'a', 'p'),
             ('a', 'a', 'q'),
             ('a', 'a', 'r'),
             ('a', 'b', 'p'),
             ('a', 'b', 'q'),
             ('a', 'b', 'r'),
             ('a', 'c', 'p'),
             ('a', 'c', 'q'),
             ('a', 'c', 'r')],
           names=['qux', 'corge', 'baz'])

In [114]: idx.set_levels(['a', 'b', 'c'], level='bar')
Out[114]: 
MultiIndex([('a', 'a', 'p'),
             ('a', 'a', 'q'),
             ('a', 'a', 'r'),
             ('a', 'b', 'p'),
             ('a', 'b', 'q'),
             ('a', 'b', 'r'),
             ('a', 'c', 'p'),
             ('a', 'c', 'q'),
             ('a', 'c', 'r')],
           names=['qux', 'corge', 'baz'])

(continues on next page)
('a', 'c', 'p'),
('a', 'c', 'q'),
('a', 'c', 'r'),
names=['foo', 'bar', 'baz'])

In [115]: idx.set_levels([['a', 'b', 'c'], [1, 2, 3]], level=[1, 2])
Out[115]:
MultiIndex([(a, 'a', 1),
 (a, 'a', 2),
 (a, 'a', 3),
 (a, 'b', 1),
 (a, 'b', 2),
 (a, 'b', 3),
 (a, 'c', 1),
 (a, 'c', 2),
 (a, 'c', 3)],
 names=['foo', 'bar', 'baz'])

• Index.isin now supports a level argument to specify which index level to use for membership tests (GH7892, GH7890)

In [1]: idx = pd.MultiIndex.from_product([[0, 1], ['a', 'b', 'c']])

In [2]: idx.values
Out[2]: array([[0, 'a'), (0, 'b'), (0, 'c'), (1, 'a'), (1, 'b'), (1, 'c')],
       dtype=object)

In [3]: idx.isin(['a', 'c', 'e'], level=1)
Out[3]: array([True, False, True, True, False, True], dtype=bool)

• Index now supports duplicated and drop_duplicates. (GH4060)

In [116]: idx = pd.Index([1, 2, 3, 4, 1, 2])

In [117]: idx
Out[117]: Int64Index([1, 2, 3, 4, 1, 2], dtype='int64')

In [118]: idx.duplicated()
Out[118]: array([False, False, False, False, True, True])

In [119]: idx.drop_duplicates()
Out[119]: Int64Index([1, 2, 3, 4], dtype='int64')

• add copy=True argument to pd.concat to enable pass through of complete blocks (GH8252)

• Added support for numpy 1.8+ data types (bool_, int_, float_, string_) for conversion to R dataframe (GH8400)
Performance

- Performance improvements in `DatetimeIndex.__iter__` to allow faster iteration (GH7683)
- Performance improvements in `Period` creation (and `PeriodIndex` setitem) (GH5155)
- Improvements in `Series.transform` for significant performance gains (revised) (GH6496)
- Performance improvements in `StataReader` when reading large files (GH8040, GH8073)
- Performance improvements in `StataWriter` when writing large files (GH8079)
- Performance and memory usage improvements in multi-key `groupby` (GH8128)
- Performance improvements in `groupby .agg` and `.apply` where builtins max/min were not mapped to numpy/cythonized versions (GH7722)
- Performance improvement in writing to sql (`to_sql`) of up to 50% (GH8208).
- Performance benchmarking of `groupby` for large value of `ngroups` (GH6787)
- Performance improvement in `CustomBusinessDay`, `CustomBusinessMonth` (GH8236)
- Performance improvement for `MultiIndex.values` for multi-level indexes containing datetimes (GH8543)

Bug fixes

- Bug in `pivot_table`, when using margins and a dict `aggfunc` (GH8349)
- Bug in `read_csv` where `squeeze=True` would return a view (GH8217)
- Bug in checking of table name in `read_sql` in certain cases (GH7826).
- Bug in `DataFrame.groupby` where `Grouper` does not recognize level when frequency is specified (GH7885)
- Bug in `DataFrame.groupby` where `Grouper` does not recognize level when frequency is specified (GH7885)
- Bug in `MultiIndex` slicing with missing indexers (GH7866)
- Bug in `MultiIndex` slicing with various edge cases (GH8132)
- Regression in `MultiIndex` indexing with a non-scalar type object (GH7914)
- Bug in `Timestamp` comparisons with `==` and `int64` dtype (GH8058)
• Bug in pickles contains `DateOffset` may raise `AttributeError` when `normalize` attribute is referred internally (GH7748)

• Bug in `Panel` when using `major_xs` and `copy=False` is passed (deprecation warning fails because of missing warnings) (GH8152).

• Bug in pickle deserialization that failed for pre-0.14.1 containers with dup items trying to avoid ambiguity when matching block and manager items, when there’s only one block there’s no ambiguity (GH7794).

• Bug in putting a `PeriodIndex` into a `Series` would convert to `int64` dtype, rather than `object` of `Periods` (GH7932).

• Bug in `HDFStore` iteration when passing a where (GH8014)

• Bug in `DataFrameGroupby.transform` when transforming with a passed non-sorted key (GH8046, GH8430).

• Bug in repeated timeseries line and area plot may result in `ValueError` or incorrect kind (GH7733).

• Bug in inference in a `MultiIndex` with `datetime.date` inputs (GH7888).

• Bug in `get` where an `IndexError` would not cause the default value to be returned (GH7725).

• Bug in `offsets.apply`, `rollforward` and `rollback` may reset nanosecond (GH7697).

• Bug in `offsets.apply`, `rollforward` and `rollback` may raise `AttributeError` if `Timestamp` has `dateutil tzinfo` (GH7697).

• Bug in sorting a `MultiIndex` frame with a `Float64Index` (GH8017).

• Bug in inconsistent panel setitem with a rhs of a `DataFrame` for alignment (GH7763).

• Bug in `is_superperiod` and `is_subperiod` cannot handle higher frequencies than `S` (GH7760, GH7772, GH7803).

• Bug in 32-bit platforms with `Series.shift` (GH8129).

• Bug in `PeriodIndex.unique` returns `int64 np.ndarray` (GH7540).

• Bug in `groupby.apply` with a non-affecting mutation in the function (GH8467).

• Bug in `DataFrame.reset_index` which has `MultiIndex contains PeriodIndex or DatetimeIndex with tz` raises `ValueError` (GH7746, GH7793).

• Bug in `DataFrame.plot` with subplots=True may draw unnecessary minor xticks and yticks (GH7801).

• Bug in `StataReader` which did not read variable labels in 117 files due to difference between Stata documentation and implementation (GH7816).

• Bug in `StataReader` where strings were always converted to 244 characters-fixed width irrespective of underlying string size (GH7858).

• Bug in `DataFrame.plot` and `Series.plot` may ignore `rot` and `fontsize` keywords (GH7844).

• Bug in `DatetimeIndex.value_counts` doesn’t preserve `tz` (GH7735).

• Bug in `PeriodIndex.value_counts` results in `Int64Index` (GH7735).

• Bug in `DataFrame.join` when doing left join on index and there are multiple matches (GH5391).

• Bug in `GroupBy.transform()` where int groups with a transform that didn’t preserve the index were incorrectly truncated (GH7972).

• Bug in `groupby` where callable objects without name attributes would take the wrong path, and produce a `DataFrame` instead of a `Series` (GH7929).

• Bug in `groupby` error message when a `DataFrame` grouping column is duplicated (GH7511)
• Bug in `read_html` where the `infer_types` argument forced coercion of date-likes incorrectly (GH7762, GH7032).

• Bug in `Series.str.cat` with an index which was filtered as to not include the first item (GH7857).

• Bug in `Timestamp` cannot parse nanosecond from string (GH7878).

• Bug in `Timestamp` with string offset and tz results incorrect (GH7833).

• Bug in `tslib.tz_convert` and `tslib.tz_convert_single` may return different results (GH7798).

• Bug in `DatetimeIndex.intersection` of non-overlapping timestamps with tz raises `IndexError` (GH7880).

• Bug in alignment with TimeOps and non-unique indexes (GH8363).

• Bug in `GroupBy.filter()` where fast path vs. slow path made the filter return a non scalar value that appeared valid but wasn’t (GH7870).

• Bug in `date_range()`/`DatetimeIndex()` when the timezone was inferred from input dates yet incorrect times were returned when crossing DST boundaries (GH7835, GH7901).

• Bug in `to_excel()` where a negative sign was being prepended to positive infinity and was absent for negative infinity (GH7949).

• Bug in area plot draws legend with incorrect `alpha` when `stacked=True` (GH8027).

• Period and `PeriodIndex` addition/subtraction with `np.timedelta64` results in incorrect internal representations (GH7740).

• Bug in `Holiday` with no offset or observance (GH7987).

• Bug in `DataFrame.to_latex` formatting when columns or index is a `MultiIndex` (GH7982).

• Bug in `DateOffset` around Daylight Savings Time produces unexpected results (GH5175).

• Bug in `DataFrame.shift` where empty columns would throw `ZeroDivisionError` on numpy 1.7 (GH8019).

• Bug in installation where `html_encoding/*.html` wasn’t installed and therefore some tests were not running correctly (GH7927).

• Bug in `read_html` where bytes objects were not tested for in `_read` (GH7927).

• Bug in `DataFrame.stack()` when one of the column levels was a datelike (GH8039).

• Bug in broadcasting numpy scalars with `DataFrame` (GH8116).

• Bug in `pivot_table` performed with nameless index and columns raises `KeyError` (GH8103).

• Bug in `DataFrame.plot(kind='scatter')` draws points and errorbars with different colors when the color is specified by `c` keyword (GH8081).

• Bug in `Float64Index` where `iat` and `at` were not testing and were failing (GH8092).

• Bug in `DataFrame.boxplot()` where y-limits were not set correctly when producing multiple axes (GH7528, GH5517).

• Bug in `read_csv` where line comments were not handled correctly given a custom line terminator or `delim_whitespace=True` (GH8122).

• Bug in `read_html` where empty tables caused a `StopIteration` (GH7575).

• Bug in `read_html` where empty tables caused a `StopIteration` (GH7575).

• Bug in casting when setting a column in a same-dtype block (GH7704).

• Bug in accessing groups from a `GroupBy` when the original grouper was a tuple (GH8121).

• Bug in `.at` that would accept integer indexers on a non-integer index and do fallback (GH7814).
• Bug with kde plot and NaNs (GH8182)
• Bug in GroupBy.count with float32 data type were nan values were not excluded (GH8169).
• Bug with stacked barplots and NaNs (GH8175).
• Bug in resample with non evenly divisible offsets (e.g. ’7s’) (GH8371)
• Bug in interpolation methods with the limit keyword when no values needed interpolating (GH7173).
• Bug where col_space was ignored in DataFrame.to_string() when header=False (GH8230).
• Bug with DateTimeIndex.asof incorrectly matching partial strings and returning the wrong date (GH8245).
• Bug in plotting methods modifying the global matplotlib rcParams (GH8242).
• Bug in DataFrame.__setitem__ that caused errors when setting a dataframe column to a sparse array (GH8131)
• Bug where DataFrame.boxplot() failed when entire column was empty (GH8181).
• Bug with messed variables in radviz visualization (GH8199).
• Bug in interpolation methods with the limit keyword when no values needed interpolating (GH7173).
• Bug where col_space was ignored in DataFrame.to_string() when header=False (GH8230).
• Bug into_clipboard that would clip long column data (GH8305)
• Bug in DataFrame terminal display: Setting max_column/max_rows to zero did not trigger auto-resizing of dfs to fit terminal width/height (GH7180).
• Bug in OLS where running with “cluster” and “nw_lags” parameters did not work correctly, but also did not throw an error (GH5884).
• Bug in DataFrame.dropna that interpreted non-existent columns in the subset argument as the ‘last column’ (GH8303)
• Bug in Index.intersection on non-monotonic non-unique indexes (GH8362).
• Bug in masked series assignment where mismatching types would break alignment (GH8387)
• Bug in NDFrame.equals gives false negatives with dtype=object (GH8437)
• Bug in assignment with indexer where type diversity would break alignment (GH8258)
• Bug in NDFrame.loc indexing when row/column names were lost when target was a list/ndarray (GH6552)
• Regression in NDFrame.loc indexing when rows/columns were converted to Float64Index if target was an empty list/ndarray (GH7774)
• Bug in Series that allows it to be indexed by a DataFrame which has unexpected results. Such indexing is no longer permitted (GH8444)
• Bug in item assignment of a DataFrame with MultiIndex columns where right-hand-side columns were not aligned (GH7655)
• Suppress FutureWarning generated by NumPy when comparing object arrays containing Nan for equality (GH7065)
• Bug in DataFrame.eval() where the dtype of the not operator (~) was not correctly inferred as bool.
Contributors

A total of 80 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Aaron Schumacher +
- Adam Greenhall
- Andy Hayden
- Anthony O’Brien +
- Artemy Kolchinsky +
- Ben Schiller +
- Benedikt Sauer
- Benjamin Thyreau +
- BorisVerk +
- Chris Reynolds +
- Chris Stofer +
- DSM
- Dav Clark +
- FragLegs +
- German Gomez-Herrero +
- Hsiaoming Yang +
- Huan Li +
- Hyungtae Kim +
- Isaac Slavitt +
- Jacob Schaer
- Jacob Wasserman +
- Jan Schulz
- Jeff Reback
- Jeff Tratner
- Jesse Farnham +
- Joe Bradish +
- Joerg Rittinger +
- John W. O’Brien
- Joris Van den Bossche
- Kevin Sheppard
- Kyle Meyer
- Max Chang +
- Michael Mueller
- Michael W Schatzow +
- Mike Kelly
- Mortada Mehyar
- Nathan Sanders +
- Nathan Typanski +
- Paul Masurel +
- Phillip Cloud
- Pietro Battiston
- RenzoBertocchi +
- Ross Petchler +
- Shahul Hameed +
- Shashank Agarwal +
- Stephan Hoyer
- Tom Augspurger
- TomAugspurger
- Tony Lorenzo +
- Wes Turner
- Wilfred Hughes +
- Yevgeniy Grechka +
- Yoshiki Vázquez Baeza +
- behzad nouri +
- benjamin
- bjonen +
- dlovell +
- dsm054
- hunterowens +
- immerrr
- ischwabacher
- jmorris0x0 +
- jmclarty +
- jreback
- klonuo +
- lexual
- mcjcode +
- mtrbean +
- onesandzeroes
This is a minor release from 0.14.0 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

- Highlights include:
  - New methods `select_dtypes()` to select columns based on the dtype and `sem()` to calculate the standard error of the mean.
  - Support for dateutil timezones (see `docs`).
  - Support for ignoring full line comments in the `read_csv()` text parser.
  - New documentation section on `Options and Settings`.
  - Lots of bug fixes.

5.14.1 Version 0.14.1 (July 11, 2014)
API changes

- Openpyxl now raises a ValueError on construction of the openpyxl writer instead of warning on pandas import (GH7284).

- For StringMethods.extract, when no match is found, the result - only containing NaN values - now also has dtype=object instead of float (GH7242)

- Period objects no longer raise a TypeError when compared using == with another object that isn’t a Period. Instead when comparing a Period with another object using == if the other object isn’t a Period False is returned. (GH7376)

- Previously, the behaviour on resetting the time or not in offsets.apply, rollforward and rollback operations differed between offsets. With the support of the normalize keyword for all offsets(see below) with a default value of False (preserve time), the behaviour changed for certain offsets (BusinessMonthBegin, MonthEnd, BusinessMonthEnd, CustomBusinessMonthEnd, BusinessYearBegin, LastWeekOfMonth, FY5253Quarter, LastWeekOfMonth, Easter):

```
In [6]: from pandas.tseries import offsets
In [7]: d = pd.Timestamp('2014-01-01 09:00')
# old behaviour < 0.14.1
In [8]: d + offsets.MonthEnd()
Out[8]: pd.Timestamp('2014-01-31 00:00:00')
```

Starting from 0.14.1 all offsets preserve time by default. The old behaviour can be obtained with normalize=True

```
# new behaviour
In [1]: d + offsets.MonthEnd()
Out[1]: Timestamp('2014-01-31 09:00:00')
In [2]: d + offsets.MonthEnd(normalize=True)
Out[2]: Timestamp('2014-01-31 00:00:00')
```

Note that for the other offsets the default behaviour did not change.

- Add back #N/A N/A as a default NA value in text parsing. (regression from 0.12) (GH5521)

- Raise a TypeError on inplace-setting with a .where and a non np.nan value as this is inconsistent with a set-item expression like df[mask] = None (GH7656)

Enhancements

- Add dropna argument to value_counts and nunique (GH5569).

- Add select_dtypes() method to allow selection of columns based on dtype (GH7316). See the docs.

- All offsets supports the normalize keyword to specify whether offsets.apply, rollforward and rollback resets the time (hour, minute, etc) or not (default False, preserves time) (GH7156):

```python
import pandas.tseries.offsets as offsets
day = offsets.Day()
day.apply(pd.Timestamp('2014-01-01 09:00'))

day = offsets.Day(normalize=True)
day.apply(pd.Timestamp('2014-01-01 09:00'))
```
PeriodIndex is represented as the same format as DatetimeIndex (GH7601)

StringMethods now work on empty Series (GH7242)

The file parsers read_csv and read_table now ignore line comments provided by the parameter comment, which accepts only a single character for the C reader. In particular, they allow for comments before file data begins (GH2685)

Add NotImplementedError for simultaneous use of chunksize and nrows for read_csv() (GH6774).

Tests for basic reading of public S3 buckets now exist (GH7281).

read_html now sports an encoding argument that is passed to the underlying parser library. You can use this to read non-ascii encoded web pages (GH7323).

read_excel now supports reading from URLs in the same way that read_csv does. (GH6809)

Support for dateutil timezones, which can now be used in the same way as pytz timezones across pandas. (GH4688)

```
In [3]: rng = pd.date_range('3/6/2012 00:00', periods=10, freq='D',
                      ...:                 tz='dateutil/Europe/London')
                      ...

In [4]: rng.tz
Out[4]: tzfile('/usr/share/zoneinfo/Europe/London')
```

See the docs.

Implemented sem (standard error of the mean) operation for Series, DataFrame, Panel, and Groupby (GH6897)

Add nlargest and nsmallest to the Series groupby allowlist, which means you can now use these methods on a SeriesGroupBy object (GH7053).

All offsets apply, rollforward and rollback can now handle np.datetime64, previously results in ApplyTypeError (GH7452)

Period and PeriodIndex can contain NaT in its values (GH7485)

Support pickling Series, DataFrame and Panel objects with non-unique labels along item axis (index, columns and items respectively) (GH7370).

Improved inference of datetime/timedelta with mixed null objects. Regression from 0.13.1 in interpretation of an object Index with all null elements (GH7431)

### Performance

- Improvements in dtype inference for numeric operations involving yielding performance gains for dtypes: int64, timedelta64, datetime64 (GH7223)
- Improvements in Series.transform for significant performance gains (GH6496)
- Improvements in DataFrame.transform with ufuncs and built-in grouper functions for significant performance gains (GH7383)
- Regression in groupby aggregation of datetime64 dtypes (GH7555)
- Improvements in MultiIndex.from_product for large iterables (GH7627)
Experimental

- `pandas.io.data.Options` has a new method, `get_all_data` method, and now consistently returns a MultiIndexed DataFrame (GH5602)
- `io.gbq.read_gbq` and `io.gbq.to_gbq` were refactored to remove the dependency on the Google bq.py command line client. This submodule now uses http/2 and the Google apiclient and oauth2client API client libraries which should be more stable and, therefore, reliable than bq.py. See the docs. (GH6937).

Bug fixes

- Bug in `DataFrame.where` with a symmetric shaped frame and a passed other of a DataFrame (GH7506)
- Bug in Panel indexing with a MultiIndex axis (GH7516)
- Regression in datetimelike slice indexing with a duplicated index and non-exact end-points (GH7523)
- Bug in setitem with list-of-lists and single vs mixed types (GH7551)
- Bug in time ops with non-aligned Series (GH7500)
- Bug in timedelta inference when assigning an incomplete Series (GH7592)
- Bug in groupby `.nth` with a Series and integer-like column name (GH7559)
- Bug in `Series.set` with a boolean accessor (GH7407)
- Bug in `value_counts` where NaT did not qualify as missing (NaN) (GH7423)
- Bug in `to_timedelta` that accepted invalid units and misinterpreted ‘m/h’ (GH7611, GH6423)
- Bug in line plot doesn’t set correct `xlim` if `secondary_y=True` (GH7459)
- Bug in grouped `hist` and `scatter` plots use old `figsize` default (GH7394)
- Bug in plotting subplots with `DataFrame.plot.hist` clears passed `ax` even if the number of subplots is one (GH7391).
- Bug in plotting subplots with `DataFrame.boxplot` with `by` kw raises `ValueError` if the number of subplots exceeds 1 (GH7391).
- Bug in `DataFrame.bar` and `barh` plot raises `TypeError` when `bottom` and `left` keyword is specified (GH7226)
- Bug in `Index.delete` does not preserve `name` and `freq` attributes (GH7302)
• Bug in `DataFrame.query()`/`eval` where local string variables with the @ sign were being treated as temporaries attempting to be deleted (GH7300).
• Bug in `Float64Index` which didn’t allow duplicates (GH7149).
• Bug in `DataFrame.replace()` where truthy values were being replaced (GH7140).
• Bug in `StringMethods.extract()` where a single match group Series would use the matcher’s name instead of the group name (GH7313).
• Bug in `isnull()` when mode.use_inf_as_null == True where isnull wouldn’t test True when it encountered an inf/-inf (GH7315).
• Bug in inferred_freq results in None for eastern hemisphere timezones (GH7310)
• Bug in `Easter` returns incorrect date when offset is negative (GH7195)
• Bug in broadcasting with `.div`, integer dtypes and divide-by-zero (GH7325)
• Bug in `CustomBusinessDay.apply` raises NameError when np.datetime64 object is passed (GH7196)
• Bug in `MultiIndex.append`, `concat` and `pivot_table` don’t preserve timezone (GH6606)
• Bug in `.loc` with a list of indexers on a single-multi index level (that is not nested) (GH7349)
• Bug in `Series.map` when mapping a dict with tuple keys of different lengths (GH7333)
• Bug all `StringMethods` now work on empty Series (GH7242)
• Fix delegation of `read_sql` to `read_sql_query` when query does not contain 'select' (GH7324).
• Bug where a string column name assignment to a `DataFrame` with a `Float64Index` raised a TypeError during a call to np.isnan (GH7366).
• Bug where `NDFrame.replace()` didn’t correctly replace objects with Period values (GH7379).
• Bug in `.ix` getitem should always return a Series (GH7150)
• Bug in `MultiIndex` slicing with incomplete indexers (GH7399)
• Bug in `MultiIndex` slicing with a step in a sliced level (GH7400)
• Bug where negative indexers in `DatetimeIndex` were not correctly sliced (GH7408)
• Bug where NaT wasn’t repr’d correctly in a `MultiIndex` (GH7406, GH7409).
• Bug where bool objects were converted to nan in `convert_objects` (GH7416).
• Bug in `quantile` ignoring the axis keyword argument (GH7306)
• Bug where nanops._maybe_null_out doesn’t work with complex numbers (GH7353)
• Bug in several nanops functions when axis==0 for 1-dimensional nan arrays (GH7354)
• Bug where nanops.nanmedian doesn’t work when axis==None (GH7352)
• Bug where nanops._has_infs doesn’t work with many dtypes (GH7357)
• Bug in StataReader.data where reading a 0-observation dta failed (GH7369)
• Bug in StataReader when reading Stata 13 (117) files containing fixed width strings (GH7360)
• Bug in StataWriter where encoding was ignored (GH7286)
• Bug in `DatetimeIndex` comparison doesn’t handle NaT properly (GH7529)
• Bug in passing input with tzinfo to some offsets apply, rollforward or rollback resets tzinfo or raises ValueError (GH7465)
• Bug in `DatetimeIndex.to_period`, `PeriodIndex.asobject`, `PeriodIndex.to_timestamp` doesn’t preserve name (GH7485)

• Bug in `DatetimeIndex.to_period` and `PeriodIndex.to_timestamp` handle NaT incorrectly (GH7228)

• Bug in `offsets.apply`, `rollforward` and `rollback` may return normal datetime (GH7502)

• Bug in `resample` raises `ValueError` when target contains NaT (GH7227)

• Bug in `Timestamp.tz_localize` resets nanosecond info (GH7534)

• Bug in `DatetimeIndex.asobject` raises `ValueError` when it contains NaT (GH7539)

• Bug in `timestamp.__new__` doesn’t preserve nanosecond properly (GH7610)

• Bug in `Index.astype(float)` where it would return an object dtype `Index` (GH7464).

• Bug in `DataFrame.reset_index` loses tz (GH3950)

• Bug in `DatetimeIndex.freqstr` raises `AttributeError` when freq is None (GH7606)

• Bug in `GroupBy.size` created by `TimeGrouper` raises `AttributeError` (GH7453)

• Bug in single column bar plot is misaligned (GH7498).

• Bug in `area plot` with tz-aware time series raises `ValueError` (GH7471)

• Bug in `non-monotonic Index.union` may preserve name incorrectly (GH7458)

• Bug in `DatetimeIndex.intersection` doesn’t preserve timezone (GH4690)

• Bug in `rolling_var` where a window larger than the array would raise an error(GH7297)

• Bug with last plotted timeseries dictating `xlim` (GH2960)

• Bug with `secondary_y` axis not being considered for timeseries `xlim` (GH3490)

• Bug in `Float64Index` assignment with a non scalar indexer (GH7586)

• Bug in `pandas.core.strings.str_contains` does not properly match in a case insensitive fashion when `regex=False` and `case=False` (GH7505)

• Bug in `expanding_cov`, `expanding_corr`, `rolling_cov`, and `rolling_corr` for two arguments with mismatched index (GH7512)

• Bug in `to_sql` taking the boolean column as text column (GH7678)

• Bug in `grouped hist` doesn’t handle `rot` kw and `sharex` kw properly (GH7234)

• Bug in `.loc` performing fallback integer indexing with object dtype indices (GH7496)

• Bug (regression) in `PeriodIndex` constructor when passed `Series` objects (GH7701).

**Contributors**

A total of 46 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

• Andrew Rosenfeld

• Andy Hayden

• Benjamin Adams +

• Benjamin M. Gross +

• Brian Quistorff +
- Brian Wignall +
- DSM
- Daniel Waeber
- David Bew +
- David Stephens
- Jacob Schaer
- Jan Schulz
- John David Reaver
- John W. O’Brien
- Joris Van den Bossche
- Julien Danjou +
- K.-Michael Aye
- Kevin Sheppard
- Kyle Meyer
- Matt Wittmann
- Matthew Brett +
- Michael Mueller +
- Mortada Mehyar
- Phillip Cloud
- Rob Levy +
- Schaer, Jacob C +
- Stephan Hoyer
- Thomas Kluyver
- Todd Jennings
- Tom Augspurger
- TomAugspurger
- bwignall
- clham
- dsm054 +
- helger +
- immerrr
- jaimefrio
- jreback
- lexual
- onesandzeroes
- rockg
• sanguineturtle +
• seth-p +
• sinhks
• unknown
• yelite +

5.14.2 Version 0.14.0 (May 31, 2014)

This is a major release from 0.13.1 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

• Highlights include:
  – Officially support Python 3.4
  – SQL interfaces updated to use sqlalchemy, See Here.
  – Display interface changes, See Here
  – MultiIndexing Using Slicers, See Here.
  – Ability to join a singly-indexed DataFrame with a MultiIndexed DataFrame, see Here
  – More consistency in groupby results and more flexible groupby specifications, See Here
  – Holiday calendars are now supported in CustomBusinessDay, see Here
  – Several improvements in plotting functions, including: hexbin, area and pie plots, see Here.
  – Performance doc section on I/O operations, See Here

• Other Enhancements
• API Changes
• Text Parsing API Changes
• Groupby API Changes
• Performance Improvements
• Prior Deprecations
• Deprecations
• Known Issues
• Bug Fixes

Warning: In 0.14.0 all DataFrame based containers have undergone significant internal refactoring. Before that each block of homogeneous data had its own labels and extra care was necessary to keep those in sync with the parent container’s labels. This should not have any visible user/API behavior changes (GH6745)
API changes

- `read_excel` uses 0 as the default sheet (GH6573)
- `iloc` will now accept out-of-bounds indexers for slices, e.g. a value that exceeds the length of the object being indexed. These will be excluded. This will make pandas conform more with python/numpy indexing of out-of-bounds values. A single indexer that is out-of-bounds and drops the dimensions of the object will still raise `IndexError` (GH6296, GH6299). This could result in an empty axis (e.g. an empty DataFrame being returned)

```python
In [1]: df1 = pd.DataFrame(np.random.randn(5, 2), columns=list('AB'))

In [2]: df1
Out[2]:
       A       B
0  0.469112 -0.282863
1 -1.509059 -1.135632
2  1.212112 -0.173215
3  0.119209 -1.044236
4 -0.861849 -2.104569
[5 rows x 2 columns]

In [3]: df1.iloc[:, 2:3]
Out[3]:
Empty DataFrame
Columns: []
Index: [0, 1, 2, 3, 4]
[5 rows x 0 columns]

In [4]: df1.iloc[:, 1:3]
Out[4]:
       B
0 -0.282863
1 -1.135632
2 -0.173215
3 -1.044236
4 -2.104569
[5 rows x 1 columns]

In [5]: df1.iloc[4:6]
Out[5]:
       A       B
4  0.861849 -2.104569
[1 rows x 2 columns]
```

These are out-of-bounds selections

```python
>>> df1.iloc[[4, 5, 6]]
IndexError: positional indexers are out-of-bounds

>>> df1.iloc[:, 4]
IndexError: single positional indexer is out-of-bounds
```

- Slicing with negative start, stop & step values handles corner cases better (GH6531):
- `df.iloc[:-len(df)]` is now empty
- `df.iloc[len(df)::]` now enumerates all elements in reverse

- The `DataFrame.interpolate()` keyword `downcast default` has been changed from `infer` to `None`. This is to preserve the original dtype unless explicitly requested otherwise (GH6290).

- When converting a dataframe to HTML it used to return `Empty DataFrame`. This special case has been removed, instead a header with the column names is returned (GH6062).

- Series and Index now internally share more common operations, e.g. `factorize()`, `nunique()`, `value_counts()` are now supported on Index types as well. The `Series.weekday` property from is removed from Series for API consistency. Using a DatetimeIndex/PeriodIndex method on a Series will now raise a `TypeError` (GH4551, GH4056, GH5519, GH6380, GH7206).

- Add `is_month_start`, `is_month_end`, `is_quarter_start`, `is_quarter_end`, `is_year_start`, `is_year_end` accessors for `DateTimeIndex / Timestamp` which return a boolean array of whether the timestamp(s) are at the start/end of the month/quarter/year defined by the frequency of the `DateTimeIndex / Timestamp` (GH4565, GH6998).

- Local variable usage has changed in `pandas.eval() / DataFrame.eval() / DataFrame.query()` (GH5987). For the `DataFrame` methods, two things have changed
  - Column names are now given precedence over locals
  - Local variables must be referred to explicitly. This means that even if you have a local variable that is not a column you must still refer to it with the '@' prefix.
  - You can have an expression like `df.query('@a < a')` with no complaints from pandas about ambiguity of the name a.
  - The top-level `pandas.eval()` function does not allow you use the '@' prefix and provides you with an error message telling you so.
  - `NameResolutionError` was removed because it isn’t necessary anymore.

- Define and document the order of column vs index names in `query/eval` (GH6676)

- `concat` will now concatenate mixed Series and DataFrames using the Series name or numbering columns as needed (GH2385). See the docs

- Slicing and advanced/boolean indexing operations on Index classes as well as `Index.delete()` and `Index.drop()` methods will no longer change the type of the resulting index (GH6440, GH7040)

```
In [6]: i = pd.Index([1, 2, 3, 'a', 'b', 'c'])

In [7]: i[[0, 1, 2]]
Out[7]: Index([1, 2, 3], dtype='object')

In [8]: i.drop(['a', 'b', 'c'])
Out[8]: Index([1, 2, 3], dtype='object')
```

Previously, the above operation would return `Int64Index`. If you’d like to do this manually, use `Index.astype()`

```
In [9]: i[[0, 1, 2]].astype(np.int_)
Out[9]: Int64Index([1, 2, 3], dtype='int64')
```

- `set_index` no longer converts MultiIndexes to an Index of tuples. For example, the old behavior returned an Index in this case (GH6459):
# Old behavior, casted MultiIndex to an Index

```python
In [10]: tuple_ind
Out[10]: Index([('a', 'c'), ('a', 'd'), ('b', 'c'), ('b', 'd')], dtype='object')
```

```python
In [11]: df_multi.set_index(tuple_ind)
Out[11]:
   0    1
(a, c) 0.471435 -1.190976
(a, d) 1.432707 -0.312652
(b, c) -0.720589  0.887163
(b, d)  0.859588 -0.636524
[4 rows x 2 columns]
```

# New behavior

```python
In [12]: mi
Out[12]: MultiIndex([('a', 'c'),
                  ('a', 'd'),
                  ('b', 'c'),
                  ('b', 'd')],
                  )
```

```python
In [13]: df_multi.set_index(mi)
Out[13]:
   0    1
 a c  0.471435 -1.190976
d  1.432707 -0.312652
 b c -0.720589  0.887163
d  0.859588 -0.636524
[4 rows x 2 columns]
```

This also applies when passing multiple indices to `set_index`:

```python
# Old output, 2-level MultiIndex of tuples
In [14]: df_multi.set_index([df_multi.index, df_multi.index])
Out[14]:
   0    1
(a, c) (a, c) 0.471435 -1.190976
(a, d) (a, d) 1.432707 -0.312652
(b, c) (b, c) -0.720589  0.887163
(b, d) (b, d)  0.859588 -0.636524
[4 rows x 2 columns]
```

# New output, 4-level MultiIndex

```python
In [15]: df_multi.set_index([df_multi.index, df_multi.index])
Out[15]:
   0    1
 a c a c  0.471435 -1.190976
da d  1.432707 -0.312652
 b c b c -0.720589  0.887163
bd bd  0.859588 -0.636524
[4 rows x 2 columns]
```

• **pairwise** keyword was added to the statistical moment functions `rolling_cov`, `rolling_corr`,
ewmcov, ewmcorr, expanding_cov, expanding_corr to allow the calculation of moving window covariance and correlation matrices (GH4950). See Computing rolling pairwise covariances and correlations in the docs.

```
In [1]: df = pd.DataFrame(np.random.randn(10, 4), columns=list('ABCD'))
In [4]: covs = pd.rolling_cov(df[['A', 'B', 'C']],
                        ...:                      df[['B', 'C', 'D']],
                        ...:                      5,
                        ...:                      pairwise=True)
In [5]: covs[df.index[-1]]
Out[5]:
         B      C      D
A  0.035310  0.326593 -0.505430
B  0.137748 -0.006888 -0.005383
C -0.006888  0.861040  0.020762
```

- Series.iteritems() is now lazy (returns an iterator rather than a list). This was the documented behavior prior to 0.14. (GH6760)
- Added nunique and value_counts functions to Index for counting unique elements. (GH6734)
- stack and unstack now raise a ValueError when the level keyword refers to a non-unique item in the Index (previously raised a KeyError). (GH6738)
- drop unused order argument from Series.sort; args now are in the same order as Series.order; add na_position arg to conform to Series.order (GH6847)
- default sorting algorithm for Series.order is now quicksort, to conform with Series.sort (and numpy defaults)
- add inplace keyword to Series.order/sort to make them inverses (GH6859)
- DataFrame.sort now places NaNs at the beginning or end of the sort according to the na_position parameter. (GH3917)
- accept TextFileReader in concat, which was affecting a common user idiom (GH6583), this was a regression from 0.13.1
- Added factorize functions to Index and Series to get indexer and unique values (GH7090)
- describe on a DataFrame with a mix of Timestamp and string like objects returns a different Index (GH7088). Previously the index was unintentionally sorted.
- Arithmetic operations with only bool dtypes now give a warning indicating that they are evaluated in Python space for +, -, and * operations and raise for all others (GH7011, GH6762, GH7015, GH7210)

```
>>> x = pd.Series(np.random.rand(10) > 0.5)
>>> y = True
>>> x + y  # warning generated: should do x | y instead
UserWarning: evaluating in Python space because the '+' operator is not supported by numexpr for the bool dtype, use '|' instead
>>> x / y  # this raises because it doesn't make sense
NotImplementedError: operator '/' not implemented for bool dtypes
```

- In HDFStore, select_as_multiple will always raise a KeyError, when a key or the selector is not found (GH6177)
- df['col'] = value and df.loc[:, 'col'] = value are now completely equivalent; previously the .loc would not necessarily coerce the dtype of the resultant series (GH6149)
• `dtypes` and `ftypes` now return a series with `dtype=object` on empty containers (GH5740)
• `df.to_csv` will now return a string of the CSV data if neither a target path nor a buffer is provided (GH6061)
• `pd.infer_freq()` will now raise a `TypeError` if given an invalid `Series/Index` type (GH6407, GH6463)
• A tuple passed to `DataFrame.sort_index` will be interpreted as the levels of the index, rather than requiring a list of tuple (GH4370)
• all offset operations now return `Timestamp` types (rather than `datetime`), Business/Week frequencies were incorrect (GH4069)
• `to_excel` now converts `np.inf` into a string representation, customizable by the `inf_rep` keyword argument (Excel has no native inf representation) (GH6782)
• Replace `pandas.compat.scipy.scoreatpercentile` with `numpy.percentile` (GH6810)
• `.quantile` on a `datetime[ns]` series now returns `Timestamp` instead of `np.datetime64` objects (GH6810)
• change `AssertionError` to `TypeError` for invalid types passed to `concat` (GH6583)
• Raise a `TypeError` when `DataFrame` is passed an iterator as the `data` argument (GH5357)

Display changes

• The default way of printing large DataFrames has changed. DataFrames exceeding `max_rows` and/or `max_columns` are now displayed in a centrally truncated view, consistent with the printing of a `pandas.Series` (GH5603).

In previous versions, a DataFrame was truncated once the dimension constraints were reached and an ellipse (...) signaled that part of the data was cut off.

```python
In [1]: import pandas as pd
In [2]: import numpy as np
In [3]: pd.options.display.max_rows = 6
In [4]: pd.options.display.max_columns = 6
In [5]: index = pd.DatetimeIndex(start='2001-01-01', freq='D', periods=10)
In [6]: pd.DataFrame(np.arange(10*10).reshape((10,10)), index=index)
Out[6]:
   0  1  2  3  4  5
2001-01-01  0  1  2  3  4  5 ...
2001-01-02 10 11 12 13 14 15 ...
2001-01-03 20 21 22 23 24 25 ...
2001-01-04 30 31 32 33 34 35 ...
2001-01-05 40 41 42 43 44 45 ...
2001-01-06 50 51 52 53 54 55 ...
   ...   ...   ...   ...   ...   ...
[10 rows x 10 columns]
```
In the current version, large DataFrames are centrally truncated, showing a preview of head and tail in both dimensions.

```python
In [24]: pd.DataFrame(np.arange(10*10).reshape((10,10)),index=index)
Out[24]:
          0  1  2  ...  7  8  9
2001-01-01 0  1  2  ...  7  8  9
2001-01-02 10 11 12  ... 17 18 19
2001-01-03 20 21 22  ... 27 28 29
...       ...       ...     ...   ...   ...
2001-01-08 70 71 72  ... 77 78 79
2001-01-09 80 81 82  ... 87 88 89
2001-01-10 90 91 92  ... 97 98 99

[10 rows x 10 columns]
```

- allow option 'truncate' for `display.show_dimensions` to only show the dimensions if the frame is truncated (GH6547).

The default for `display.show_dimensions` will now be `truncate`. This is consistent with how Series display length.

```python
In [16]: dfd = pd.DataFrame(np.arange(25).reshape(-1, 5),
                         index=[0, 1, 2, 3, 4],
                         columns=[0, 1, 2, 3, 4])

# show dimensions since this is truncated
In [17]: with pd.option_context('display.max_rows', 2, 'display.max_columns', 2,
                             'display.show_dimensions', 'truncate'):
    print(dfd)
   0 ... 4
  0  1  2  3  4
  1  5  6  7  8  9
  2 10 11 12 13 14
  3 15 16 17 18 19
  4 20 21 22 23 24

[5 rows x 5 columns]

# will not show dimensions since it is not truncated
In [18]: with pd.option_context('display.max_rows', 10, 'display.max_columns', 40,
                             'display.show_dimensions', 'truncate'):
    print(dfd)
   0  1  2  3  4
  0  1  2  3  4
  1  5  6  7  8  9
  2 10 11 12 13 14
  3 15 16 17 18 19
  4 20 21 22 23 24
```

- Regression in the display of a MultiIndexed Series with `display.max_rows` is less than the length of the series (GH7101)

- Fixed a bug in the HTML repr of a truncated Series or DataFrame not showing the class name with the `large_repr` set to ‘info’ (GH7105)
• The `verbose` keyword in `DataFrame.info()`, which controls whether to shorten the `info` representation, is now `None` by default. This will follow the global setting in `display.max_info_columns`. The global setting can be overridden with `verbose=True` or `verbose=False`.

• Fixed a bug with the `info` repr not honoring the `display.max_info_columns` setting (GH6939)

• Offset/freq info now in Timestamp `__repr__` (GH4553)

## Text parsing API changes

`read_csv()`/`read_table()` will now be noisier w.r.t invalid options rather than falling back to the PythonParser.

• Raise `ValueError` when `sep` specified with `delim_whitespace=True` in `read_csv()`/`read_table()` (GH6607)

• Raise `ValueError` when `engine='c'` specified with unsupported options in `read_csv()`/`read_table()` (GH6607)

• Raise `ValueError` when fallback to python parser causes options to be ignored (GH6607)

• Produce `ParserWarning` on fallback to python parser when no options are ignored (GH6607)

• Translate `sep='\s+'` to `delim_whitespace=True` in `read_csv()`/`read_table()` if no other C-unsupported options specified (GH6607)

## GroupBy API changes

More consistent behavior for some groupby methods:

• `groupby head` and `tail` now act more like `filter` rather than an aggregation:

```
In [19]: df = pd.DataFrame([[1, 2], [1, 4], [5, 6]], columns=['A', 'B'])
In [20]: g = df.groupby('A')
In [21]: g.head(1)  # filters DataFrame
Out[21]:
   A  B
0  1  2
2  5  6
[2 rows x 2 columns]
In [22]: g.apply(lambda x: x.head(1))  # used to simply fall-through
Out[22]:
   A  B
A  1  2
5  2  6
[2 rows x 2 columns]
```

• `groupby head` and `tail` respect column selection:

```
In [23]: g[['B']].head(1)
Out[23]:
   B
0  2
2  6
```

(continues on next page)
• groupby nth now reduces by default; filtering can be achieved by passing `as_index=False`. With an optional `dropna` argument to ignore NaN. See the docs.

Reducing

```python
In [24]: df = pd.DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=['A', 'B'])
In [25]: g = df.groupby('A')
In [26]: g.nth(0)
Out[26]:
   B
A  
  1 NaN
  5  6.0
[2 rows x 1 columns]
# this is equivalent to g.first()
In [27]: g.nth(0, dropna='any')
Out[27]:
   B
A  
  1  4.0
  5  6.0
[2 rows x 1 columns]
# this is equivalent to g.last()
In [28]: g.nth(-1, dropna='any')
Out[28]:
   B
A  
  1  4.0
  5  6.0
[2 rows x 1 columns]
```

Filtering

```python
In [29]: gf = df.groupby('A', as_index=False)
In [30]: gf.nth(0)
Out[30]:
   A   B
 0  1  NaN
 2  5  6.0
[2 rows x 2 columns]
In [31]: gf.nth(0, dropna='any')
Out[31]:
   A   B
 0  1  NaN
 2  5  6.0
```

(continues on next page)
A B
A
1 1 4.0
5 5 6.0
[2 rows x 2 columns]

• groupby will now not return the grouped column for non-cython functions (GH5610, GH5614, GH6732), as its already the index

In [32]: df = pd.DataFrame([[1, np.nan], [1, 4], [5, 6], [5, 8]], columns=[A, B])
In [33]: g = df.groupby(A)
In [34]: g.count()
Out[34]:
A B
0 1 1
1 5 2
[2 rows x 1 columns]
In [35]: g.describe()
Out[35]:
A B
count mean std min 25% 50% 75% max
count mean std min 25% 50% 75% max
0 2.0 1.0 0.0 1.0 1.0 1.0 1.0 4.0 NaN 4.0 4.0 4.0 4.0
1 2.0 7.0 1.414214 6.0 6.5 7.0 7.5 8.0
[2 rows x 8 columns]

• passing as_index will leave the grouped column in-place (this is not change in 0.14.)

In [36]: df = pd.DataFrame([[1, np.nan], [1, 4], [5, 6], [5, 8]], columns=[A, B])
In [37]: g = df.groupby(A, as_index=False)
In [38]: g.count()
Out[38]:
A B
0 1 1
1 5 2
[2 rows x 2 columns]
In [39]: g.describe()
Out[39]:
A B
count mean  std  min 25% 50% 75% max count mean  std  min 25% 50% 75% max
0 2.0 1.0 0.0 1.0 1.0 1.0 1.0 1.0 4.0 NaN 4.0 4.0 4.0 4.0
1 2.0 7.0 1.414214 6.0 6.5 7.0 7.5 8.0
[Continues on next page]
• Allow specification of a more complex groupby via `pd.Grouper`, such as grouping by a Time and a string field simultaneously. See the docs. (GH3794)

• Better propagation/preservation of Series names when performing groupby operations:
  – `SeriesGroupBy.agg` will ensure that the name attribute of the original series is propagated to the result (GH6265).
  – If the function provided to `GroupBy.apply` returns a named series, the name of the series will be kept as the name of the column index of the DataFrame returned by `GroupBy.apply` (GH6124). This facilitates `DataFrame.stack` operations where the name of the column index is used as the name of the inserted column containing the pivoted data.

**SQL**

The SQL reading and writing functions now support more database flavors through SQLAlchemy (GH2717, GH4163, GH5950, GH6292). All databases supported by SQLAlchemy can be used, such as PostgreSQL, MySQL, Oracle, Microsoft SQL server (see documentation of SQLAlchemy on included dialects).

The functionality of providing DBAPI connection objects will only be supported for sqlite3 in the future. The 'mysql' flavor is deprecated.

The new functions `read_sql_query()` and `read_sql_table()` are introduced. The function `read_sql()` is kept as a convenience wrapper around the other two and will delegate to specific function depending on the provided input (database table name or sql query).

In practice, you have to provide a SQLAlchemy engine to the sql functions. To connect with SQLAlchemy you use the `create_engine()` function to create an engine object from database URI. You only need to create the engine once per database you are connecting to. For an in-memory sqlite database:

```python
In [40]: from sqlalchemy import create_engine

# Create your connection.
In [41]: engine = create_engine('sqlite:///::memory::)
```

This engine can then be used to write or read data to/from this database:

```python
In [42]: df = pd.DataFrame({'A': [1, 2, 3], 'B': ['a', 'b', 'c']})
In [43]: df.to_sql('db_table', engine, index=False)
```

You can read data from a database by specifying the table name:

```python
In [44]: pd.read_sql_table('db_table', engine)
Out[44]:
   A  B
0  1  a
1  2  b
2  3  c
```

[3 rows x 2 columns]
or by specifying a sql query:

```python
In [45]: pd.read_sql_query('SELECT * FROM db_table', engine)
Out[45]:
          A  B
0        1  a
1        2  b
2        3  c
[3 rows x 2 columns]
```

Some other enhancements to the sql functions include:

- support for writing the index. This can be controlled with the `index` keyword (default is True).
- specify the column label to use when writing the index with `index_label`.
- specify string columns to parse as datetimes with the `parse_dates` keyword in `read_sql_query()` and `read_sql_table()`.

**Warning:** Some of the existing functions or function aliases have been deprecated and will be removed in future versions. This includes: `tquery`, `uquery`, `read_frame`, `frame_query`, `write_frame`.

**Warning:** The support for the ‘mysql’ flavor when using DBAPI connection objects has been deprecated. MySQL will be further supported with SQLAlchemy engines (GH6900).

### Multi-indexing using slicers

In 0.14.0 we added a new way to slice MultiIndexed objects. You can slice a MultiIndex by providing multiple indexers.

You can provide any of the selectors as if you are indexing by label, see *Selection by Label*, including slices, lists of labels, labels, and boolean indexers.

You can use `slice(None)` to select all the contents of that level. You do not need to specify all the deeper levels, they will be implied as `slice(None)`.

As usual, **both sides** of the slicers are included as this is label indexing.

See *the docs* See also issues (GH6134, GH4036, GH3057, GH2598, GH5641, GH7106)

**Warning:**

You should specify all axes in the `.loc` specifier, meaning the indexer for the `index` and for the `columns`. Their are some ambiguous cases where the passed indexer could be mis-interpreted as indexing both axes, rather than into say the MultiIndex for the rows.

You should do this:

```python
>>> df.loc[(slice('A1', 'A3'), ...), :] # noqa: E901
```

rather than this:

```python
>>> df.loc[(slice('A1', 'A3'), ...)] # noqa: E901
```
In [46]: def mklbl(prefix, n):
   ....:    return ["%s%d" % (prefix, i) for i in range(n)]
   ....:

In [47]: index = pd.MultiIndex.from_product([mklbl('A', 4),
   ....:    mklbl('B', 2),
   ....:    mklbl('C', 4),
   ....:    mklbl('D', 2)])
   ....:

In [48]: columns = pd.MultiIndex.from_tuples([('a', 'foo'), ('a', 'bar'),
   ....:    ('b', 'foo'), ('b', 'bah')],
   ....:    names=['lvl0', 'lvl1'])
   ....:

In [49]: df = pd.DataFrame(np.arange(len(index) * len(columns)).reshape((len(index),
   ....:    len(columns))),
   ....:    index=index,
   ....:    columns=columns).sort_index().sort_index(axis=1)
   ....:

In [50]: df
Out[50]:
lvl0    a    b
lvl1     bar  foo  bah  foo
A0  B0  C0  D0  1  0  3  2
   D1  5  4  7  6
   C1  9  8 11 10
   D1 13 12 15 14
   C2 17 16 19 18
   ...    ...    ...    ...
A3  B1  C1  D1 237 236 239 238
   C2 241 240 243 242
   D1 245 244 247 246
   C3 249 248 251 250
   D1 253 252 255 254
[64 rows x 4 columns]

Basic MultiIndex slicing using slices, lists, and labels.

In [51]: df.loc[(slice('A1', 'A3'), slice(None), ['C1', 'C3']), :]
Out[51]:
lvl0    a    b
lvl1     bar  foo  bah  foo
A1  B0  C1  D0  73  72  75  74
   D1  77  76  79  78
   C3  89  88  91  90
   D1  93  92  95  94
   B1  C1  D0 105 104 107 106
   ...    ...    ...    ...
A3  B0  C3  D1 221 220 223 222
   B1  C1  D0 233 232 235 234
   D1 237 236 239 238
(continues on next page)
You can use a `pd.IndexSlice` to shortcut the creation of these slices

```
In [52]: idx = pd.IndexSlice

In [53]: df.loc[idx[:, :, ['C1', 'C3']], idx[:, 'foo']]
```

```
Out[53]:
lvl0   a   b
lvl1  foo  foo
A0 B0 C1 D0   8   10
   D1  12  14
   C3 D0  24  26
   D1  28  30
   B1 C1 D0  40  42
... ... ...
A3 B0 C3 D1 220 222
   B1 C1 D0 232 234
   D1 236 238
   C3 D0 248 250
   D1 252 254

[32 rows x 2 columns]
```

It is possible to perform quite complicated selections using this method on multiple axes at the same time.

```
In [54]: df.loc['A1', (slice(None), 'foo')]
```

```
Out[54]:
lvl0   a   b
lvl1  foo  foo
B0 C0 D0  64  66
   D1  68  70
   C1 D0  72  74
   D1  76  78
   C2 D0  80  82
... ... ...
B1 C1 D1 108 110
   C2 D0 112 114
   D1 116 118
   C3 D0 120 122
   D1 124 126

[16 rows x 2 columns]
```

```
In [55]: df.loc[idx[:, :, ['C1', 'C3']], idx[:, 'foo']]
```

```
Out[55]:
lvl0   a   b
lvl1  foo  foo
A0 B0 C1 D0   8   10
   D1  12  14
   C3 D0  24  26
   D1  28  30
   B1 C1 D0  40  42
... ... ...
```

(continues on next page)
Using a boolean indexer you can provide selection related to the values.

```
In [56]: mask = df[('a', 'foo')] > 200

In [57]: df.loc[idx[mask, :, ['C1', 'C3']], idx[:, 'foo']]
Out[57]:
  lvl0   a   b
  lvl1 foo foo
   A3 B0 C1 D1 204 206
   C3 D0 216 218
   D1 220 222
   B1 C1 D0 232 234
   D1 236 238
   C3 D0 248 250
   D1 252 254

[7 rows x 2 columns]
```

You can also specify the axis argument to .loc to interpret the passed slicers on a single axis.

```
In [58]: df.loc(axis=0)[:, :, ['C1', 'C3']]
Out[58]:
  lvl0   a   b
  lvl1 bar foo bah foo
   A0 B0 C0 D0  1   0   3   2
   D1 13 12 15 14
   C3 D0 25 24 27 26
   D1 29 28 31 30
   B1 C1 D0 41 40 43 42
   ... ... ... ... ...
   A3 B0 C3 D1 221 220 223 222
   B1 C1 D0 233 232 235 234
   D1 237 236 239 238
   C3 D0 249 248 251 250
   D1 253 252 255 254

[32 rows x 4 columns]
```

Furthermore you can set the values using these methods

```
In [59]: df2 = df.copy()

In [60]: df2.loc(axis=0)[:, :, ['C1', 'C3']] = -10

In [61]: df2
Out[61]:
  lvl0   a   b
  lvl1 bar foo bah foo
   A0 B0 C0 D0  1   0   3   2
   D1 13 12 15 14
   C3 D0 25 24 27 26
   D1 29 28 31 30
   B1 C1 D0 41 40 43 42
   ... ... ... ... ...
   A3 B0 C3 D1 221 220 223 222
   B1 C1 D0 233 232 235 234
   D1 237 236 239 238
   C3 D0 249 248 251 250
   D1 253 252 255 254

[32 rows x 4 columns]
```
```python
D1  5  4  7  6
C1  D0 -10 -10 -10 -10
     D1 -10 -10 -10 -10
     C2  D0  17  16  19  18
     D1 -10 -10 -10 -10
...  ...  ...  ...  ...
A3  B1  C1  D1 -10 -10 -10 -10
     C2  D0  241 240 243 242
     D1  245 244 247 246
     C3  D0 -10 -10 -10 -10
     D1 -10 -10 -10 -10
```

You can use a right-hand-side of an alignable object as well.

```python
In [62]: df2 = df.copy()
In [63]: df2.loc[idx[:, :, ['C1', 'C3']], :] = df2 * 1000
In [64]: df2
Out[64]:
```

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>b</td>
<td></td>
<td></td>
</tr>
<tr>
<td>lv0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>lv11</td>
<td>bar</td>
<td>foo</td>
<td>bah</td>
</tr>
<tr>
<td>A0</td>
<td>B0</td>
<td>C0</td>
<td>D0</td>
</tr>
<tr>
<td>D1</td>
<td>5</td>
<td>4</td>
<td>7</td>
</tr>
<tr>
<td>C1</td>
<td>D0</td>
<td>9000</td>
<td>8000</td>
</tr>
<tr>
<td>D1</td>
<td>13000</td>
<td>12000</td>
<td>15000</td>
</tr>
<tr>
<td>C2</td>
<td>D0</td>
<td>17</td>
<td>16</td>
</tr>
<tr>
<td>C3</td>
<td>D0</td>
<td>249000</td>
<td>248000</td>
</tr>
<tr>
<td>D1</td>
<td>253000</td>
<td>252000</td>
<td>255000</td>
</tr>
</tbody>
</table>
```

[64 rows x 4 columns]

### Plotting

- Hexagonal bin plots from `DataFrame.plot` with `kind='hexbin'` (GH5478), See the docs.
- `DataFrame.plot` and `Series.plot` now supports area plot with specifying `kind='area'` (GH6656), See the docs.
- Pie plots from `Series.plot` and `DataFrame.plot` with `kind='pie'` (GH6976), See the docs.
- Plotting with Error Bars is now supported in the `.plot` method of `DataFrame` and `Series` objects (GH3796, GH6834), See the docs.
- `DataFrame.plot` and `Series.plot` now support a `table` keyword for plotting `matplotlib.Table`, See the docs. The `table` keyword can receive the following values.
  - `False`: Do nothing (default).
  - `True`: Draw a table using the `DataFrame` or `Series` called `plot` method. Data will be transposed to meet `matplotliblib`'s default layout.
DataFrame or Series: Draw matplotlib.table using the passed data. The data will be drawn as displayed in print method (not transposed automatically). Also, helper function pandas.tools.plotting.table is added to create a table from DataFrame and Series, and add it to an matplotlib.Axes.

- `plot(legend='reverse')` will now reverse the order of legend labels for most plot kinds. (GH6014)
- Line plot and area plot can be stacked by `stacked=True` (GH6656)
- Following keywords are now acceptable for `DataFrame.plot()` with `kind='bar'` and `kind='barh'`:
  - `width`: Specify the bar width. In previous versions, static value 0.5 was passed to matplotlib and it cannot be overwritten. (GH6604)
  - `align`: Specify the bar alignment. Default is `center` (different from matplotlib). In previous versions, pandas passes `align='edge'` to matplotlib and adjust the location to `center` by itself, and it results `align` keyword is not applied as expected. (GH4525)
  - `position`: Specify relative alignments for bar plot layout. From 0 (left/bottom-end) to 1(right/top-end). Default is 0.5 (center). (GH6604)

Because of the default `align` value changes, coordinates of bar plots are now located on integer values (0.0, 1.0, 2.0 ...). This is intended to make bar plot be located on the same coordinates as line plot. However, bar plot may differs unexpectedly when you manually adjust the bar location or drawing area, such as using `set_xlim`, `set_ylim`, etc. In this cases, please modify your script to meet with new coordinates.

- The `parallel_coordinates()` function now takes argument `color` instead of `colors`. A FutureWarning is raised to alert that the old `colors` argument will not be supported in a future release. (GH6956)
- The `parallel_coordinates()` and `andrews_curves()` functions now take positional argument `frame` instead of `data`. A FutureWarning is raised if the old `data` argument is used by name. (GH6956)
- `DataFrame.boxplot()` now supports layout keyword (GH6769)
- `DataFrame.boxplot()` has a new keyword argument, `return_type`. It accepts 'dict', 'axes', or 'both', in which case a namedtuple with the matplotlib axes and a dict of matplotlib Lines is returned.

Prior version deprecations/changes

There are prior version deprecations that are taking effect as of 0.14.0.

- Remove `DateRange` in favor of `DatetimeIndex` (GH6816)
- Remove `column` keyword from `DataFrame.sort` (GH4370)
- Remove `precision` keyword from `set_eng_float_format()` (GH395)
- Remove `force_unicode` keyword from `DataFrame.to_string()`, `DataFrame.to_latex()`, and `DataFrame.to_html()`; these function encode in unicode by default (GH2224, GH2225)
- Remove `nanRep` keyword from `DataFrame.to_csv()` and `DataFrame.to_string()` (GH275)
- Remove `unique` keyword from `HDFStore.select_column()` (GH3256)
- Remove `inferTimeRule` keyword from `Timestamp.offset()` (GH1042)
- Remove `name` keyword from `get_data_yahoo()` and `get_data_google()` (commit b921d1a)
- Remove `offset` keyword from `DatetimeIndex` constructor (commit 3136390)
- Remove `time_rule` from several rolling-moment statistical functions, such as `rolling_sum()` (GH1042)
• Removed neg -- boolean operations on numpy arrays in favor of inv ~, as this is going to be deprecated in numpy 1.9 (GH6960)

Deprecations

• The \texttt{pivot\_table()}/\texttt{DataFrame.pivot\_table()} and \texttt{crosstab()} functions now take arguments \texttt{index} and \texttt{columns} instead of \texttt{rows} and \texttt{cols}. A FutureWarning is raised to alert that the old \texttt{rows} and \texttt{cols} arguments will not be supported in a future release (GH5505)

• The \texttt{DataFrame.drop\_duplicates()} and \texttt{DataFrame.duplicated()} methods now take argument \texttt{subset} instead of \texttt{cols} to better align with \texttt{DataFrame.dropna()}. A FutureWarning is raised to alert that the old \texttt{cols} arguments will not be supported in a future release (GH6680)

• The \texttt{DataFrame.to\_csv()} and \texttt{DataFrame.to\_excel()} functions now takes argument \texttt{columns} instead of \texttt{cols}. A FutureWarning is raised to alert that the old \texttt{cols} arguments will not be supported in a future release (GH6645)

• Indexers will warn FutureWarning when used with a scalar indexer and a non-floating point Index (GH4892, GH6960)

```
# non-floating point indexes can only be indexed by integers / labels
In [1]: pd.Series(1, np.arange(5))[3.0]
   pandas/core/index.py:469: FutureWarning: scalar indexers for index type Int64Index should be integers and not floating point
Out[1]: 1

In [2]: pd.Series(1, np.arange(5)).iloc[3.0]
   pandas/core/index.py:469: FutureWarning: scalar indexers for index type Int64Index should be integers and not floating point
Out[2]: 1

In [3]: pd.Series(1, np.arange(5)).iloc[3.0:4]
   pandas/core/index.py:527: FutureWarning: slice indexers when using iloc should be integers and not floating point
Out[3]:
   3 1
   dtype: int64

# these are Float64Indexes, so integer or floating point is acceptable
In [4]: pd.Series(1, np.arange(5.))[3]
Out[4]: 1

In [5]: pd.Series(1, np.arange(5.))[3.0]
Out[6]: 1
```

• Numpy 1.9 compat w.r.t. deprecation warnings (GH6960)

• \texttt{Panel.shift()} now has a function signature that matches \texttt{DataFrame.shift()}. The old positional argument \texttt{lags} has been changed to a keyword argument \texttt{periods} with a default value of 1. A FutureWarning is raised if the old argument \texttt{lags} is used by name. (GH6910)

• The \texttt{order} keyword argument of \texttt{factorize()} will be removed. (GH6926)

• Remove the \texttt{copy} keyword from \texttt{DataFrame.xs()}, \texttt{Panel.major\_xs()}, \texttt{Panel.minor\_xs()}. A view will be returned if possible, otherwise a copy will be made. Previously the user could think that \texttt{copy=False} would ALWAYS return a view. (GH6894)

• The \texttt{parallel\_coordinates()} function now takes argument \texttt{color} instead of \texttt{colors}. A FutureWarning is raised to alert that the old \texttt{colors} argument will not be supported in a future release.
The `parallel_coordinates()` and `andrews_curves()` functions now take positional argument `frame` instead of `data`. A `FutureWarning` is raised if the old `data` argument is used by name. (GH6956)

The support for the `mysql` flavor when using DBAPI connection objects has been deprecated. MySQL will be further supported with SQLAlchemy engines (GH6900).

The following `io.sql` functions have been deprecated: `tquery, uquery, read_frame, frame_query, write_frame`.

The `percentile_width` keyword argument in `describe()` has been deprecated. Use the `percentiles` keyword instead, which takes a list of percentiles to display. The default output is unchanged.

The default return type of `boxplot()` will change from a dict to a matplotlib Axes in a future release. You can use the future behavior now by passing `return_type='axes'` to `boxplot`.

**Known issues**

- OpenPyXL 2.0.0 breaks backwards compatibility (GH7169)

**Enhancements**

- DataFrame and Series will create a MultiIndex object if passed a tuples dict, See the docs (GH3323)

```python
In [65]: pd.Series({('a', 'b'): 1, ('a', 'a'): 0,
                   ....:          ('a', 'c'): 2, ('b', 'a'): 3, ('b', 'b'): 4})
Out[65]:
   a b
   a 1
   b 4
Length: 5, dtype: int64
```

```python
In [66]: pd.DataFrame({('a', 'b'): {('A', 'B'): 1, ('A', 'C'): 2},
                   ....:           ('a', 'a'): {('A', 'C'): 3, ('A', 'B'): 4},
                   ....:           ('a', 'c'): {('A', 'B'): 5, ('A', 'C'): 6},
                   ....:           ('b', 'a'): {('A', 'C'): 7, ('A', 'B'): 8},
                   ....:           ('b', 'b'): {('A', 'D'): 9, ('A', 'B'): 10}})
Out[66]:
     a b
   A B 1.0 4.0 5.0 8.0 10.0
   C 2.0 3.0 6.0 7.0 NaN
   D NaN NaN NaN NaN 9.0
[3 rows x 5 columns]
```

- Added the `sym_diff` method to Index (GH5543)
- `DataFrame.to_latex` now takes a longtable keyword, which if True will return a table in a longtable environment. (GH6617)
- Add option to turn off escaping in `DataFrame.to_latex` (GH6472)
pd.read_clipboard will, if the keyword sep is unspecified, try to detect data copied from a spreadsheet and parse accordingly. (GH6223)

Joining a singly-indexed DataFrame with a MultiIndexed DataFrame (GH3662)

See the docs. Joining MultiIndex DataFrames on both the left and right is not yet supported ATM.

```
In [67]: household = pd.DataFrame({'household_id': [1, 2, 3],
                               'male': [0, 1, 0],
                               'wealth': [196087.3, 316478.7, 294750],
                               columns=['household_id', 'male', 'wealth'])
In [68]: household
Out[68]:
            male  wealth
household_id
1          0   196087.3
2          1   316478.7
3          0     294750
[3 rows x 2 columns]
```

```
In [69]: portfolio = pd.DataFrame({'household_id': [1, 2, 2, 3, 3, 3, 4],
                              'asset_id': ["nl0000301109", "nl0000289783", "gb00b03mlx29", "gb00b03mlx29", "lu0197800237", "nl0000289965", np.nan],
                              'name': ["ABN Amro", "Robeco", "Royal Dutch Shell", "Royal Dutch Shell", "AAB Eastern Europe Equity Fund", "Postbank BioTech Fonds", np.nan],
                              'share': [1.0, 0.4, 0.6, 0.15, 0.6, 0.25, 1.0],
                              columns=['household_id', 'asset_id', 'name', 'share'])
In [70]: portfolio
Out[70]:
            name  share
household_id asset_id
1     nl0000301109    ABN Amro  1.00
2      nl0000289783   Robeco  0.40
3      gb00b03mlx29 Royal Dutch Shell  0.60
4      gb00b03mlx29 Royal Dutch Shell  0.15
5      lu0197800237  AAB Eastern Europe Equity Fund  0.60
6    nl0000289965  Postbank BioTech Fonds  0.25
7            NaN          NaN  1.00
(continues on next page)
```
import datetime

df = pd.DataFrame(
    {'Branch': ['A A A A A B'].split(),
     'Buyer': ['Carl Mark Carl Carl Joe Joe'].split(),
     'Quantity': [1, 3, 5, 1, 8, 1],
     'Date': [datetime.datetime(2013, 11, 1, 13, 0),
              datetime.datetime(2013, 11, 13, 0),
              datetime.datetime(2013, 1, 13, 5),
              datetime.datetime(2013, 10, 1, 20, 0),
              datetime.datetime(2013, 10, 2, 10, 0),
              datetime.datetime(2013, 11, 1, 20, 0)],
    )
...:          datetime.datetime(2013, 10, 2, 10, 0),
...:          'PayDay': [datetime.datetime(2013, 10, 4, 0, 0),
...:          datetime.datetime(2013, 10, 15, 13, 5),
...:          datetime.datetime(2013, 9, 5, 20, 0),
...:          datetime.datetime(2013, 11, 2, 10, 0),
...:          datetime.datetime(2013, 10, 7, 20, 0),
...:          datetime.datetime(2013, 9, 5, 10, 0))

In [74]: df
Out[74]:
[72x748]
Branch Buyer Quantity Date PayDay
0 A Carl 1 2013-11-01 13:00:00 2013-10-04 00:00:00
1 A Mark 3 2013-09-01 13:05:00 2013-10-15 13:05:00
2 A Carl 5 2013-10-01 20:00:00 2013-09-05 20:00:00
3 A Carl 1 2013-10-02 10:00:00 2013-11-02 10:00:00
4 A Joe 8 2013-11-01 20:00:00 2013-10-07 20:00:00
5 B Joe 1 2013-10-02 10:00:00 2013-09-05 10:00:00

[6 rows x 5 columns]

In [75]: df.pivot_table(values='Quantity',
...:                  index=pd.Grouper(freq='M', key='Date'),
...:                  columns=pd.Grouper(freq='M', key='PayDay'),
...:                  aggfunc=np.sum)

Out[75]:
[72x748]
Date
2013-09-30 NaN  3.0 NaN
2013-10-31  6.0 NaN  1.0
2013-11-30 NaN  9.0 NaN

[3 rows x 3 columns]

• Arrays of strings can be wrapped to a specified width (str.wrap) (GH6999)

• Add nsmallest() and Series.nlargest() methods to Series, See the docs (GH3960)

• PeriodIndex fully supports partial string indexing like DatetimeIndex (GH7043)

In [76]: prng = pd.period_range('2013-01-01 09:00', periods=100, freq='H')

In [77]: ps = pd.Series(np.random.randn(len(prng)), index=prng)

In [78]: ps
Out[78]:
[72x748]
2013-01-01 09:00    0.015696
2013-01-01 10:00   -2.242685
2013-01-01 11:00    1.150036
2013-01-01 12:00    0.991946
2013-01-01 13:00    0.953324 ...
2013-01-05 08:00    0.285296
2013-01-05 09:00    0.484288
2013-01-05 10:00    1.363482
2013-01-05 11:00   -0.781105

(continues on next page)
2013-01-05 12:00  -0.468018
Freq: H, Length: 100, dtype: float64

In [79]: ps['2013-01-02']
Out[79]:
2013-01-02 00:00  0.553439
2013-01-02 01:00  1.318152
2013-01-02 02:00  -0.469305
2013-01-02 03:00  0.675554
2013-01-02 04:00  -1.817027
...
2013-01-02 19:00  0.036142
2013-01-02 20:00  -2.074978
2013-01-02 21:00  0.247792
2013-01-02 22:00  -0.897157
2013-01-02 23:00  -0.136795
Freq: H, Length: 24, dtype: float64

• **read_excel** can now read milliseconds in Excel dates and times with xlrd >= 0.9.3. (GH5945)
• **pd.stats.moments.rolling_var** now uses Welford’s method for increased numerical stability (GH6817)
• **pd.expanding_apply** and **pd.rolling_apply** now take args and kwargs that are passed on to the func (GH6289)
• **DataFrame.rank()** now has a percentage rank option (GH5971)
• **Series.rank()** now has a percentage rank option (GH5971)
• **Series.rank()** and **DataFrame.rank()** now accept method='dense' for ranks without gaps (GH6514)
• Support passing **encoding** with xlwt (GH3710)
• Refactor **Block** classes removing **Block.items** attributes to avoid duplication in item handling (GH6745, GH6988).
• Testing statements updated to use specialized asserts (GH6175)

**Performance**

• Performance improvement when converting **DatetimeIndex** to floating ordinals using **DatetimeConverter** (GH6636)
• Performance improvement for **DataFrame.shift** (GH5609)
• Performance improvement in indexing into a MultiIndexed Series (GH5567)
• Performance improvements in single-dtyped indexing (GH6484)
• Improve performance of DataFrame construction with certain offsets, by removing faulty caching (e.g. MonthEnd,BusinessMonthEnd), (GH6479)
• Improve performance of **CustomBusinessDay** (GH6584)
• Improve performance of slice indexing on Series with string keys (GH6341, GH6372)
• Performance improvement for **DataFrame.from_records** when reading a specified number of rows from an iterable (GH6700)
• Performance improvements in timedelta conversions for integer dtypes (GH6754)
• Improved performance of compatible pickles (GH6899)
• Improve performance in certain reindexing operations by optimizing take_2d (GH6749)
• GroupBy.count() is now implemented in Cython and is much faster for large numbers of groups (GH7016).

Experimental
There are no experimental changes in 0.14.0

Bug fixes
• Bug in Series ValueError when index doesn’t match data (GH6532)
• Prevent segfault due to MultiIndex not being supported in HDFStore table format (GH1848)
• Bug in pd.DataFrame.sort_index where mergesort wasn’t stable when ascending=False (GH6399)
• Bug in pd.tseries.frequencies.to_offset when argument has leading zeros (GH6391)
• Bug in version string gen. for dev versions with shallow clones / install from tarball (GH6127)
• Inconsistent tz parsing Timestamp / to_datetime for current year (GH5958)
• Indexing bugs with reordered indexes (GH6252, GH6254)
• Bug in .xs with a Series multiindex (GH6258, GH5684)
• Bug in conversion of a string types to a DatetimeIndex with a specified frequency (GH6273, GH6274)
• Bug in eval where type-promotion failed for large expressions (GH6205)
• Bug in interpolate with inplace=True (GH6281)
• HDFStore.remove now handles start and stop (GH6177)
• HDFStore.select_as_multiple handles start and stop the same way as select (GH6177)
• HDFStore.select_as_coordinates and select_column works with a where clause that results in filters (GH6177)
• Regression in join of non_unique_indexes (GH6329)
• Issue with groupby agg with a single function and a a mixed-type frame (GH6337)
• Bug in DataFrame.replace() when passing a non-bool to_replace argument (GH6332)
• Raise when trying to align on different levels of a MultiIndex assignment (GH3738)
• Bug in setting complex dtypes via boolean indexing (GH6345)
• Bug in TimeGrouper/resample when presented with a non-monotonic DatetimeIndex that would return invalid results. (GH4161)
• Bug in index name propagation in TimeGrouper/resample (GH4161)
• TimeGrouper has a more compatible API to the rest of the groupers (e.g. groups was missing) (GH3881)
• Bug in multiple grouping with a TimeGrouper depending on target column order (GH6764)
• Bug in pd.eval when parsing strings with possible tokens like ‘&’ (GH6351)
• Bug correctly handle placements of -inf in Panels when dividing by integer 0 (GH6178)
• DataFrame.shift with axis=1 was raising (GH6371)
- Disabled clipboard tests until release time (run locally with nosetests -A disabled) (GH6048).
- Bug in DataFrame.replace() when passing a nested dict that contained keys not in the values to be replaced (GH6342).
- str.match ignored the na flag (GH6609).
- Bug in take with duplicate columns that were not consolidated (GH6240).
- Bug in interpolate changing dtypes (GH6290).
- Bug in Series.get, was using a buggy access method (GH6383).
- Bug in hdfstore queries of the form where=[('date', '>=', datetime(2013,1,1)), ('date', '<=', datetime(2014,1,1))] (GH6313).
- Bug in DataFrame.dropna with duplicate indices (GH6355).
- Regression in chained getitem indexing with embedded list-like from 0.12 (GH6394).
- Float64Index with nans not comparing correctly (GH6401).
- eval/query expressions with strings containing the @ character will now work (GH6366).
- Bug in Series.reindex when specifying a method with some nan values was inconsistent (noted on a resample) (GH6418).
- Bug in DataFrame.replace() where nested dicts were erroneously depending on the order of dictionary keys and values (GH5338).
- Performance issue in concatenating with empty objects (GH3259).
- Clarify sorting of sym_diff on Index objects with NaN values (GH6444).
- Regression in MultiIndex.from_product with a DatetimeIndex as input (GH6439).
- Bug in str.extract when passed a non-default index (GH6348).
- Bug in str.split when passed pat=None and n=1 (GH6466).
- Bug in io.data.DataReader when passed "F-F_Momentum_Factor" and data_source="famafrench" (GH6460).
- Bug in sum of a timedelta64[ns] series (GH6462).
- Bug in resample with a timezone and certain offsets (GH6397).
- Bug in iat/iloc with duplicate indices on a Series (GH6493).
- Bug in read_html where nan’s were incorrectly being used to indicate missing values in text. Should use the empty string for consistency with the rest of pandas (GH5129).
- Bug in read_html tests where redirected invalid URLs would make one test fail (GH6445).
- Bug in multi-axis indexing using .loc on non-unique indices (GH6504).
- Bug that caused _ref_locs corruption when slice indexing across columns axis of a DataFrame (GH6525).
- Regression from 0.13 in the treatment of numpy datetime64 non-ns dtypes in Series creation (GH6529).
- .names attribute of MultiIndexes passed to set_index are now preserved (GH6459).
- Bug in setitem with a duplicate index and an alignable rhs (GH6541).
- Bug in setitem with .loc on mixed integer Indexes (GH6546).
- Bug in pd.read_stata which would use the wrong data types and missing values (GH6327).
• Bug in `DataFrame.to_stata` that lead to data loss in certain cases, and could be exported using the wrong data types and missing values (GH6335)
• StataWriter replaces missing values in string columns by empty string (GH6802)
• Inconsistent types in `Timestamp` addition/subtraction (GH6543)
• Bug in preserving frequency across `Timestamp` addition/subtraction (GH4547)
• Bug in empty list lookup caused `IndexError` exceptions (GH6536, GH6551)
• `Series.quantile` raising on an object `dtype` (GH6555)
• Bug in `.xs` with a `nan` in level when dropped (GH6574)
• Bug in `fillna` with `method='bfill/ffill'` and `datetime64[ns]` `dtype` (GH6587)
• Bug in sql writing with mixed dtypes possibly leading to data loss (GH6509)
• Bug in `Series.pop` (GH6600)
• Bug in `iloc` indexing when positional indexer matched `Int64Index` of the corresponding axis and no re-ordering happened (GH6612)
• Bug in `fillna` with `limit` and `value` specified
• Bug in `DataFrame.to_stata` when columns have non-string names (GH4558)
• Bug in compat with `np.compress`, surfaced in (GH6658)
• Bug in binary operations with a rhs of a `Series` not aligning (GH6681)
• Bug in `DataFrame.to_stata` which incorrectly handles `nan` values and ignores `with_index` keyword argument (GH6685)
• Bug in resample with extra bins when using an evenly divisible frequency (GH4076)
• Bug in consistency of groupby aggregation when passing a custom function (GH6715)
• Bug in resample when `how=None` resample freq is the same as the axis frequency (GH5955)
• Bug in downcasting inference with empty arrays (GH6733)
• Bug in `obj.blocks` on sparse containers dropping all but the last items of same for `dtype` (GH6748)
• Bug in unpickling `NaT` (NaTTyep) (GH4606)
• Bug in `DataFrame.replace()` where regex meta characters were being treated as regex even when `regex=False` (GH6777).
• Bug in `timedelta` ops on 32-bit platforms (GH6808)
• Bug in setting a tz-aware index directly via `.index` (GH6785)
• Bug in `expressions.py` where numexpr would try to evaluate arithmetic ops (GH6762).
• Bug in `Makefile` where it didn’t remove Cython generated C files with `make clean` (GH6768)
• Bug with `numpy < 1.7.2` when reading long strings from `HDFStore` (GH6166)
• Bug in `DataFrame._reduce` where non bool-like (0/1) integers were being converted into bools. (GH6806)
• Regression from 0.13 with `fillna` and a `Series` on `datetime-like` (GH6344)
• Bug in `DataFrame.replace()` where changing a `dtype` through replacement would only replace the first occurrence of a value (GH6689)
• Better error message when passing a frequency of ‘MS’ in `Period` construction (GH5332)
• Bug in Series.__unicode__ when max_rows=None and the Series has more than 1000 rows. (GH6863)
• Bug in groupby.get_group where a datelike wasn’t always accepted (GH5267)
• Bug in groupBy.get_group created by TimeGrouper raises AttributeError (GH6914)
• Bug in DatetimeIndex.tz_localize and DatetimeIndex.tz_convert converting NaT incorrectly (GH5546)
• Bug in arithmetic operations affecting NaT (GH6873)
• Bug in Series.str.extract where the resulting Series from a single group match wasn’t renamed to the group name
• Bug in DataFrame.to_csv where setting index=False ignored the header kwarg (GH6186)
• Bug in DataFrame.plot and Series.plot, where the legend behave inconsistently when plotting to the same axes repeatedly (GH6678)
• Internal tests for patching __finalize__ / bug in merge not finalizing (GH6923, GH6927)
• accept TextFileReader in concat, which was affecting a common user idiom (GH6583)
• Bug in C parser with leading white space (GH3374)
• Bug in C parser with delim_whitespace=True and \r-delimited lines
• Bug in python parser with explicit MultiIndex in row following column header (GH6893)
• Bug in Series.rank and DataFrame.rank that caused small floats (<1e-13) to all receive the same rank (GH6886)
• Bug in DataFrame.apply with functions that used *args or **kwargs and returned an empty result (GH6952)
• Bug in sum/mean on 32-bit platforms on overflows (GH6915)
• Moved Panel.shift to NDFrame.slice_shift and fixed to respect multiple dtypes. (GH6959)
• Bug in enabling subplots=True in DataFrame.plot only has single column raises TypeError, and Series.plot raises AttributeError (GH6951)
• Bug in DataFrame.plot draws unnecessary axes when enabling subplots and kind=scatter (GH6951)
• Bug in read_csv from a filesystem with non-utf-8 encoding (GH6807)
• Bug in iloc when setting / aligning (GH6766)
• Bug causing UnicodeEncodeError when get_dummies called with unicode values and a prefix (GH6885)
• Bug in timeseries-with-frequency plot cursor display (GH5453)
• Bug surfaced in groupby.plot when using a Float64Index (GH7025)
• Stopped tests from failing if options data isn’t able to be downloaded from Yahoo (GH7034)
• Bug in parallel_coordinates and radviz where reordering of class column caused possible color/class mismatch (GH6956)
• Bug in radviz and andrews_curves where multiple values of ‘color’ were being passed to plotting method (GH6956)
• Bug in Float64Index.isin() where containing NaNs would make indices claim that they contained all the things (GH7066).
• Bug in DataFrame.boxplot where it failed to use the axis passed as the ax argument (GH3578)
• Bug in the XlsxWriter and XlwtWriter implementations that resulted in datetime columns being formatted without the time (GH7075) were being passed to plotting method

• read_fwf() treats None in colspec like regular python slices. It now reads from the beginning or until the end of the line when colspec contains a None (previously raised a TypeError)

• Bug in cache coherence with chained indexing and slicing; add _is_view property to NDFrame to correctly predict views; mark is_copy on xs only if its an actual copy (and not a view) (GH7084)

• Bug in DatetimeIndex creation from string ndarray with dayfirst=True (GH5917)

• Bug in MultiIndex.from_arrays created from DatetimeIndex doesn’t preserve freq and tz (GH7090)

• Bug in unstack raises ValueError when MultiIndex contains PeriodIndex (GH4342)

• Bug in boxplot and hist draws unnecessary axes (GH6769)

• Regression in groupby.nth() for out-of-bounds indexers (GH6621)

• Bug in quantile with datetime values (GH6965)

• Bug in Dataframe.set_index, reindex and pivot don’t preserve DatetimeIndex and PeriodIndex attributes (GH3950, GH5878, GH6631)

• Bug in MultiIndex.get_level_values doesn’t preserve DatetimeIndex and PeriodIndex attributes (GH7092)

• Bug in Groupby doesn’t preserve tz (GH3950)

• Bug in PeriodIndex partial string slicing (GH6716)

• Bug in the HTML repr of a truncated Series or DataFrame not showing the class name with the large_repr set to ‘info’ (GH7105)

• Bug in DatetimeIndex specifying freq raises ValueError when passed value is too short (GH7098)

• Fixed a bug with the info repr not honoring the display.max_info_columns setting (GH6939)

• Bug PeriodIndex string slicing with out of bounds values (GH5407)

• Fixed a memory error in the hashtable implementation/factorizer on resizing of large tables (GH7157)

• Bug in isnull when applied to 0-dimensional object arrays (GH7176)

• Bug in query/eval where global constants were not looked up correctly (GH7178)

• Bug in recognizing out-of-bounds positional list indexers with iloc and a multi-axis tuple indexer (GH7189)

• Bug in setitem with a single value, MultiIndex and integer indices (GH7190, GH7218)

• Bug in expressions evaluation with reversed ops, showing in series-dataframe ops (GH7198, GH7192)

• Bug in multi-axis indexing with > 2 ndim and a MultiIndex (GH7199)

• Fix a bug where invalid eval/query operations would blow the stack (GH5198)
Contributors

A total of 94 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Acanthostega +
- Adam Marcus +
- Alex Gaudio
- Alex Rothberg
- AllenDowney +
- Andrew Rosenfeld +
- Andy Hayden
- Antoine Mazières +
- Benedikt Sauer
- Brad Buran
- Christopher Whelan
- Clark Fitzgerald
- DSM
- Dale Jung
- Dan Allan
- Dan Birken
- Daniel Waeber
- David Jung +
- David Stephens +
- Douglas McNeil
- Garrett Drapala
- Gouthaman Balamaram +
- Guillaume Poulin +
- Jacob Howard +
- Jacob Schaer
- Jason Sexauer +
- Jeff Reback
- Jeff Tratner
- Jeffrey Starr +
- John David Reaver +
- John McNamara
- John W. O’Brien
- Jonathan Chambers
• Joris Van den Bossche
• Julia Evans
• Júlio +
• K.-Michael Aye
• Katie Atkinson +
• Kelsey Jordahl
• Kevin Sheppard +
• Matt Wittmann +
• Matthias Kuhn +
• Max Grender-Jones +
• Michael E. Gruen +
• Mike Kelly
• Nipun Batra +
• Noah Spies +
• PKEuS
• Patrick O’Keeffe
• Phillip Cloud
• Pietro Battiston +
• Randy Carnevale +
• Robert Gibboni +
• Skipper Seabold
• SplashDance +
• Stephan Hoyer +
• Tim Cera +
• Tobias Brandt
• Todd Jennings +
• Tom Augspurger
• TomAugspurger
• Yaroslav Halchenko
• agijsberts +
• akittredge
• ankostis +
• anomrake
• anton-d +
• bashtage +
• benjamin +
5.15 Version 0.13

5.15.1 Version 0.13.1 (February 3, 2014)

This is a minor release from 0.13.0 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- Added `infer_datetime_format` keyword to `read_csv/to_datetime` to allow speedups for homogeneously formatted datetimes.
- Will intelligently limit display precision for datetime/timedelta formats.
- Enhanced Panel `apply()` method.
• Suggested tutorials in new Tutorials section.
• Our pandas ecosystem is growing. We now feature related projects in a new Pandas Ecosystem section.
• Much work has been taking place on improving the docs, and a new Contributing section has been added.
• Even though it may only be of interest to devs, we <3 our new CI status page: ScatterCI.

**Warning:** 0.13.1 fixes a bug that was caused by a combination of having numpy < 1.8, and doing chained assignment on a string-like array. Please review the docs, chained indexing can have unexpected results and should generally be avoided.

This would previously segfault:

```python
In [1]: df = pd.DataFrame({'A': np.array(['foo', 'bar', 'bah', 'foo', 'bar'])})
In [2]: df['A'].iloc[0] = np.nan
In [3]: df
Out[3]:
    A
0  NaN
1  bar
2  bah
3  foo
4  bar
```

The recommended way to do this type of assignment is:

```python
In [4]: df = pd.DataFrame({'A': np.array(['foo', 'bar', 'bah', 'foo', 'bar'])})
In [5]: df.loc[0, 'A'] = np.nan
In [6]: df
Out[6]:
    A
0  NaN
1  bar
2  bah
3  foo
4  bar
```

**Output formatting enhancements**

• df.info() view now display dtype info per column (GH5682)
• df.info() now honors the option max_info_rows, to disable null counts for large frames (GH5974)

```python
In [7]: max_info_rows = pd.get_option('max_info_rows')
In [8]: df = pd.DataFrame({'A': np.random.randn(10),
                          'B': np.random.randn(10),
                          'C': pd.date_range('20130101', periods=10))
In [9]: df.iloc[3:6, [0, 2]] = np.nan
```
# set to not display the null counts
In [10]: pd.set_option('max_info_rows', 0)

In [11]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 3 columns):
# Column Dtype
--- ------ -----  
0 A       float64  
1 B       float64  
2 C       datetime64[ns]  
dtypes: datetime64[ns](1), float64(2)
memory usage: 368.0 bytes

# this is the default (same as in 0.13.0)
In [12]: pd.set_option('max_info_rows', max_info_rows)

In [13]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 3 columns):
# Column Non-Null Count Dtype
--- ------ -------------- -----  
0 A 7 non-null     float64  
1 B 10 non-null    float64  
2 C 7 non-null     datetime64[ns]  
dtypes: datetime64[ns](1), float64(2)
memory usage: 368.0 bytes

• Add **show_dimensions** display option for the new DataFrame repr to control whether the dimensions print.

In [14]: df = pd.DataFrame([[1, 2], [3, 4]])

In [15]: pd.set_option('show_dimensions', False)

In [16]: df
Out[16]:
0 1 2 3 4
0 1 2
1 3 4

In [17]: pd.set_option('show_dimensions', True)

In [18]: df
Out[18]:
0 1 2 3 4
0 1 2
1 3 4
[2 rows x 2 columns]

• The **ArrayFormatter** for datetime and timedelta64 now intelligently limit precision based on the values in the array (**GH3401**)

Previously output might look like:
Now the output looks like:

```
In [19]: df = pd.DataFrame([pd.Timestamp('20010101'),
                   pd.Timestamp('20040601')], columns=['age'])
In [20]: df['today'] = pd.Timestamp('20130419')
In [21]: df['diff'] = df['today'] - df['age']
In [22]: df
```

```
Out[22]:
   age       today       diff
0 2001-01-01 2013-04-19  4491 days
1 2004-06-01 2013-04-19  3244 days
```

**API changes**

- Add -NaN and -nan to the default set of NA values (GH5952). See *NA Values*.
- Added `Series.str.get_dummies` vectorized string method (GH6021), to extract dummy/indicator variables for separated string columns:

```
In [23]: s = pd.Series(['a', 'a|b', np.nan, 'a|c'])
In [24]: s.str.get_dummies(sep='|')
```

```
a b c
0 1 0 0
1 1 1 0
2 0 0 0
3 1 0 1
```

- Added the `NDFrame.equals()` method to compare if two NDFrames are equal have equal axes, dtypes, and values. Added the `array_equivalent` function to compare if two ndarrays are equal. NaNs in identical locations are treated as equal. (GH5283) See also the docs for a motivating example.

```
df = pd.DataFrame({'col': ['foo', 0, np.nan]})
df2 = pd.DataFrame({'col': [np.nan, 0, 'foo']}, index=[2, 1, 0])
df.equals(df2)
df.equals(df2.sort_index())
```

- `DataFrame.apply` will use the `reduce` argument to determine whether a Series or a DataFrame should be returned when the DataFrame is empty (GH6007).

Previously, calling `DataFrame.apply` an empty DataFrame would return either a DataFrame if there were no columns, or the function being applied would be called with an empty Series to guess whether a Series or DataFrame should be returned:
In [32]: def applied_func(col):
   ....:     print("Apply function being called with: ", col)
   ....:     return col.sum()
   ....:
In [33]: empty = DataFrame(columns=['a', 'b'])
In [34]: empty.apply(applied_func)
Apply function being called with: Series([], Length: 0, dtype: float64)
Out[34]:
a  NaN
b  NaN
Length: 2, dtype: float64

Now, when apply is called on an empty DataFrame: if the reduce argument is True a Series will returned, if it is False a DataFrame will be returned, and if it is None (the default) the function being applied will be called with an empty series to try and guess the return type.

In [35]: empty.apply(applied_func, reduce=True)
Out[35]:
a  NaN
b  NaN
Length: 2, dtype: float64
In [36]: empty.apply(applied_func, reduce=False)
Out[36]:
Empty DataFrame
Columns: [a, b]
Index: []
[0 rows x 2 columns]

Prior version deprecations/changes

There are no announced changes in 0.13 or prior that are taking effect as of 0.13.1

Deprecations

There are no deprecations of prior behavior in 0.13.1

Enhancements

- pd.read_csv and pd.to_datetime learned a new infer_datetime_format keyword which greatly improves parsing perf in many cases. Thanks to @exual for suggesting and @danbirken for rapidly implementing. (GH5490, GH6021)

If parse_dates is enabled and this flag is set, pandas will attempt to infer the format of the datetime strings in the columns, and if it can be inferred, switch to a faster method of parsing them. In some cases this can increase the parsing speed by ~5-10x.
• **date_format** and **datetime_format** keywords can now be specified when writing to excel files (GH4133)

• **MultiIndex.from_product** convenience function for creating a MultiIndex from the cartesian product of a set of iterables (GH6055):

```python
In [25]: shades = ['light', 'dark']
In [26]: colors = ['red', 'green', 'blue']
In [27]: pd.MultiIndex.from_product([shades, colors], names=['shade', 'color'])
Out[27]:
MultiIndex([('light', 'red'),
            ('light', 'green'),
            ('light', 'blue'),
            ('dark', 'red'),
            ('dark', 'green'),
            ('dark', 'blue')],
           names=['shade', 'color'])
```

• **Panel apply()** will work on non-ufuncs. See the docs.

```python
In [28]: import pandas._testing as tm
In [29]: panel = tm.makePanel(5)
In [30]: panel
Out[30]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: A to D
In [31]: panel['ItemA']
Out[31]:
       A     B     C     D
2000-01-03 -0.673690 0.577046 -1.344312 -1.469388
2000-01-04 0.113648 -1.715002 0.844885 0.357021
2000-01-05 -1.478427 -1.039268 1.075770 -0.674600
2000-01-06 0.524988 -0.370647 -0.109050 -1.776904
2000-01-07 0.404705 -1.157892 1.643563 -0.968914
[5 rows x 4 columns]
```

Specifying an apply that operates on a Series (to return a single element)

```python
In [32]: panel.apply(lambda x: x.dtype, axis='items')
Out[32]:
       A     B     C     D
2000-01-03 float64 float64 float64 float64
2000-01-04 float64 float64 float64 float64
2000-01-05 float64 float64 float64 float64
2000-01-06 float64 float64 float64 float64
2000-01-07 float64 float64 float64 float64
[5 rows x 4 columns]
```

A similar reduction type operation
In [33]: panel.apply(lambda x: x.sum(), axis='major_axis')
Out[33]:
<table>
<thead>
<tr>
<th>ItemA</th>
<th>ItemB</th>
<th>ItemC</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>-1.108775</td>
<td>-1.090118</td>
</tr>
<tr>
<td>B</td>
<td>-3.705764</td>
<td>0.409204</td>
</tr>
<tr>
<td>C</td>
<td>2.110856</td>
<td>2.960500</td>
</tr>
<tr>
<td>D</td>
<td>-4.532785</td>
<td>0.303202</td>
</tr>
</tbody>
</table>

[4 rows x 3 columns]

This is equivalent to

In [34]: panel.sum('major_axis')
Out[34]:
<table>
<thead>
<tr>
<th>ItemA</th>
<th>ItemB</th>
<th>ItemC</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>-1.108775</td>
<td>-1.090118</td>
</tr>
<tr>
<td>B</td>
<td>-3.705764</td>
<td>0.409204</td>
</tr>
<tr>
<td>C</td>
<td>2.110856</td>
<td>2.960500</td>
</tr>
<tr>
<td>D</td>
<td>-4.532785</td>
<td>0.303202</td>
</tr>
</tbody>
</table>

[4 rows x 3 columns]

A transformation operation that returns a Panel, but is computing the z-score across the major_axis

In [35]: result = panel.apply(lambda x: (x - x.mean()) / x.std(), axis='major_axis')

In [36]: result
Out[36]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: A to D

In [37]: result['ItemA']

Out[37]:
<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-03</td>
<td>-0.535778</td>
<td>1.500802</td>
<td>-1.506416</td>
<td>-0.681456</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>0.397628</td>
<td>-1.108752</td>
<td>0.360481</td>
<td>1.529895</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>-1.489811</td>
<td>-0.339412</td>
<td>0.557374</td>
<td>0.280845</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>0.885279</td>
<td>0.421830</td>
<td>-0.453013</td>
<td>-1.053785</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>0.742682</td>
<td>-0.474468</td>
<td>1.041575</td>
<td>-0.075499</td>
</tr>
</tbody>
</table>

[5 rows x 4 columns]

- Panel apply() operating on cross-sectional slabs. (GH1148)

In [38]: def f(x):
   ....:     return ((x.T - x.mean(1)) / x.std(1)).T
   ....:

In [39]: result = panel.apply(f, axis=['items', 'major_axis'])

In [40]: result
Out[40]:

(continues on next page)
<class 'pandas.core.panel.Panel'>
Dimensions: 4 (items) x 5 (major_axis) x 3 (minor_axis)
Items axis: A to D
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: ItemA to ItemC

In [41]: result.loc[:, :, 'ItemA']
Out [41]:
          A    B    C    D
2000-01-03 0.012922 -0.030874 -0.629546 -0.757034
2000-01-04 0.392053 -1.071665 0.163228  0.548188
2000-01-05 -1.093650 -0.640898  0.385734 -1.154310
2000-01-06  1.005446 -1.154593 -0.595615 -0.809185
2000-01-07  0.783051 -0.198053  0.919339 -1.052721
[5 rows x 4 columns]

This is equivalent to the following

In [42]: result = pd.Panel({ax: f(panel.loc[:, :, ax]) for ax in panel.minor_axis})

In [43]: result
Out [43]:
<class 'pandas.core.panel.Panel'>
Dimensions: 4 (items) x 5 (major_axis) x 3 (minor_axis)
Items axis: A to D
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: ItemA to ItemC

In [44]: result.loc[:, :, 'ItemA']
Out [44]:
          A    B    C    D
2000-01-03 0.012922 -0.030874 -0.629546 -0.757034
2000-01-04 0.392053 -1.071665 0.163228  0.548188
2000-01-05 -1.093650 -0.640898  0.385734 -1.154310
2000-01-06  1.005446 -1.154593 -0.595615 -0.809185
2000-01-07  0.783051 -0.198053  0.919339 -1.052721
[5 rows x 4 columns]

Performance

Performance improvements for 0.13.1

- Series datetime/timedelta binary operations (GH5801)
- DataFrame `count/dropna` for axis=1
- Series.str.contains now has a `regex=False` keyword which can be faster for plain (non-regex) string patterns. (GH5879)
- Series.str.extract (GH5944)
- dtypes/ftypes methods (GH5968)
- indexing with object dtypes (GH5968)
• DataFrame.apply (GH6013)
• Regression in JSON IO (GH5765)
• Index construction from Series (GH6150)

Experimental

There are no experimental changes in 0.13.1

Bug fixes

• Bug in io.wb.get_countries not including all countries (GH6008)
• Bug in Series replace with timestamp dict (GH5797)
• read_csv/read_table now respects the prefix kwarg (GH5732).
• Bug in selection with missing values via .ix from a duplicate indexed DataFrame failing (GH5835)
• Fix issue of boolean comparison on empty DataFrames (GH5808)
• Bug in isnull handling NaT in an object array (GH5443)
• Bug in to_datetime when passed a np.nan or integer datelike and a format string (GH5863)
• Bug in groupby dtype conversion with datetimelike (GH5869)
• Regression in handling of empty Series as indexers to Series (GH5877)
• Bug in internal caching, related to (GH5727)
• Testing bug in reading JSON/msgpack from a non-filepath on windows under py3 (GH5874)
• Bug when assigning to .ix[tuple(…)] (GH5896)
• Bug in fully reindexing a Panel (GH5905)
• Bug in idxmin/max with object dtypes (GH5914)
• Bug in BusinessDay when adding n days to a date not on offset when n>5 and n%5==0 (GH5890)
• Bug in assigning to chained series with a series via ix (GH5928)
• Bug in creating an empty DataFrame, copying, then assigning (GH5932)
• Bug in DataFrame.tail with empty frame (GH5846)
• Bug in propagating metadata on resample (GH5862)
• Fixed string-representation of NaT to be "NaN" (GH5708)
• Fixed string-representation for Timestamp to show nanoseconds if present (GH5912)
• pd.match not returning passed sentinel
• Panel.to_frame() no longer fails when major_axis is a MultiIndex (GH5402).
• Bug in pd.read_msgpack with inferring a DateTimeIndex frequency incorrectly (GH5947)
• Fixed to_datetime for array with both Tz-aware datetimes and NaT’s (GH5961)
• Bug in rolling skew/kurtosis when passed a Series with bad data (GH5749)
• Bug in scipy interpolate methods with a datetime index (GH5975)
• Bug in NaT comparison if a mixed datetime/np.datetime64 with NaT were passed (GH5968)
- Fixed bug with `pd.concat` losing dtype information if all inputs are empty (GH5742)
- Recent changes in IPython cause warnings to be emitted when using previous versions of pandas in QTConsole, now fixed. If you're using an older version and need to suppress the warnings, see (GH5922).
- Bug in merging `timedelta` dtypes (GH5695)
- Bug in plotting `scatter_matrix` function. Wrong alignment among diagonal and off-diagonal plots, see (GH5497).
- Regression in Series with a MultiIndex via `ix` (GH6018)
- Bug in Series `xs` with a MultiIndex (GH6018)
- Bug in Series construction of mixed type with datelike and an integer (which should result in object type and not automatic conversion) (GH6028)
- Possible segfault when chained indexing with an object array under NumPy 1.7.1 (GH6026, GH6056)
- Bug in setting using fancy indexing a single element with a non-scalar (e.g. a list), (GH6043)
- `to_sql` did not respect `if_exists` (GH4110 GH4304)
- Regression in `.get` (None) indexing from 0.12 (GH5652)
- Subtle `iloc` indexing bug, surfaced in (GH6059)
- Bug with insert of strings into `DatetimeIndex` (GH5818)
- Fixed unicode bug in `to_html/HTML` repr (GH6098)
- Fixed missing arg validation in `get_options_data` (GH6105)
- Bug in assignment with duplicate columns in a frame where the locations are a slice (e.g. next to each other) (GH6120)
- Bug in propagating `_ref_locs` during construction of a DataFrame with dups index/columns (GH6121)
- Bug in `DataFrame.apply` when using mixed datelike reductions (GH6125)
- Bug in `DataFrame.append` when appending a row with different columns (GH6129)
- Bug in `DataFrame` construction with recarray and non-ns datetime dtype (GH6140)
- Bug in `.loc` setitem indexing with a dataframe on rhs, multiple item setting, and a datetimelike (GH6152)
- Fixed a bug in `query/eval` during lexicographic string comparisons (GH6155).
- Fixed a bug in `query` where the index of a single-element Series was being thrown away (GH6148).
- Bug in `HDFStore` on appending a dataframe with MultiIndexed columns to an existing table (GH6167)
- Consistency with dtypes in setting an empty DataFrame (GH6171)
- Bug in selecting on a MultiIndex `HDFStore` even in the presence of under specified column spec (GH6169)
- Bug in `nanops.var` with `ddof=1` and 1 elements would sometimes return `inf` rather than `nan` on some platforms (GH6136)
- Bug in Series and DataFrame bar plots ignoring the `use_index` keyword (GH6209)
- Bug in groupby with mixed str/int under python3 fixed; `argsort` was failing (GH6212)
Contributors

A total of 52 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Alex Rothberg
- Alok Singhal +
- Andrew Burrows +
- Andy Hayden
- Bjorn Arneson +
- Brad Buran
- Caleb Epstein
- Chapman Siu
- Chase Albert +
- Clark Fitzgerald +
- DSM
- Dan Birken
- Daniel Waeber +
- David Wolever +
- Doran Deluz +
- Douglas McNeil +
- Douglas Rudd +
- Drazen Lucanin
- Elliot S +
- Felix Lawrence +
- George Kuan +
- Guillaume Gay +
- Jacob Schaer
- Jan Wagner +
- Jeff Tratner
- John McNamara
- Joris Van den Bossche
- Julia Evans +
- Kieran O’Mahony
- Michael Schatzow +
- Naveen Michaud-Agrawal +
- Patrick O’Keeffe +
- Phillip Cloud
5.15.2 Version 0.13.0 (January 3, 2014)

This is a major release from 0.12.0 and includes a number of API changes, several new features and enhancements along with a large number of bug fixes.

Highlights include:

- support for a new index type `Float64Index` and other Indexing enhancements
- `HDFStore` has a new string based syntax for query specification
- support for new methods of interpolation
- updated `timedelta` operations
- a new string manipulation method `extract`
- Nanosecond support for Offsets
- `isin` for DataFrames

Several experimental features are added, including:

- new `eval/query` methods for expression evaluation
- support for `msgpack` serialization
- an i/o interface to Google’s `BigQuery`

Their are several new or updated docs sections including:
• **Comparison with SQL**, which should be useful for those familiar with SQL but still learning pandas.

• **Comparison with R**, idiom translations from R to pandas.

• **Enhancing Performance**, ways to enhance pandas performance with `eval/query`.

---

**Warning:** In 0.13.0 Series has internally been refactored to no longer sub-class `ndarray` but instead subclass `NDFrame`, similar to the rest of the pandas containers. This should be a transparent change with only very limited API implications. See **Internal Refactoring**

---

**API changes**

• **read_excel** now supports an integer in its `sheetname` argument giving the index of the sheet to read in (GH4301).

• Text parser now treats anything that reads like inf ("inf", "Inf", "-Inf", "iNf", etc.) as infinity. (GH4220, GH4219), affecting `read_table`, `read_csv`, etc.

• pandas now is Python 2/3 compatible without the need for 2to3 thanks to @jtratner. As a result, pandas now uses iterators more extensively. This also led to the introduction of substantive parts of the Benjamin Peterson’s six library into compat. (GH4384, GH4375, GH4372)

• pandas.util.compat and pandas.util.py3compat have been merged into pandas.compat.

• `pandas.compat` now includes many functions allowing 2/3 compatibility. It contains both list and iterator versions of range, filter, map and zip, plus other necessary elements for Python 3 compatibility. `lmap`, `lzip`, `lrange` and `lfilter` all produce lists instead of iterators, for compatibility with `numpy`, `subscripting` and `pandas constructors.`(GH4384, GH4375, GH4372)

• Series.get with negative indexers now returns the same as `[ ]` (GH4390)

• Changes to how Index and MultiIndex handle metadata (levels, labels, and names) (GH4039):

```python
# previously, you would have set levels or labels directly
>>> pd.index.levels = [[1, 2, 3, 4], [1, 2, 4, 4]]

# now, you use the set_levels or set_labels methods
>>> index = pd.index.set_levels([[1, 2, 3, 4], [1, 2, 4, 4]])

# similarly, for names, you can rename the object
# but setting names is not deprecated
>>> index = pd.index.set_names(["bob", "cranberry"])

# and all methods take an inplace kwarg - but return None
>>> pd.index.set_names(["bob", "cranberry"], inplace=True)
```

• All division with NDFrame objects is now `truedivision`, regardless of the future import. This means that operating on pandas objects will by default use floating point division, and return a floating point dtype. You can use `//` and `floordiv` to do integer division.

**Integer division**

```python
In [3]: arr = np.array([1, 2, 3, 4])

In [4]: arr2 = np.array([5, 3, 2, 1])

In [5]: arr / arr2
Out[5]: array([0, 0, 1, 4])
```

(continues on next page)
In [6]: pd.Series(arr) // pd.Series(arr2)
Out[6]:
0   0
1   0
2   1
3   4
dtype: int64

True Division

In [7]: pd.Series(arr) / pd.Series(arr2)  # no future import required
Out[7]:
0  0.200000
1  0.666667
2  1.500000
3  4.000000
dtype: float64

- Infer and downcast dtype if downcast='infer' is passed to fillna/ffill/bfill (GH4604)
- __nonzero__ for all NDFrame objects, will now raise a ValueError, this reverts back to (GH1073, GH4633) behavior. See gotchas for a more detailed discussion.

This prevents doing boolean comparison on entire pandas objects, which is inherently ambiguous. These all will raise a ValueError.

```python
>>> df = pd.DataFrame({'A': np.random.randn(10),
... 'B': np.random.randn(10),
... 'C': pd.date_range('20130101', periods=10))
...}
...if df:
...    pass
...Traceback (most recent call last):
...    ValueError: The truth value of a DataFrame is ambiguous. Use a.empty, a.bool(), a.item(), a.any() or a.all().
```

```python
>>> df1 = df
>>> df2 = df
>>> df1 and df2
Traceback (most recent call last):
...    ValueError: The truth value of a DataFrame is ambiguous. Use a.empty, a.bool(), a.item(), a.any() or a.all().
```

```python
>>> d = [1, 2, 3]
>>> s1 = pd.Series(d)
>>> s2 = pd.Series(d)
>>> s1 and s2
Traceback (most recent call last):
...    ValueError: The truth value of a DataFrame is ambiguous. Use a.empty, a.bool(), a.item(), a.any() or a.all().
```

Added the .bool() method to NDFrame objects to facilitate evaluating of single-element boolean Series:
In [1]: pd.Series([True]).bool()
Out[1]: True

In [2]: pd.Series([False]).bool()
Out[2]: False

In [3]: pd.DataFrame([[True]]).bool()
Out[3]: True

In [4]: pd.DataFrame([[False]]).bool()
Out[4]: False

• All non-Index NDFrames (Series, DataFrame, Panel, Panel4D, SparsePanel, etc.), now support the entire set of arithmetic operators and arithmetic flex methods (add, sub, mul, etc.). SparsePanel does not support pow or mod with non-scalars. (GH3765)

• Series and DataFrame now have a mode() method to calculate the statistical mode(s) by axis/Series. (GH5367)

• Chained assignment will now by default warn if the user is assigning to a copy. This can be changed with the option mode.chained_assignment, allowed options are raise/warn/None. See the docs.

```python
In [5]: dfc = pd.DataFrame({'A': ['aaa', 'bbb', 'ccc'], 'B': [1, 2, 3]})
In [6]: pd.set_option('chained_assignment', 'warn')
```

The following warning / exception will show if this is attempted.

```python
In [7]: dfc.loc[0]['A'] = 1111
```

```
Traceback (most recent call last)
...  # setting with copy warning
SettingWithCopyWarning:
   A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row_index,col_indexer] = value instead
```

Here is the correct method of assignment.

```python
In [8]: dfc.loc[0, 'A'] = 11
```

```python
In [9]: dfc
```

```
Out[9]:
   A  B
0  11 1
1  bbb 2
2  ccc 3
```

• Panel.reindex has the following call signature Panel.reindex(items=None, major_axis=None, minor_axis=None, **kwargs) to conform with other NDFrame objects. See Internal Refactoring for more information.

• Series.argmin and Series.argmax are now aliased to Series.idxmin and Series.idxmax. These return the index of the min or max element respectively. Prior to 0.13.0 these would return the position of the min / max element. (GH6214)
Prior version deprecations/changes

These were announced changes in 0.12 or prior that are taking effect as of 0.13.0

- Remove deprecated `Factor` (GH3650)
- Remove deprecated `set_printoptions/reset_printoptions` (GH3046)
- Remove deprecated `_verbose_info` (GH3215)
- Remove deprecated `read_clipboard/to_clipboard/ExcelFile/ExcelWriter` from pandas. `io.parsers` (GH3717) These are available as functions in the main pandas namespace (e.g. `pd.read_clipboard`)
- default for `tupleize_cols` is now `False` for both `to_csv` and `read_csv`. Fair warning in 0.12 (GH3604)
- default for `display.max_seq_len` is now 100 rather than `None`. This activates truncated display (“...”) of long sequences in various places. (GH3391)

Deprecations

Deprecated in 0.13.0

- deprecated `iterkv`, which will be removed in a future release (this was an alias of `iteritems` used to bypass `2to3`’s changes). (GH4384, GH4375, GH4372)
- deprecated the string method `match`, whose role is now performed more idiomatically by `extract`. In a future release, the default behavior of `match` will change to become analogous to `contains`, which returns a boolean indexer. (Their distinction is strictness: `match` relies on `re.match` while `contains` relies on `re.search`.) In this release, the deprecated behavior is the default, but the new behavior is available through the keyword argument `as_indexer=True`.

Indexing API changes

Prior to 0.13, it was impossible to use a label indexer (`.loc/.ix`) to set a value that was not contained in the index of a particular axis. (GH2578). See the docs

In the `Series` case this is effectively an appending operation

```
In [10]: s = pd.Series([1, 2, 3])

In [11]: s
Out[11]:
0 1
1 2
2 3
dtype: int64


In [13]: s
Out[13]:
0 1.0
1 2.0
2 3.0
5 5.0
dtype: float64
```
In [14]: dfi = pd.DataFrame(np.arange(6).reshape(3, 2),
                    columns=['A', 'B'])

In [15]: dfi
Out[15]:
     A  B
0   0  1
1   2  3
2   4  5

This would previously KeyError

In [16]: dfi.loc[:, 'C'] = dfi.loc[:, 'A']

In [17]: dfi
Out[17]:
     A  B  C
0   0  1  0
1   2  3  2
2   4  5  4

This is like an append operation.

In [18]: dfi.loc[3] = 5

In [19]: dfi
Out[19]:
     A  B  C
0   0  1  0
1   2  3  2
2   4  5  4
3   5  5  5

A Panel setting operation on an arbitrary axis aligns the input to the Panel

In [20]: p = pd.Panel(np.arange(16).reshape(2, 4, 2),
                    items=['Item1', 'Item2'],
                    major_axis=pd.date_range('2001/1/12', periods=4),
                    minor_axis=['A', 'B'], dtype='float64')

In [21]: p
Out[21]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 4 (major_axis) x 2 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2001-01-12 00:00:00 to 2001-01-15 00:00:00
Minor_axis axis: A to B

In [22]: p.loc[:, :, 'C'] = pd.Series([30, 32], index=p.items)

In [23]: p
Out[23]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 4 (major_axis) x 3 (minor_axis)
Items axis: Item1 to Item2
Float64Index API change

- Added a new index type, Float64Index. This will be automatically created when passing floating values in index creation. This enables a pure label-based slicing paradigm that makes [], ix, loc for scalar indexing and slicing work exactly the same. See the docs (GH263)

Construction is by default for floating type values.

Scalar selection for [], ix, loc will always be label based. An integer will match an equal float index (e.g. 3 is equivalent to 3.0)

The only positional indexing is via iloc

A scalar index that is not found will raise KeyError

Slicing is ALWAYS on the values of the index, for [], ix, loc and ALWAYS positional with iloc
2.0 1
3.0 2
dtype: int64

In [28]: s.loc[2:4]
Out[28]:
2.0 1
3.0 2
dtype: int64

In [29]: s.iloc[2:4]
Out[29]:
3.0 2
4.5 3
dtype: int64

In float indexes, slicing using floats are allowed

In [30]: s[2.1:4.6]
Out[30]:
3.0 2
4.5 3
dtype: int64

In [31]: s.loc[2.1:4.6]
Out[31]:
3.0 2
4.5 3
dtype: int64

• Indexing on other index types are preserved (and positional fallback for [], ix), with the exception, that floating point slicing on indexes on non Float64Index will now raise a TypeError.

In [1]: pd.Series(range(5))[3.5]
TypeError: the label [3.5] is not a proper indexer for this index type
  →(Int64Index)

In [1]: pd.Series(range(5))[3.5:4.5]
TypeError: the slice start [3.5] is not a proper indexer for this index type
  →(Int64Index)

Using a scalar float indexer will be deprecated in a future version, but is allowed for now.

In [3]: pd.Series(range(5))[3.0]
Out[3]: 3
HDFStore API changes

- Query Format Changes. A much more string-like query format is now supported. See the docs.

```python
In [32]: path = 'test.h5'

In [33]: dfq = pd.DataFrame(np.random.randn(10, 4),
...:                     columns=list('ABCD'),
...:                     index=pd.date_range('20130101', periods=10))

In [34]: dfq.to_hdf(path, 'dfq', format='table', data_columns=True)
```

Use boolean expressions, with in-line function evaluation.

```python
In [35]: pd.read_hdf(path, 'dfq',
...:                where="index>Timestamp('20130104') & columns=[A', 'B']")

Out[35]:
    A   B
2013-01-05 -0.424972 0.567020
2013-01-06 -0.673690 0.113648
2013-01-07  0.404705 0.577046
2013-01-08 -0.370647 -1.157892
2013-01-09  1.075770 -0.109050
2013-01-10  0.357021 -0.674600
```

Use an inline column reference

```python
In [36]: pd.read_hdf(path, 'dfq',
...:                where="A>0 or C>0")

Out[36]:
    A   B   C   D
2013-01-01  0.469112 -0.282863 -1.509059 -1.135632
2013-01-02  1.212112 -0.173215  0.119209 -1.044236
2013-01-04  0.721555 -0.706771 -1.039575  0.271860
2013-01-05 -0.424972  0.567020  0.276232 -1.087401
2013-01-07  0.404705  0.577046 -1.715002 -1.039268
2013-01-09  1.075770 -0.109050  1.643563 -1.469388
2013-01-10  0.357021 -0.674600 -1.776904 -0.968914
```

- the format keyword now replaces the table keyword; allowed values are fixed(f) or table(t) the same defaults as prior < 0.13.0 remain, e.g. put implies fixed format and append implies table format. This default format can be set as an option by setting io.hdf.default_format.

```python
In [37]: path = 'test.h5'

In [38]: df = pd.DataFrame(np.random.randn(10, 2))

In [39]: df.to_hdf(path, 'df_table', format='table')

In [40]: df.to_hdf(path, 'df_table2', append=True)

In [41]: df.to_hdf(path, 'df_fixed')

In [42]: with pd.HDFStore(path) as store:
...:     print(store)
```
• Significant table writing performance improvements

• handle a passed Series in table format (GH4330)

• can now serialize a timedelta64[ns] dtype in a table (GH3577), See the docs.

• added an is_open property to indicate if the underlying file handle is_open; a closed store will now report ‘CLOSED’ when viewing the store (rather than raising an error) (GH4409)

• a close of a HDFStore now will close that instance of the HDFStore but will only close the actual file if the ref count (by PyTables) w.r.t. all of the open handles are 0. Essentially you have a local instance of HDFStore referenced by a variable. Once you close it, it will report closed. Other references (to the same file) will continue to operate until they themselves are closed. Performing an action on a closed file will raise ClosedFileError

```python
In [43]: path = 'test.h5'
In [44]: df = pd.DataFrame(np.random.randn(10, 2))
In [45]: store1 = pd.HDFStore(path)
In [46]: store2 = pd.HDFStore(path)
In [47]: store1.append('df', df)
In [48]: store2.append('df2', df)
In [49]: store1
Out[49]:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5
In [50]: store2
Out[50]:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5
In [51]: store1.close()
In [52]: store2
Out[52]:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5
In [53]: store2.close()
In [54]: store2
Out[54]:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5
```

• removed the _quiet attribute, replace by a DuplicateWarning if retrieving duplicate rows from a table (GH4367)
• removed the warn argument from open. Instead a PossibleDataLossError exception will be raised if you try to use mode='w' with an OPEN file handle (GH4367)
• allow a passed locations array or mask as a where condition (GH4467). See the docs for an example.
• add the keyword dropna=True to append to change whether ALL nan rows are not written to the store (default is True, ALL nan rows are NOT written), also settable via the option io.hdf.dropna_table (GH4625)
• pass through store creation arguments; can be used to support in-memory stores

DataFrame repr changes

The HTML and plain text representations of DataFrame now show a truncated view of the table once it exceeds a certain size, rather than switching to the short info view (GH4886, GH5550). This makes the representation more consistent as small DataFrames get larger.

<table>
<thead>
<tr>
<th>Date</th>
<th>2010-03-29</th>
<th>2010-03-30</th>
</tr>
</thead>
<tbody>
<tr>
<td>...</td>
<td>... ... ... ... ... ...</td>
<td></td>
</tr>
</tbody>
</table>

771 rows × 6 columns

To get the info view, call DataFrame.info(). If you prefer the info view as the repr for large DataFrames, you can set this by running set_option('display.large_repr', 'info').

Enhancements

• df.to_clipboard() learned a new excel keyword that let’s you paste df data directly into excel (enabled by default). (GH5070).
• read_html now raises a URLError instead of catching and raising a ValueError (GH4303, GH4305)
• Added a test for read_clipboard() and to_clipboard() (GH4282)
• Clipboard functionality now works with PySide (GH4282)
• Added a more informative error message when plot arguments contain overlapping color and style arguments (GH4402)
• to_dict now takes records as a possible out type. Returns an array of column-keyed dictionaries. (GH4936)
• NaN handing in get_dummies (GH4446) with dummy_na

```python
# previously, nan was erroneously counted as 2 here
# now it is not counted at all
In [55]: pd.get_dummies([1, 2, np.nan])
Out[55]:
   1.0  2.0
0   1   0
1   0   1
2   0   0
# unless requested
```

(continues on next page)
• timedelta64[ns] operations. See the docs.

Warning: Most of these operations require numpy >= 1.7

Using the new top-level to_timedelta, you can convert a scalar or array from the standard timedelta format (produced by to_csv) into a timedelta type (np.timedelta64 in nanoseconds).

A Series of dtype timedelta64[ns] can now be divided by another timedelta64[ns] object, or astyped to yield a float64 dtyped Series. This is frequency conversion. See the docs for the docs.
# to days
In [67]: td / np.timedelta64(1, 'D')
Out[67]:
0   31.000000
1   31.000000
2   31.003507
3     NaN
dtype: float64

In [68]: td.astype('timedelta64[D]')
Out[68]:
0   31.0
1   31.0
2   31.0
3     NaN
dtype: float64

# to seconds
In [69]: td / np.timedelta64(1, 's')
Out[69]:
0   2678400.0
1   2678400.0
2   2678703.0
3     NaN
dtype: float64

In [70]: td.astype('timedelta64[s]')
Out[70]:
0   2678400.0
1   2678400.0
2   2678703.0
3     NaN
dtype: float64

Dividing or multiplying a timedelta64[ns] Series by an integer or integer Series

In [71]: td * -1
Out[71]:
0  -31 days +00:00:00
1  -31 days +00:00:00
2  -32 days +23:54:57
3     NaT
dtype: timedelta64[ns]

In [72]: td * pd.Series([1, 2, 3, 4])
Out[72]:
0   31 days 00:00:00
1   62 days 00:00:00
2   93 days 00:15:09
3     NaT
dtype: timedelta64[ns]

Absolute DateOffset objects can act equivalently to timedeltas

In [73]: from pandas import offsets

In [74]: td + offsets.Minute(5) + offsets.Milli(5)
(continues on next page)
Fillna is now supported for timedeltas

```python
In [75]: td.fillna(pd.Timedelta(0))
Out[75]:
0  31 days 00:00:00
1  31 days 00:00:00
2  31 days 00:05:03
3   0 days 00:00:00
dtype: timedelta64[ns]
```

```python
In [76]: td.fillna(datetime.timedelta(days=1, seconds=5))
Out[76]:
0  31 days 00:00:00
1  31 days 00:00:00
2  31 days 00:05:03
3   1 days 00:00:05
dtype: timedelta64[ns]
```

You can do numeric reduction operations on timedeltas.

```python
In [77]: td.mean()
Out[77]: Timedelta('31 days 00:01:41')
```

```python
In [78]: td.quantile(.1)
Out[78]: Timedelta('31 days 00:00:00')
```

- `plot(kind='kde')` now accepts the optional parameters `bw_method` and `ind`, passed to `scipy.stats.gaussian_kde()` (for scipy >= 0.11.0) to set the bandwidth, and to `gkde.evaluate()` to specify the indices at which it is evaluated, respectively. See scipy docs. (GH4298)

- DataFrame constructor now accepts a numpy masked record array (GH3478)

- The new vectorized string method `extract` return regular expression matches more conveniently.

Elements that do not match return NaN. Extracting a regular expression with more than one group returns a DataFrame with one column per group.
Elements that do not match return a row of NaN. Thus, a Series of messy strings can be converted into a like-indexed Series or DataFrame of cleaned-up or more useful strings, without necessitating get() to access tuples or re.match objects.

Named groups like

```
In [81]: pd.Series(['a1', 'b2', 'c3']).str.extract(
    ....:   '(?P<letter>[ab])(?P<digit>\d)')
```

```
Out[81]:
          letter digit
    0       a       1
    1       b       2
    2  NaN  NaN
```

and optional groups can also be used.

```
In [82]: pd.Series(['a1', 'b2', '3']).str.extract(
    ....:   '(?P<letter>[ab])?(?P<digit>\d)')
```

```
Out[82]:
          letter digit
    0       a       1
    1       b       2
    2  NaN       3
```

• read_stata now accepts Stata 13 format (GH4291)

• read_fwf now infers the column specifications from the first 100 rows of the file if the data has correctly separated and properly aligned columns using the delimiter provided to the function (GH4488).

• support for nanosecond times as an offset

**Warning:** These operations require numpy >= 1.7

Period conversions in the range of seconds and below were reworked and extended up to nanoseconds. Periods in the nanosecond range are now available.

```
In [83]: pd.date_range('2013-01-01', periods=5, freq='5N')
```

```
Out[83]:
 DatetimeIndex(['2013-01-01 00:00:00',
               '2013-01-01 00:00:00.000000005',
               '2013-01-01 00:00:00.000000010',
               '2013-01-01 00:00:00.000000015',
               '2013-01-01 00:00:00.000000020'],
dtype='datetime64[ns]', freq='5N')
```

or with frequency as offset

```
In [84]: pd.date_range('2013-01-01', periods=5, freq=pd.offsets.Nano(5))
```

```
Out[84]:
 DatetimeIndex(['2013-01-01 00:00:00',
               '2013-01-01 00:00:00.000000005',
               '2013-01-01 00:00:00.000000010',
               '2013-01-01 00:00:00.000000015',
               '2013-01-01 00:00:00.000000020'],
dtype='datetime64[ns]', freq='5N')
```
Timestamps can be modified in the nanosecond range

```python
In [85]: t = pd.Timestamp('20130101 09:01:02')
In [86]: t + pd.tseries.offsets.Nano(123)
Out[86]: Timestamp('2013-01-01 09:01:02.000000123')
```

- A new method, `isin` for DataFrames, which plays nicely with boolean indexing. The argument to `isin`, what we’re comparing the DataFrame to, can be a DataFrame, Series, dict, or array of values. See the docs for more.

To get the rows where any of the conditions are met:

```python
In [87]: dfi = pd.DataFrame({'A': [1, 2, 3, 4], 'B': ['a', 'b', 'f', 'n']})
In [88]: dfi
Out[88]:
   A  B
0  1  a
1  2  b
2  3  f
3  4  n
In [89]: other = pd.DataFrame({'A': [1, 3, 3, 7], 'B': ['e', 'f', 'f', 'e']})
In [90]: mask = dfi.isin(other)
In [91]: mask
Out[91]:
   A  B
0  True False
1  False False
2  True  True
3  False  False
In [92]: dfi[mask.any(1)]
Out[92]:
   A  B
0  1  a
2  3  f
```

- Series now supports a `to_frame` method to convert it to a single-column DataFrame (GH5164)
- All R datasets listed here http://stat.ethz.ch/R-manual/R-devel/library/datasets/html/00Index.html can now be loaded into Pandas objects

```python
# note that pandas.rpy was deprecated in v0.16.0
import pandas.rpy.common as com
com.load_data('Titanic')
```

- `tz_localize` can infer a fall daylight savings transition based on the structure of the unlocalized data (GH4230), see the docs
- `DatetimeIndex` is now in the API documentation, see the docs
- `json_normalize()` is a new method to allow you to create a flat table from semi-structured JSON data. See the docs (GH1067)
- Added PySide support for the qtpandas DataFrameModel and DataFrameWidget.
- Python csv parser now supports usecols (GH4335)
• Frequencies gained several new offsets:
  – LastWeekOfMonth (GH4637)
  – FY5253, and FY5253Quarter (GH4511)
• DataFrame has a new interpolate method, similar to Series (GH4434, GH1892)

```python
In [93]: df = pd.DataFrame({"A": [1, 2.1, np.nan, 4.7, 5.6, 6.8],  
      ....:       'B': [.25, np.nan, np.nan, 4, 12.2, 14.4]})
In [94]: df.interpolate()
Out[94]:
    A    B
0   1.0  0.25
1  2.1  1.50
2  3.4  2.75
3  4.7  4.00
4  5.6 12.20
5  6.8 14.40
```

Additionally, the method argument to interpolate has been expanded to include 'nearest', 'zero', 'slinear', 'quadratic', 'cubic', 'barycentric', 'krogh', 'piecewise_polynomial', 'pchip', 'polynomial', 'spline'. The new methods require scipy. Consult the Scipy reference guide and documentation for more information about when the various methods are appropriate. See the docs.

Interpolate now also accepts a limit keyword argument. This works similar tofillna's limit:

```python
In [95]: ser = pd.Series([1, 3, np.nan, np.nan, np.nan, 11])
In [96]: ser.interpolate(limit=2)
Out[96]:
    0   1.0
    1   3.0
    2   5.0
    3   7.0
    4  NaN
    5  11.0
dtype: float64
```

• Added wide_to_long panel data convenience function. See the docs.

```python
In [97]: np.random.seed(123)
In [98]: df = pd.DataFrame({"A1970": {0 : "a", 1 : "b", 2 : "c"},  
      ....:       "A1980": {0 : "d", 1 : "e", 2 : "f"},  
      ....:       "B1970": {0 : 2.5, 1 : 1.2, 2 : 0.7},  
      ....:       "B1980": {0 : 3.2, 1 : 1.3, 2 : 1.1},  
      ....:       "X" : dict(zip(range(3), np.random.randn(3)))})
In [99]: df["id"] = df.index
In [100]: df
Out[100]:
0      a       d      2.5     3.2  1.961553 0
1      b       e      1.2     1.3 -0.819620 1
2      c       f      0.7     1.1 -0.693257 2
```
(continues on next page)
In [101]: pd.wide_to_long(df, ["A", "B"], i="id", j="year")
Out[101]:
    id  year
 0  1970  -1.085631   a  2.5
 1  1970   0.997345   b  1.2
 2  1970   0.282978   c  0.7
 0  1980  -1.085631   d  3.2
 1  1980   0.997345   e  1.3
 2  1980   0.282978   f  0.1

• `to_csv` now takes a `date_format` keyword argument that specifies how output datetime objects should be formatted. Datetimes encountered in the index, columns, and values will all have this formatting applied. (GH4313)

• `DataFrame.plot` will scatter plot x versus y by passing `kind='scatter'` (GH2215)

• Added support for Google Analytics v3 API segment IDs that also supports v2 IDs. (GH5271)

**Experimental**

• The new `eval()` function implements expression evaluation using `numexpr` behind the scenes. This results in large speedups for complicated expressions involving large DataFrames/Series. For example,

```python
In [102]: nrows, ncols = 20000, 100
In [103]: df1, df2, df3, df4 = [pd.DataFrame(np.random.randn(nrows, ncols))
    ......:         for _ in range(4)]

# eval with NumExpr backend
In [104]: %timeit pd.eval('df1 + df2 + df3 + df4')
21.6 ms ± 2.22 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

# pure Python evaluation
In [105]: %timeit df1 + df2 + df3 + df4
24.1 ms ± 3.43 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)
```

For more details, see the the docs

• Similar to `pandas.eval`, `DataFrame` has a new `DataFrame.eval` method that evaluates an expression in the context of the DataFrame. For example,

```python
In [106]: df = pd.DataFrame(np.random.randn(10, 2), columns=['a', 'b'])
In [107]: df.eval('a + b')
Out[107]:
   0  -0.685204
   1   1.589745
   2   0.325441
   3  -1.784153
```

(continues on next page)
query() method has been added that allows you to select elements of a DataFrame using a natural query syntax nearly identical to Python syntax. For example:

```python
In [108]: n = 20
In [109]: df = pd.DataFrame(np.random.randint(n, size=(n, 3)), columns=['a', 'b', 'c'])
In [110]: df.query('a < b < c')
Out[110]:
   a  b  c
11  1  5  8
15  8 16 19
```

selects all the rows of df where \( a < b < c \) evaluates to True. For more details see the docs.

- `pd.read_msgpack()` and `pd.to_msgpack()` are now a supported method of serialization of arbitrary pandas (and python objects) in a lightweight portable binary format. See the docs

**Warning:** Since this is an EXPERIMENTAL LIBRARY, the storage format may not be stable until a future release.

```python
def = pd.DataFrame(np.random.rand(5, 2), columns=list('AB'))
df.to_msgpack('foo.msg')
pd.read_msgpack('foo.msg')

s = pd.Series(np.random.rand(5), index=pd.date_range('20130101', periods=5))
pd.to_msgpack('foo.msg', df, s)
pd.read_msgpack('foo.msg')
```

You can pass `iterator=True` to iterator over the unpacked results

```python
for o in pd.read_msgpack('foo.msg', iterator=True):
    print(o)
```

- `pandas.io.gbq` provides a simple way to extract from, and load data into, Google’s BigQuery Data Sets by way of pandas DataFrames. BigQuery is a high performance SQL-like database service, useful for performing ad-hoc queries against extremely large datasets. See the docs

```python
from pandas.io import gbq

# A query to select the average monthly temperatures in the
# in the year 2000 across the USA. The dataset,
# publicata:samples.gsod, is available on all BigQuery accounts,
# and is based on NOAA gsod data.
```
query = """SELECT station_number as STATION, month as MONTH, AVG(mean_temp) as MEAN_TEMP
FROM publicdata:samples.gsod
WHERE YEAR = 2000
GROUP BY STATION, MONTH
ORDER BY STATION, MONTH ASC"""

# Fetch the result set for this query

# Your Google BigQuery Project ID
# To find this, see your dashboard:
# https://console.developers.google.com/iam-admin/projects?authuser=0
projectid = 'xxxxxxxxx'
df = gbq.read_gbq(query, project_id=projectid)

# Use pandas to process and reshape the dataset

df2 = df.pivot(index='STATION', columns='MONTH', values='MEAN_TEMP')
df3 = pd.concat([df2.min(), df2.mean(), df2.max()],
                axis=1, keys=['Min Temp', 'Mean Temp', 'Max Temp'])

The resulting DataFrame is:

<table>
<thead>
<tr>
<th>MONTH</th>
<th>Min Temp</th>
<th>Mean Temp</th>
<th>Max Temp</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-53.33667</td>
<td>39.827892</td>
<td>89.770968</td>
</tr>
<tr>
<td>2</td>
<td>-49.837500</td>
<td>43.685219</td>
<td>93.437932</td>
</tr>
<tr>
<td>3</td>
<td>-77.926087</td>
<td>48.708355</td>
<td>96.099998</td>
</tr>
<tr>
<td>4</td>
<td>-82.892858</td>
<td>55.070087</td>
<td>97.317240</td>
</tr>
<tr>
<td>5</td>
<td>-92.378261</td>
<td>61.428117</td>
<td>102.042856</td>
</tr>
<tr>
<td>6</td>
<td>-77.703334</td>
<td>65.858888</td>
<td>102.900000</td>
</tr>
<tr>
<td>7</td>
<td>-87.821428</td>
<td>68.169663</td>
<td>106.510714</td>
</tr>
<tr>
<td>8</td>
<td>-89.431999</td>
<td>68.614215</td>
<td>105.500000</td>
</tr>
<tr>
<td>9</td>
<td>-86.611112</td>
<td>63.436935</td>
<td>107.142856</td>
</tr>
<tr>
<td>10</td>
<td>-78.209677</td>
<td>56.880838</td>
<td>92.103333</td>
</tr>
<tr>
<td>11</td>
<td>-50.125000</td>
<td>48.861228</td>
<td>94.996428</td>
</tr>
<tr>
<td>12</td>
<td>-50.332258</td>
<td>42.286879</td>
<td>94.396774</td>
</tr>
</tbody>
</table>

**Warning:** To use this module, you will need a BigQuery account. See <https://cloud.google.com/products/big-query> for details.

As of 10/10/13, there is a bug in Google’s API preventing result sets from being larger than 100,000 rows. A patch is scheduled for the week of 10/14/13.
## Internal refactoring

In 0.13.0 there is a major refactor primarily to subclass `Series` from `NDFrame`, which is the base class currently for `DataFrame` and `Panel`, to unify methods and behaviors. `Series` formerly subclassed directly from `ndarray`. (GH4080, GH3862, GH816)

**Warning:** There are two potential incompatibilities from < 0.13.0

- Using certain numpy functions would previously return a `Series` if passed a `Series` as an argument. This seems only to affect `np.ones_like`, `np.empty_like`, `np.diff` and `np.where`. These now return `ndarrays`.

```python
In [111]: s = pd.Series([1, 2, 3, 4])
```

Numpy Usage

```python
In [112]: np.ones_like(s)
Out[112]: array([1, 1, 1, 1])

In [113]: np.diff(s)
Out[113]: array([1, 1, 1])

In [114]: np.where(s > 1, s, np.nan)
Out[114]: array([nan, 2., 3., 4.])
```

Pandonic Usage

```python
In [115]: pd.Series(1, index=s.index)
Out[115]:
   0  1
   1  1
   2  1
   3  1
   dtype: int64

In [116]: s.diff()
Out[116]:
       0    NaN
       1    1.0
       2    1.0
       3    1.0
   dtype: float64

In [117]: s.where(s > 1)
Out[117]:
       0    NaN
       1    2.0
       2    3.0
       3    4.0
   dtype: float64
```

- Passing a `Series` directly to a cython function expecting an `ndarray` type will no long work directly, you must pass `Series.values`, See *Enhancing Performance*

- `Series(0.5)` would previously return the scalar 0.5, instead this will return a 1-element `Series`

- This change breaks `rpy2<=2.3.8` an Issue has been opened against `rpy2` and a workaround is detailed in `GH5698`. Thanks @JanSchulz.

- Pickle compatibility is preserved for pickles created prior to 0.13. These must be unpickled with `pd`.
read_pickle, see *Pickling.*

- Refactor of series.py/frame.py/panel.py to move common code to generic.py
  - added _setup_axes to created generic NDFrame structures
  - moved methods
    * from_axes, _wrap_array, axes, ix, loc, iloc, shape, empty, swapaxes, transpose, pop
    * __iter__, keys, __contains__, __len__, __neg__, __invert__
    * convert_objects, as_blocks, as_matrix, values
    * __getstate__, __setstate__ (compat remains in frame/panel)
    * __getattr__, __setattr__
    * _indexed_same, reindex_like, align, where, mask
    * fillna, replace (Series replace is now consistent with DataFrame)
    * filter (also added axis argument to selectively filter on a different axis)
    * reindex, reindex_axis, take
    * truncate (moved to become part of NDFrame)

- These are API changes which make Panel more consistent with DataFrame
  - swapaxes on a Panel with the same axes specified now return a copy
  - support attribute access for setting
  - filter supports the same API as the original DataFrame filter

- Reindex called with no arguments will now return a copy of the input object

- TimeSeries is now an alias for Series. the property is_time_series can be used to distinguish (if desired)

- Refactor of Sparse objects to use BlockManager
  - Created a new block type in internals, SparseBlock, which can hold multi-dtypes and is non-consolidatable. SparseSeries and SparseDataFrame now inherit more methods from there hierarchy (Series/DataFrame), and no longer inherit from SparseArray (which instead is the object of the SparseBlock)
  - Sparse suite now supports integration with non-sparse data. Non-float sparse data is supportable (partially implemented)
  - Operations on sparse structures within DataFrames should preserve sparseness, merging type operations will convert to dense (and back to sparse), so might be somewhat inefficient
  - enable setitem on SparseSeries for boolean/integer/slices
  - SparsePanels implementation is unchanged (e.g. not using BlockManager, needs work)

- added ftypes method to Series/DataFrame, similar to dtypes, but indicates if the underlying is sparse/dense (as well as the dtype)

- All NDFrame objects can now use __finalize__() to specify various values to propagate to new objects from an existing one (e.g. name in Series will follow more automatically now)

- Internal type checking is now done via a suite of generated classes, allowing isinstance(value, klass) without having to directly import the klass, courtesy of @jtratner
Bug fixes

- **HDFStore**
  - raising an invalid `TypeError` rather than `ValueError` when appending with a different block ordering (GH4096)
  - `read_hdf` was not respecting as passed `mode` (GH4504)
  - appending a 0-len table will work correctly (GH4273)
  - `to_hdf` was raising when passing both arguments `append` and `table` (GH4584)
  - reading from a store with duplicate columns across dtypes would raise (GH4767)
  - Fixed a bug where `ValueError` wasn’t correctly raised when column names weren’t strings (GH4956)
  - A zero length series written in Fixed format not deserializing properly. (GH4708)
  - Fixed decoding perf issue on py3 (GH5441)
  - Validate levels in a MultiIndex before storing (GH5527)
  - Correctly handle `data_columns` with a Panel (GH5717)

- Fixed bug in `tslib.tz_convert(vals, tz1, tz2)`: it could raise `IndexError` exception while trying to access `trans[pos + 1]` (GH4496)

- The `by` argument now works correctly with the `layout` argument (GH4102, GH4014) in `.hist` plotting methods
- Fixed bug in `PeriodIndex.map` where using `str` would return the str representation of the index (GH4136)
- Fixed test failure `test_time_series_plot_color_with_empty_kwargs` when using custom matplotlib default colors (GH4345)
- Fix running of stata IO tests. Now uses temporary files to write (GH4353)
- Fixed an issue where `DataFrame.sum` was slower than `DataFrame.mean` for integer valued frames (GH4365)
- `read_html` tests now work with Python 2.6 (GH4351)
- Fixed bug where network testing was throwing `NameError` because a local variable was undefined (GH4381)
- In `to_json`, raise if a passed `orient` would cause loss of data because of a duplicate index (GH4359)
- In `to_json`, fix date handling so milliseconds are the default timestamp as the docstring says (GH4362)
- `as_index` is no longer ignored when doing groupby apply (GH4648, GH3417)
- JSON NaT handling fixed, NaTs are now serialized to `null` (GH4498)
- Fixed JSON handling of escapable characters in JSON object keys (GH4593)
- Fixed passing `keep_default_na=False` when `na_values=None` (GH4318)
- Fixed bug with `values` raising an error on a DataFrame with duplicate columns and mixed dtypes, surfaced in (GH4377)
- Fixed bug with duplicate columns and type conversion in `read_json` when `orient='split'` (GH4377)
- Fixed JSON bug where locales with decimal separators other than ‘.’ threw exceptions when encoding / decoding certain values. (GH4918)
- Fix `.iat` indexing with a `PeriodIndex` (GH4390)
- Fixed an issue where `PeriodIndex` joining with self was returning a new instance rather than the same instance (GH4379); also adds a test for this for the other index types
- Fixed a bug with all the dtypes being converted to object when using the CSV cparsor with the usecols parameter (GH3192)
- Fix an issue in merging blocks where the resulting DataFrame had partially set `_ref_locs` (GH4403)
- Fixed an issue where hist subplots were being overwritten when they were called using the top level matplotlib API (GH4408)
- Fixed a bug where calling `Series.astype(str)` would truncate the string (GH4405, GH4437)
- Fixed a py3 compat issue where bytes were being repr’d as tuples (GH4455)
- Fixed Panel attribute naming conflict if item is named ‘a’ (GH3440)
- Fixed an issue where duplicate indexes were raising when plotting (GH4486)
- Fixed an issue where cumsum and cumprod didn’t work with bool dtypes (GH4170, GH4440)
- Fixed Panel slicing issued in `xs` that was returning an incorrect dimmed object (GH4016)
- Fix resampling bug where custom reduce function not used if only one group (GH3849, GH4494)
- Fixed Panel assignment with a transposed frame (GH3830)
- Raise on set indexing with a Panel and a Panel as a value which needs alignment (GH3777)
- frozenset objects now raise in the `Series` constructor (GH4482, GH4480)
- Fixed issue with sorting a duplicate MultiIndex that has multiple dtypes (GH4516)
• Fixed bug in `DataFrame.set_values` which was causing name attributes to be lost when expanding the index. (GH3742, GH4039)
• Fixed issue where individual `names`, `levels` and `labels` could be set on `MultiIndex` without validation (GH3714, GH4039)
• Fixed (GH3334) in `pivot_table`. Margins did not compute if values is the index.
• Fix bug in having a rhs of `np.timedelta64` or `np.offsets.DateOffset` when operating with dates (GH4532)
• Fix arithmetic with series/datetimeindex and `np.timedelta64` not working the same (GH4134) and buggy timedelta in NumPy 1.6 (GH4135)
• Fix bug in `pd.read_clipboard` on windows with PY3 (GH4561); not decoding properly
• `tslib.get_period_field()` and `tslib.get_period_field_arr()` now raise if code argument out of range (GH4519, GH4520)
• Fix boolean indexing on an empty series loses index names (GH4235), `infer_dtype` works with empty arrays.
• Fix reindexing with multiple axes; if an axes match was not replacing the current axes, leading to a possible lazy frequency inference issue (GH3317)
• Fixed issue where `DataFrame.apply` was reraising exceptions incorrectly (causing the original stack trace to be truncated).
• Fix selection with `ix/loc` and non_unique selectors (GH4619)
• Fix assignment with `iloc/loc` involving a dtype change in an existing column (GH4312, GH5702) have internal `setitem_with_indexer` in core/indexing to use `Block.setitem`
• Fixed bug where thousands operator was not handled correctly for floating point numbers in csv_import (GH4322)
• Fix an issue with `CacheableOffset` not properly being used by many DateOffset; this prevented the DateOffset from being cached (GH4609)
• Fix boolean comparison with a DataFrame on the lhs, and a list/tuple on the rhs (GH4576)
• Fix error/dtype conversion with `setitem` of `None` on Series/DataFrame (GH4667)
• Fix decoding based on a passed in non-default encoding in `pd.read_stata` (GH4626)
• Fix `DataFrame.from_records` with a plain-vanilla ndarray. (GH4727)
• Fix some inconsistencies with `Index.rename` and `MultiIndex.rename`, etc. (GH4718, GH4628)
• Bug in using `iloc/loc` with a cross-sectional and duplicate indices (GH4726)
• Bug with using `QUOTE_NONE` with `to_csv` causing Exception. (GH4328)
• Bug with Series indexing not raising an error when the right-hand-side has an incorrect length (GH2702)
• Bug in MultiIndexing with a partial string selection as one part of a MultiIndex (GH4758)
• Bug with reindexing on the index with a non-unique index will now raise `ValueError` (GH4746)
• Bug in setting with `loc/ix` a single indexer with a MultiIndex axis and a NumPy array, related to (GH3777)
• Bug in concatenation with duplicate columns across dtypes not merging with axis=0 (GH4771, GH4975)
• Bug in `iloc` with a slice index failing (GH4771)
• Incorrect error message with no colspecs or width in `read_fwf`. (GH4774)
• Fix bugs in indexing in a Series with a duplicate index (GH4548, GH4550)
• Fixed bug with reading compressed files with read_fwf in Python 3. (GH3963)
• Fixed an issue with a duplicate index and assignment with a dtype change (GH4686)
• Fixed an issue related to ticklocs/ticklabels with log scale bar plots across different versions of matplotlib (GH4789)
• Suppressed DeprecationWarning associated with internal calls issued by repr() (GH4391)
• Fixed an issue with a duplicate index and duplicate selector with .loc (GH4825)
• Fixed an issue with DataFrame.sort_index where, when sorting by a single column and passing a list for ascending, the argument for ascending was being interpreted as True (GH4839, GH4846)
• Fixed Panel.tshift not working. Added freq support to Panel.shift (GH4853)
• Fix an issue in TextFileReader w/ Python engine (i.e. PythonParser) with thousands != ," (GH4596)
• Bug in getitem with a duplicate index when using where (GH4879)
• Fix Type inference code coerces float column into datetime (GH4601)
• Fixed _ensure_numeric does not check for complex numbers (GH4902)
• Fixed a bug in Series.hist where two figures were being created when the by argument was passed (GH4112, GH4113).
• Fixed a bug in convert_objects for > 2 ndims (GH4937)
• Fixed a bug in DataFrame/Panel cache insertion and subsequent indexing (GH4939, GH5424)
• Fixed string methods for FrozenNDArray and FrozenList (GH4929)
• Fixed a bug with setting invalid or out-of-range values in indexing enlargement scenarios (GH4940)
• Tests for fillna on empty Series (GH4346), thanks @immerrr
• Fixed copy() to shallow copy axes/indices as well and thereby keep separate metadata. (GH4202, GH4830)
• Fixed skiprows option in Python parser for read_csv (GH4382)
• Fixed bug preventing cut from working with np.inf levels without explicitly passing labels (GH3415)
• Fixed wrong check for overlapping in DatetimeIndex.union (GH4564)
• Fixed conflict between thousands separator and date parser in csv_parser (GH4678)
• Fix appending when dtypes are not the same (error showing mixing float/np.datetime64) (GH4993)
• Fix repr for DateOffset. No longer show duplicate entries in kwds. Removed unused offset fields. (GH4638)
• Fixed wrong index name during read_csv if using usecols. Applies to csv parser only. (GH4201)
• Timestamp objects can now appear in the left hand side of a comparison operation with a Series or DataFrame object (GH4982).
• Fix a bug when indexing with np.nan via iloc/loc (GH5016)
• Fixed a bug where low memory c parser could create different types in different chunks of the same file. Now coerces to numerical type or raises warning. (GH3866)
• Fix a bug where reshaping a Series to its own shape raised TypeError (GH4554) and other reshaping issues.
• Bug in setting with ix/loc and a mixed int/string index (GH4544)
• Make sure series-series boolean comparisons are label based (GH4947)
• Bug in multi-level indexing with a Timestamp partial indexer (GH4294)
• Tests/fix for MultiIndex construction of an all-nan frame (GH4078)
• Fixed a bug where `read_html()` wasn’t correctly inferring values of tables with commas (GH5029)
• Fixed a bug where `read_html()` wasn’t providing a stable ordering of returned tables (GH4770, GH5029).
• Fixed a bug where `read_html()` was incorrectly parsing when passed `index_col=0` (GH5066).
• Fixed a bug where `read_html()` was incorrectly inferring the type of headers (GH5048).
• Fixed a bug where `DatetimeIndex` joins with `PeriodIndex` caused a stack overflow (GH3899).
• Fixed a bug where `groupby` objects didn’t allow plots (GH5102).
• Fixed a bug where `groupby` objects weren’t tab-completing column names (GH5102).
• Fixed a bug where `groupby.plot()` and friends were duplicating figures multiple times (GH5102).
• Provide automatic conversion of `object` dtypes on `fillna`, related (GH5103)
• Fixed a bug where default options were being overwritten in the option parser cleaning (GH5121).
• Treat a list/ndarray identically for `iloc` indexing with list-like (GH5006)
• Fix `MultiIndex.get_level_values()` with missing values (GH5074)
• Fix bound checking for `Timestamp()` with `datetime64` input (GH4065)
• Fix a bug where `TestReadHtml` wasn’t calling the correct `read_html()` function (GH5150).
• Fix a bug with `NDFrame.replace()` which made replacement appear as though it was (incorrectly) using regular expressions (GH5143).
• Fix better error message for `to_datetime` (GH4928)
• Made sure different locales are tested on travis-ci (GH4918). Also adds a couple of utilities for getting locales and setting locales with a context manager.
• Fixed segfault on `isnull(MultiIndex)` (now raises an error instead) (GH5123, GH5125)
• Allow duplicate indices when performing operations that align (GH5185, GH5639)
• Compound dtypes in a constructor raise `NotImplementedError` (GH5191)
• Bug in comparing duplicate frames (GH4421) related
• Bug in `describe` on duplicate frames
• Bug in `to_datetime` with a format and `coerce=True` not raising (GH5195)
• Bug in `loc` setting with multiple indexers and a rhs of a Series that needs broadcasting (GH5206)
• Fixed bug where inplace setting of levels or labels on `MultiIndex` would not clear cached values property and therefore return wrong values. (GH5215)
• Fixed bug where filtering a grouped DataFrame or Series did not maintain the original ordering (GH4621).
• Fixed `Period` with a business date freq to always roll-forward if on a non-business date. (GH5203)
• Fixed bug in Excel writers where frames with duplicate column names weren’t written correctly. (GH5235)
• Fixed issue with `drop` and a non-unique index on Series (GH5248)
• Fixed segfault in C parser caused by passing more names than columns in the file. (GH5156)
• Fix `Series.isin` with date/time-like dtypes (GH5021)
• C and Python Parser can now handle the more common MultiIndex column format which doesn’t have a row for index names (GH4702)
• Bug when trying to use an out-of-bounds date as an object dtype (GH5312)
• Bug when trying to display an embedded PandasObject (GH5324)
• Allows operating of Timestamps to return a datetime if the result is out-of-bounds related (GH5312)
• Fix return value/type signature of initObjToJSON() to be compatible with numpy’s import_array() (GH5334, GH5326)
• Bug when renaming then set_index on a DataFrame (GH5344)
• Test suite no longer leaves around temporary files when testing graphics. (GH5347) (thanks for catching this @yarikoptic!)
• Fixed html tests on win32. (GH4580)
• Make sure that head/tail are iloc based, (GH5370)
• Fixed bug for PeriodIndex string representation if there are 1 or 2 elements. (GH5372)
• The GroupBy methods transform and filter can be used on Series and DataFrames that have repeated (non-unique) indices. (GH4620)
• Fix empty series not printing name in repr (GH4651)
• Make tests create temp files in temp directory by default. (GH5419)
• pd.to_timedelta of a scalar returns a scalar (GH5410)
• pd.to_timedelta accepts NaN and NaT, returning NaT instead of raising (GH5437)
• performance improvements in isnull on larger size pandas objects
• Fixed various setitem with 1d ndarray that does not have a matching length to the indexer (GH5508)
• Bug in getitem with a MultiIndex and iloc (GH5528)
• Bug in delitem on a Series (GH5542)
• Bug fix in apply when using custom function and objects are not mutated (GH5545)
• Bug in selecting from a non-unique index with loc (GH5553)
• Bug in groupby returning non-consistent types when user function returns a None, (GH5592)
• Work around regression in numpy 1.7.0 which erroneously raises IndexError from ndarray.item(GH5666)
• Bug in repeated indexing of object with resultant non-unique index (GH5678)
• Bug in fillna with Series and a passed series/dict (GH5703)
• Bug in groupby transform with a datetime-like grouper (GH5712)
• Bug in MultiIndex selection in PY3 when using certain keys (GH5725)
• Row-wise concat of differing dtypes failing in certain cases (GH5754)
Contributors

A total of 77 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Agustín Herranz +
- Alex Gaudio +
- Alex Rothberg +
- Andreas Klostermann +
- Andreas Wurl +
- Andy Hayden
- Ben Alex +
- Benedikt Sauer +
- Brad Buran
- Caleb Epstein +
- Chang She
- Christopher Whelan
- DSM +
- Dale Jung +
- Dan Birken
- David Rasch +
- Dieter Vandenbussche
- Gabi Davar +
- Garrett Drapala
- Goyo +
- Greg Reda +
- Ivan Smirnov +
- Jack Kelly +
- Jacob Schaer +
- Jan Schulz +
- Jeff Tratner
- Jeffrey Tratner
- John McNamara +
- John W. O’Brien +
- Joris Van den Bossche
- Justin Bozonier +
- Kelsey Jordahl
- Kevin Stone
• Kieran O’Mahony
• Kyle Hausmann +
• Kyle Kelley +
• Kyle Meyer
• Mike Kelly
• Mortada Mehyar +
• Nick Foti +
• Olivier Harris +
• Ondřej Čertík +
• PKEuS
• Phillip Cloud
• Pierre Haessig +
• Richard T. Guy +
• Roman Pekar +
• Roy Hyunjin Han
• Skipper Seabold
• Sten +
• Thomas A Caswell +
• Thomas Kluyver
• Tiago Requeijo +
• TomAugspurger
• Trent Hauck
• Valentin Haenel +
• Viktor Kerkez +
• Vincent Arel-Bundock
• Wes McKinney
• Wes Turner +
• Weston Renoud +
• Yaroslav Halchenko
• Zach Dwiel +
• chapman siu +
• chappers +
• d10genes +
• danielballan
• daydreamt +
• engstrom +
5.16 Version 0.12

5.16.1 Version 0.12.0 (July 24, 2013)

This is a major release from 0.11.0 and includes several new features and enhancements along with a large number of bug fixes.

Highlights include a consistent I/O API naming scheme, routines to read html, write MultiIndexes to csv files, read & write STATA data files, read & write JSON format files, Python 3 support for HDFStore, filtering of groupby expressions via filter, and a revamped replace routine that accepts regular expressions.

API changes

• The I/O API is now much more consistent with a set of top level reader functions accessed like pd. read_csv() that generally return a pandas object.
  - read_csv
  - read_excel
  - read_hdf
  - read_sql
  - read_json
  - read_html
  - read_stata
  - read_clipboard

The corresponding writer functions are object methods that are accessed like df.to_csv()
pandas: powerful Python data analysis toolkit, Release 1.1.1

– to_clipboard
• Fix modulo and integer division on Series,DataFrames to act similarly to float dtypes to return np.nan
or np.inf as appropriate (GH3590). This correct a numpy bug that treats integer and float dtypes
differently.
In [1]: p = pd.DataFrame({'first': [4, 5, 8], 'second': [0, 0, 3]})
In [2]: p % 0
Out[2]:
first second
0
NaN
NaN
1
NaN
NaN
2
NaN
NaN
In [3]: p % p
Out[3]:
first second
0
0.0
NaN
1
0.0
NaN
2
0.0
0.0
In [4]: p / p
Out[4]:
first second
0
1.0
NaN
1
1.0
NaN
2
1.0
1.0
In [5]: p / 0
Out[5]:
first second
0
inf
NaN
1
inf
NaN
2
inf
inf

• Add squeeze keyword to groupby to allow reduction from DataFrame -> Series if groups are unique. This
is a Regression from 0.10.1. We are reverting back to the prior behavior. This means groupby will return the
same shaped objects whether the groups are unique or not. Revert this issue (GH2893) with (GH3596).
In [2]: df2 = pd.DataFrame([{"val1": 1, "val2": 20},
...:
{"val1": 1, "val2": 19},
...:
{"val1": 1, "val2": 27},
...:
{"val1": 1, "val2": 12}])
In [3]: def func(dataf):
...:
return dataf["val2"] - dataf["val2"].mean()
...:
In [4]: # squeezing the result frame to a series (because we have unique groups)
...: df2.groupby("val1", squeeze=True).apply(func)
Out[4]:
0
0.5
1
-0.5
2
7.5
3
-7.5
Name: 1, dtype: float64
(continues on next page)

5.16. Version 0.12

3143


In [5]: # no squeezing (the default, and behavior in 0.10.1)
    ...: df2.groupby("val1").apply(func)
Out[5]:
     val2  0  1  2  3
  val1
  1  0.5 -0.5  7.5 -7.5

• Raise on iloc when boolean indexing with a label based indexer mask e.g. a boolean Series, even with integer labels, will raise. Since iloc is purely positional based, the labels on the Series are not alignable (GH3631) This case is rarely used, and there are plenty of alternatives. This preserves the iloc API to be purely positional based.

In [6]: df = pd.DataFrame(range(5), index=list('ABCDE'), columns=['a'])
In [7]: mask = (df.a % 2 == 0)
In [8]: mask
Out[8]:
     A   B   C   D   E
Name: a, dtype: bool
# this is what you should use
In [9]: df.loc[mask]
Out[9]:
     a
  A   0
  C   2
  E   4

# this will work as well
In [10]: df.iloc[mask.values]
Out[10]:
     a
  A   0
  C   2
  E   4
df.iloc[mask] will raise a ValueError

• The raise_on_error argument to plotting functions is removed. Instead, plotting functions raise a TypeError when the dtype of the object is object to remind you to avoid object arrays whenever possible and thus you should cast to an appropriate numeric dtype if you need to plot something.

• Add colormap keyword to DataFrame plotting methods. Accepts either a matplotlib colormap object (ie, matplotlib.cm.jet) or a string name of such an object (ie, 'jet'). The colormap is sampled to select the color for each column. Please see Colormaps for more information. (GH3860)

• DataFrame.interpolate() is now deprecated. Please use DataFrame.fillna() and DataFrame.replace() instead. (GH3582, GH3675, GH3676)

• the method and axis arguments of DataFrame.replace() are deprecated

• DataFrame.replace 's infer_types parameter is removed and now performs conversion by default. (GH3907)
• Add the keyword allow_duplicates to DataFrame.insert to allow a duplicate column to be inserted if True, default is False (same as prior to 0.12) (GH3679)
• Implement __nonzero__ for NDFrame objects (GH3691, GH3696)
• IO api
  – added top-level function read_excel to replace the following. The original API is deprecated and will be removed in a future version

```python
from pandas.io.parsers import ExcelFile
xls = ExcelFile('path_to_file.xls')
xls.parse('Sheet1', index_col=None, na_values=['NA'])
```

With

```python
import pandas as pd
pd.read_excel('path_to_file.xls', 'Sheet1', index_col=None, na_values=['NA'])
```

  – added top-level function read_sql that is equivalent to the following

```python
from pandas.io.sql import read_frame
read_frame(...)
```

• DataFrame.to_html and DataFrame.to_latex now accept a path for their first argument (GH3702)
• Do not allow astypes on datetime64[ns] except to object, and timedelta64[ns] to object/int (GH3425)
• The behavior of datetime64 dtypes has changed with respect to certain so-called reduction operations (GH3726). The following operations now raise a TypeError when performed on a Series and return an empty Series when performed on a DataFrame similar to performing these operations on, for example, a DataFrame of slice objects:
  – sum, prod, mean, std, var, skew, kurt, corr, and cov
• read_html now defaults to None when reading, and falls back on bs4 + html5lib when lxml fails to parse. a list of parsers to try until success is also valid
• The internal pandas class hierarchy has changed (slightly). The previous PandasObject now is called PandasContainer and a new PandasObject has become the base class for PandasContainer as well as Index, Categorical, GroupBy, SparseList, and SparseArray (+ their base classes). Currently, PandasObject provides string methods (from StringMixin). (GH4090, GH4092)
• New StringMixin that, given a __unicode__ method, gets python 2 and python 3 compatible string methods (__str__, __bytes__, and __repr__). Plus string safety throughout. Now employed in many places throughout the pandas library. (GH4090, GH4092)

**IO enhancements**

• pd.read_html() can now parse HTML strings, files or urls and return DataFrames, courtesy of @cpcloud. (GH3477, GH3605, GH3606, GH3616). It works with a single parser backend: BeautifulSoup4 + html5lib. See the docs

You can use pd.read_html() to read the output from DataFrame.to_html() like so

```python
In [11]: df = pd.DataFrame({'a': range(3), 'b': list('abc')})
In [12]: print(df)
```
a  b  
0 0  a  
1 1  b  
2 2  c  

In [13]: html = df.to_html()
In [14]: alist = pd.read_html(html, index_col=0)
In [15]: print(df == alist[0])

Note that alist here is a Python list so pd.read_html() and DataFrame.to_html() are not inverses.
- pd.read_html() no longer performs hard conversion of date strings (GH3656).

**Warning:** You may have to install an older version of BeautifulSoup4, See the installation docs

- Added module for reading and writing Stata files: pandas.io.stata (GH1512) accessible via read_stata top-level function for reading, and to_stata DataFrame method for writing, See the docs
- Added module for reading and writing json format files: pandas.io.json accessible via read_json top-level function for reading, and to_json DataFrame method for writing, See the docs various issues (GH1226, GH3804, GH3876, GH3867, GH1305)
- MultiIndex column support for reading and writing csv format files
  - The header option in read_csv now accepts a list of the rows from which to read the index.
  - The option, tupleize_cols can now be specified in both to_csv and read_csv, to provide compatibility for the pre 0.12 behavior of writing and reading MultiIndex columns via a list of tuples. The default in 0.12 is to write lists of tuples and not interpret list of tuples as a MultiIndex column.

Note: The default behavior in 0.12 remains unchanged from prior versions, but starting with 0.13, the default to write and read MultiIndex columns will be in the new format. (GH3571, GH1651, GH3141)
- If an index_col is not specified (e.g. you don’t have an index, or wrote it with df.to_csv(..., index=False), then any names on the columns index will be lost.

In [16]: from pandas._testing import makeCustomDataframe as mkdf
In [17]: df = mkdf(5, 3, r_idx_nlevels=2, c_idx_nlevels=4)
In [18]: df.to_csv('mi.csv')
In [19]: print(open('mi.csv').read())

C0,,C_l0_g0,C_l0_g1,C_l0_g2
C1,,C_l1_g0,C_l1_g1,C_l1_g2
C2,,C_l2_g0,C_l2_g1,C_l2_g2
C3,,C_l3_g0,C_l3_g1,C_l3_g2
R0,R1,,
R_l0_g0,R_l1_g0,R0C0,R0C1,R0C2

(continues on next page)
R_{10\_g1}, R_{11\_g1}, R_{1C0}, R_{1C1}, R_{1C2}
R_{10\_g2}, R_{11\_g2}, R_{2C0}, R_{2C1}, R_{2C2}
R_{10\_g3}, R_{11\_g3}, R_{3C0}, R_{3C1}, R_{3C2}
R_{10\_g4}, R_{11\_g4}, R_{4C0}, R_{4C1}, R_{4C2}

**In [20]:** pd.read_csv('mi.csv', header=[0, 1, 2, 3], index_col=[0, 1])
**Out[20]:**
C0 C_{10\_g0} C_{10\_g1} C_{10\_g2}
C1 C_{11\_g0} C_{11\_g1} C_{11\_g2}
C2 C_{12\_g0} C_{12\_g1} C_{12\_g2}
C3 C_{13\_g0} C_{13\_g1} C_{13\_g2}
R0 R1
R_{10\_g0} R_{11\_g0} R_{0C0} R_{0C1} R_{0C2}
R_{10\_g1} R_{11\_g1} R_{1C0} R_{1C1} R_{1C2}
R_{10\_g2} R_{11\_g2} R_{2C0} R_{2C1} R_{2C2}
R_{10\_g3} R_{11\_g3} R_{3C0} R_{3C1} R_{3C2}
R_{10\_g4} R_{11\_g4} R_{4C0} R_{4C1} R_{4C2}

- Support for HDFStore (via PyTables 3.0.0) on Python3
- Iterator support via `read_hdf` that automatically opens and closes the store when iteration is finished. This is only for tables

**In [25]:** path = 'store_iterator.h5'
**In [26]:** pd.DataFrame(np.random.randn(10, 2)).to_hdf(path, 'df', table=True)
**In [27]:** for df in pd.read_hdf(path, 'df', chunksize=3):
    ....:     print(df)
    ....:     0 1
    ....:     0 0.713216 -0.778461
    ....:     1 -0.661062 0.862877
    ....:     2 0.344342 0.149565
    ....:     3 -0.626968 -0.875772
    ....:     4 -0.930687 -0.218983
    ....:     5 0.949965 -0.442354
    ....:     6 -0.402985 1.111358
    ....:     7 -0.241527 -0.670477
    ....:     8 0.049355 0.632633
    ....:     9 -1.502767 -1.225492

- `read_csv` will now throw a more informative error message when a file contains no columns, e.g., all newline characters
Other enhancements

- **DataFrame.replace()** now allows regular expressions on contained Series with object dtype. See the examples section in the regular docs *Replacing via String Expression*

For example you can do

```python
In [21]: df = pd.DataFrame({'a': list('ab..'), 'b': [1, 2, 3, 4]})
In [22]: df.replace(regex=r'^\s*.\s*', value=np.nan)
Out[22]:
   a  b
0  a  1
1  b  2
2  NaN  3
3  NaN  4
```

...to replace all occurrences of the string `. ` with zero or more instances of surrounding white space with NaN.

Regular string replacement still works as expected. For example, you can do

```python
In [23]: df.replace('.', np.nan)
Out[23]:
   a  b
0  a  1
1  b  2
2  NaN  3
3  NaN  4
```

...to replace all occurrences of the string `. ` with NaN.

- **pd.melt()** now accepts the optional parameters *var_name* and *value_name* to specify custom column names of the returned DataFrame.

- **pd.set_option()** now allows N option, value pairs (GH3667).

  Let’s say that we had an option `'a.b'` and another option `'b.c'`. We can set them at the same time:

```python
In [31]: pd.get_option('a.b')
Out[31]: 2
In [32]: pd.get_option('b.c')
Out[32]: 3
In [33]: pd.set_option('a.b', 1, 'b.c', 4)
In [34]: pd.get_option('a.b')
Out[34]: 1
In [35]: pd.get_option('b.c')
Out[35]: 4
```

- The **filter** method for group objects returns a subset of the original object. Suppose we want to take only elements that belong to groups with a group sum greater than 2.

```python
In [24]: sf = pd.Series([1, 1, 2, 3, 3, 3])
In [25]: sf.groupby(sf).filter(lambda x: x.sum() > 2)
```

(continues on next page)
The argument of `filter` must a function that, applied to the group as a whole, returns `True` or `False`. Another useful operation is filtering out elements that belong to groups with only a couple members.

```python
In [26]: dff = pd.DataFrame({'A': np.arange(8), 'B': list('aabbbbcc'))
In [27]: dff.groupby('B').filter(lambda x: len(x) > 2)
Out[27]:
   A  B
0  0  b
1  1  b
2  2  b
3  3  b
4  4  b
5  5  b
6  6  b
7  7  b
```

Alternatively, instead of dropping the offending groups, we can return a like-indexed objects where the groups that do not pass the filter are filled with NaNs.

```python
In [28]: dff.groupby('B').filter(lambda x: len(x) > 2, dropna=False)
Out[28]:
   A  B
0 NaN NaN
1 NaN NaN
2 2.0 b
3 3.0 b
4 4.0 b
5 5.0 b
6 NaN NaN
7 NaN NaN
```

- Series and DataFrame `hist` methods now take a `figsize` argument (GH3834)
- DatetimeIndexes no longer try to convert mixed-integer indexes during join operations (GH3877)
- `Timestamp.min` and `Timestamp.max` now represent valid ` Timestamp` instances instead of the default date-time.min and datetime.max (respectively), thanks @SleepingPills
- `read_html` now raises when no tables are found and BeautifulSoup==4.2.0 is detected (GH4214)

**Experimental features**

- Added experimental `CustomBusinessDay` class to support `DateOffsets` with custom holiday calendars and custom weekmasks. (GH2301)

  **Note:** This uses the `numpy.busdaycalendar` API introduced in Numpy 1.7 and therefore requires Numpy 1.7.0 or newer.

```python
In [29]: from pandas.tseries.offsets import CustomBusinessDay
In [30]: from datetime import datetime
```
# As an interesting example, let's look at Egypt where
# a Friday-Saturday weekend is observed.
In [31]: weekmask_egypt = 'Sun Mon Tue Wed Thu'

# They also observe International Workers' Day so let's
# add that for a couple of years
In [32]: holidays = ['2012-05-01', \n                   datetime(2013, 5, 1), \n                   np.datetime64('2014-05-01')]

In [33]: bday_egypt = CustomBusinessDay(holidays=holidays, weekmask=weekmask_egypt)

In [34]: dt = datetime(2013, 4, 30)

In [35]: print(dt + 2 * bday_egypt)
2013-05-05 00:00:00

In [36]: dts = pd.date_range(dt, periods=5, freq=bday_egypt)

In [37]: print(pd.Series(dts.weekday, dts).map(pd.Series('Mon Tue Wed Thu Fri Sat Sun'.split())))

2013-04-30 Tue
2013-05-02 Thu
2013-05-05 Sun
2013-05-06 Mon
2013-05-07 Tue
Freq: C, dtype: object

Bug fixes

- Plotting functions now raise a TypeError before trying to plot anything if the associated objects have have a
dtype of object (GH1818, GH3572, GH3911, GH3912), but they will try to convert object arrays to numeric
arrays if possible so that you can still plot, for example, an object array with floats. This happens before any
drawing takes place which eliminates any spurious plots from showing up.
-fillna methods now raise a TypeError if the value parameter is a list or tuple.
- Series.str now supports iteration (GH3638). You can iterate over the individual elements of each string in
the Series. Each iteration yields a Series with either a single character at each index of the original
Series or NaN. For example,

In [38]: strs = 'go', 'bow', 'joe', 'slow'

In [39]: ds = pd.Series(strs)

In [40]: for s in ds.str:
   ....:     print(s)
   ....:
0  g
1  b
2  j
3  s
dtype: object
0  o
1  o

(continues on next page)
The last element yielded by the iterator will be a `Series` containing the last element of the longest string in the `Series` with all other elements being `NaN`. Here since 'slow' is the longest string and there are no other strings with the same length 'w' is the only non-null string in the yielded `Series`.

- **HDFStore**
  - will retain index attributes (freq, tz, name) on recreation (GH3499)
  - will warn with a `AttributeConflictWarning` if you are attempting to append an index with a different frequency than the existing, or attempting to append an index with a different name than the existing
  - support datelike columns with a timezone as `.data.columns` (GH2852)
- **Non-unique index support clarified** (GH3468).
  - Fix assigning a new index to a duplicate index in a DataFrame would fail (GH3468)
  - Fix construction of a DataFrame with a duplicate index
  - `.ref_locs` support to allow duplicative indices across dtypes, allows `iget` support to always find the index (even across dtypes) (GH2194)
  - `applymap` on a DataFrame with a non-unique index now works (removed warning) (GH2786), and fix (GH3230)
  - `to_csv` to handle non-unique columns (GH3495)
  - Duplicate indexes with `get_item` will return items in the correct order (GH3455, GH3457) and handle missing elements like unique indices (GH3561)
  - Duplicate indexes with and empty DataFrame.from_records will return a correct frame (GH3562)
  - `Concat` to produce a non-unique columns when duplicates are across dtypes is fixed (GH3602)
  - Allow `insert/delete` to non-unique columns (GH3679)
pandas: powerful Python data analysis toolkit, Release 1.1.1

- Non-unique indexing with a slice via `loc` and friends fixed (GH3659)
- Allow insert/delete to non-unique columns (GH3679)
- Extend `reindex` to correctly deal with non-unique indices (GH3679)
- `DataFrame.itertuples()` now works with frames with duplicate column names (GH3873)
- Bug in non-unique indexing via `iloc` (GH4017); added `takeable` argument to `reindex` for location-based taking
- Allow non-unique indexing in series via `.ix/.loc` and `__getitem__` (GH4246)
- Fixed non-unique indexing memory allocation issue with `.ix/.loc` (GH4280)

* DataFrame.from_records did not accept empty recarrays (GH3682)
* `read_html` now correctly skips tests (GH3741)
* Fixed a bug where DataFrame.replace with a compiled regular expression in the `to_replace` argument wasn’t working (GH3907)
* Improved `network` test decorator to catch IOError (and therefore URLError as well). Added `with_connectivity_check` decorator to allow explicitly checking a website as a proxy for seeing if there is network connectivity. Plus, new `optional_args` decorator factory for decorators. (GH3910, GH3914)
* Fixed testing issue where too many sockets where open thus leading to a connection reset issue (GH3982, GH3985, GH4028, GH4054)
* Fixed failing tests in test_yahoo, test_google where symbols were not retrieved but were being accessed (GH3982, GH3985, GH4028, GH4054)
* Series.hist will now take the figure from the current environment if one is not passed
* Fixed bug where a 1xN DataFrame would barf on a 1xN mask (GH4071)
* Fixed running of `tox` under python3 where the pickle import was getting rewritten in an incompatible way (GH4062, GH4063)
* Fixed bug where sharex and sharey were not being passed to grouped_hist (GH4089)
* Fixed bug in DataFrame.replace where a nested dict wasn’t being iterated over when `regex=False` (GH4115)
* Fixed bug in the parsing of microseconds when using the `format` argument in `to_datetime` (GH4152)
* Fixed bug in PandasAutoDateLocator where `invert_xaxis` triggered incorrectly `MilliSecondLocator` (GH3990)
* Fixed bug in plotting that wasn’t raising on invalid colormap for matplotlib 1.1.1 (GH4215)
* Fixed the legend displaying in `DataFrame.plot(kind='kde')` (GH4216)
* Fixed bug where Index slices weren’t carrying the name attribute (GH4226)
* Fixed bug in initializing `DatetimeIndex` with an array of strings in a certain time zone (GH4229)
* Fixed bug where html5lib wasn’t being properly skipped (GH4265)
* Fixed bug where `get_data_famafrench` wasn’t using the correct file edges (GH4281)

See the full release notes or issue tracker on GitHub for a complete list.
Contributors

A total of 50 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Andy Hayden
- Chang She
- Christopher Whelan
- Damien Garaud
- Dan Allan
- Dan Birken
- Dieter Vandenbussche
- Dražen Lučanin
- Gábor Lipták +
- Jeff Mellen +
- Jeff Tratner +
- Jeffrey Tratner +
- Jonathan deWerd +
- Joris Van den Bossche +
- Juraj Niznan +
- Karmel Allison
- Kelsey Jordahl
- Kevin Stone +
- Kieran O’Mahony
- Kyle Meyer +
- Mike Kelly +
- PKEuS +
- Patrick O’Brien +
- Phillip Cloud
- Richard Hochenberger +
- Skipper Seabold
- SleepingPills +
- Tobias Brandt
- Tom Farnbauer +
- TomAugspurger +
- Trent Hauck +
- Wes McKinney
- Wouter Overmeire
5.17 Version 0.11

5.17.1 Version 0.11.0 (April 22, 2013)

This is a major release from 0.10.1 and includes many new features and enhancements along with a large number of bug fixes. The methods of Selecting Data have had quite a number of additions, and Dtype support is now full-fledged. There are also a number of important API changes that long-time pandas users should pay close attention to.

There is a new section in the documentation, *10 Minutes to Pandas*, primarily geared to new users.

There is a new section in the documentation, *Cookbook*, a collection of useful recipes in pandas (and that we want contributions!).

There are several libraries that are now *Recommended Dependencies*

**Selection choices**

Starting in 0.11.0, object selection has had a number of user-requested additions in order to support more explicit location based indexing. Pandas now supports three types of multi-axis indexing.

- `.loc` is strictly label based, will raise `KeyError` when the items are not found, allowed inputs are:
  - A single label, e.g. 5 or 'a', (note that 5 is interpreted as a label of the index. This use is not an integer position along the index)
  - A list or array of labels ['a', 'b', 'c']
  - A slice object with labels 'a': 'f', (note that contrary to usual python slices, both the start and the stop are included!)
– A boolean array

See more at Selection by Label

• .iloc is strictly integer position based (from 0 to length-1 of the axis), will raise IndexError when the requested indices are out of bounds. Allowed inputs are:
  – An integer e.g. 5
  – A list or array of integers [4, 3, 0]
  – A slice object with ints 1:7
  – A boolean array

See more at Selection by Position

• .ix supports mixed integer and label based access. It is primarily label based, but will fallback to integer positional access. .ix is the most general and will support any of the inputs to .loc and .iloc, as well as support for floating point label schemes. .ix is especially useful when dealing with mixed positional and label based hierarchical indexes.

As using integer slices with .ix have different behavior depending on whether the slice is interpreted as position based or label based, it’s usually better to be explicit and use .iloc or .loc.

See more at Advanced Indexing and Advanced Hierarchical.

Selection deprecations

Starting in version 0.11.0, these methods may be deprecated in future versions.

• irow
• icol
• iget_value

See the section Selection by Position for substitutes.

Dtypes

Numeric dtypes will propagate and coexist in DataFrames. If a dtype is passed (either directly via the dtype keyword, a passed ndarray, or a passed Series, then it will be preserved in DataFrame operations. Furthermore, different numeric dtypes will NOT be combined. The following example will give you a taste.

```python
In [1]: df1 = pd.DataFrame(np.random.randn(8, 1), columns=['A'], dtype='float32')
In [2]: df1
Out[2]:
     A
0  0.469112
1 -0.282863
2 -1.509058
3 -1.135632
4  1.212112
5 -0.173215
6  0.119209
7 -1.044236
```

(continues on next page)
Out[3]:
A float32
dtype: object

In [4]: df2 = pd.DataFrame({'A': pd.Series(np.random.randn(8), dtype='float16'),
...:                      'B': pd.Series(np.random.randn(8)),
...:                      'C': pd.Series(range(8), dtype='uint8')})

...:

In [5]: df2
Out[5]:
   A     B     C
0 -0.861816 -0.424972  0
1 -2.105469  0.567020  1
2 -0.494873  0.276232  2
3  1.072266 -1.087401  3
4  0.721680 -0.673690  4
5 -0.706543  0.113648  5
6 -1.040039 -1.478427  6
7  0.271973  0.524988  7

In [6]: df2.dtypes
Out[6]:
A float16
B float64
C uint8
dtype: object

# here you get some upcasting
In [7]: df3 = df1.reindex_like(df2).fillna(value=0.0) + df2

In [8]: df3
Out[8]:
   A     B     C
0 -0.392704 -0.424972  0.0
1 -2.388332  0.567020  1.0
2 -2.003932  0.276232  2.0
3 -2.063367 -1.087401  3.0
4  1.933792 -0.673690  4.0
5 -0.879758  0.113648  5.0
6 -0.920830 -1.478427  6.0
7 -0.772263  0.524988  7.0

In [9]: df3.dtypes
Out[9]:
A float32
B float64
dtype: object
Dtype conversion

This is lower-common-denominator upcasting, meaning you get the dtype which can accommodate all of the types

```python
In [10]: df3.values.dtype
Out[10]: dtype('float64')
```

Conversion

```python
In [11]: df3.astype('float32').dtypes
Out[11]:
A   float32
B   float32
C   float32
dtype: object
```

Mixed conversion

```python
In [12]: df3['D'] = '1.'
In [13]: df3['E'] = '1'

In [14]: df3.convert_objects(convert_numeric=True).dtypes
Out[14]:
A   float32
B   float64
C   float64
D   float64
E    int64
dtype: object
```

# same, but specific dtype conversion
```python
In [15]: df3['D'] = df3['D'].astype('float16')
In [16]: df3['E'] = df3['E'].astype('int32')
```

```python
In [17]: df3.dtypes
Out[17]:
A   float32
B   float64
C   float64
D    float16
E    int32
dtype: object
```

Forcing date coercion (and setting NaT when not datelike)
```python
In [18]: import datetime
In [19]: s = pd.Series([datetime.datetime(2001, 1, 1, 0, 0), 'foo', 1.0, 1, pd.Timestamp('20010104'), '20010105'], dtype='O')
   ....:
```
```python
In [20]: s.convert_objects(convert_dates='coerce')
Out[20]:
0  2001-01-01
1    NaT
2    NaT
(continues on next page)```
Dtype gotchas

Platform gotchas

Starting in 0.11.0, construction of DataFrame/Series will use default dtypes of `int64` and `float64`, regardless of platform. This is not an apparent change from earlier versions of pandas. If you specify dtypes, they WILL be respected, however (GH2837).

The following will all result in `int64` dtypes

```python
In [21]: pd.DataFrame([1, 2], columns=['a']).dtypes
```

```
Out[21]:

<table>
<thead>
<tr>
<th>a</th>
<th>int64</th>
</tr>
</thead>
<tbody>
<tr>
<td>dtype: object</td>
<td></td>
</tr>
</tbody>
</table>
```

```python
In [22]: pd.DataFrame({'a': [1, 2]}).dtypes
```

```
Out[22]:

<table>
<thead>
<tr>
<th>a</th>
<th>int64</th>
</tr>
</thead>
<tbody>
<tr>
<td>dtype: object</td>
<td></td>
</tr>
</tbody>
</table>
```

```python
In [23]: pd.DataFrame({'a': 1}, index=range(2)).dtypes
```

```
Out[23]:

<table>
<thead>
<tr>
<th>a</th>
<th>int64</th>
</tr>
</thead>
<tbody>
<tr>
<td>dtype: object</td>
<td></td>
</tr>
</tbody>
</table>
```

Keep in mind that `DataFrame(np.array([1, 2]))` WILL result in `int32` on 32-bit platforms!

Upcasting gotchas

Performing indexing operations on integer type data can easily upcast the data. The dtype of the input data will be preserved in cases where nans are not introduced.

```python
In [24]: dfi = df3.astype('int32')
```

```python
In [25]: dfi['D'] = dfi['D'].astype('int64')
```

```python
In [26]: dfi
```

```
<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>-2</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>-2</td>
<td>0</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>-1</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>0</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>0</td>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td>6</td>
<td>0</td>
<td>-1</td>
<td>6</td>
<td>1</td>
</tr>
<tr>
<td>7</td>
<td>0</td>
<td>0</td>
<td>7</td>
<td>1</td>
</tr>
</tbody>
</table>
```

```python
In [27]: dfi.dtypes
```

```
<table>
<thead>
<tr>
<th>A</th>
<th>int32</th>
</tr>
</thead>
</table>
```

(continues on next page)
casted = df[df > 0]

In [28]:

In [29]:

Out[29]:

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>NaN</td>
<td>NaN</td>
<td>1.0</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>NaN</td>
<td>NaN</td>
<td>2.0</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>NaN</td>
<td>NaN</td>
<td>3.0</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>1.0</td>
<td>NaN</td>
<td>4.0</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>NaN</td>
<td>NaN</td>
<td>5.0</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>NaN</td>
<td>NaN</td>
<td>6.0</td>
<td>1</td>
</tr>
<tr>
<td>6</td>
<td>NaN</td>
<td>NaN</td>
<td>7.0</td>
<td>1</td>
</tr>
</tbody>
</table>

In [30]:

casted.dtypes

Out[30]:

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
</tr>
</thead>
<tbody>
<tr>
<td>float64</td>
<td>float64</td>
<td>float64</td>
<td>int64</td>
<td>int32</td>
</tr>
</tbody>
</table>

While float dtypes are unchanged.

In [31]:

df4 = df3.copy()

In [32]:

df4['A'] = df4['A'].astype('float32')

In [33]:

df4.dtypes

Out[33]:

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
</tr>
</thead>
<tbody>
<tr>
<td>float32</td>
<td>float64</td>
<td>float64</td>
<td>float16</td>
<td>int32</td>
</tr>
</tbody>
</table>

In [34]:

casted = df4[df4 > 0]

In [35]:

casted

Out[35]:

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
</tr>
</thead>
<tbody>
<tr>
<td>NaN</td>
<td>NaN</td>
<td>NaN</td>
<td>1.0</td>
<td>1</td>
</tr>
<tr>
<td>NaN</td>
<td>0.567020</td>
<td>1.0</td>
<td>1.0</td>
<td>1</td>
</tr>
<tr>
<td>NaN</td>
<td>0.276232</td>
<td>2.0</td>
<td>1.0</td>
<td>1</td>
</tr>
<tr>
<td>NaN</td>
<td>NaN</td>
<td>NaN</td>
<td>3.0</td>
<td>1.0</td>
</tr>
<tr>
<td>1.933792</td>
<td>NaN</td>
<td>4.0</td>
<td>1.0</td>
<td>1</td>
</tr>
<tr>
<td>NaN</td>
<td>0.113648</td>
<td>5.0</td>
<td>1.0</td>
<td>1</td>
</tr>
<tr>
<td>NaN</td>
<td>NaN</td>
<td>NaN</td>
<td>6.0</td>
<td>1.0</td>
</tr>
<tr>
<td>NaN</td>
<td>0.524988</td>
<td>7.0</td>
<td>1.0</td>
<td>1</td>
</tr>
</tbody>
</table>
Datetimes conversion

Datetime64[ns] columns in a DataFrame (or a Series) allow the use of np.nan to indicate a nan value, in addition to the traditional NaT, or not-a-time. This allows convenient nan setting in a generic way. Furthermore datetime64[ns] columns are created by default, when passed datetimelike objects (this change was introduced in 0.10.1) (GH2809, GH2810).

```
In [12]: df = pd.DataFrame(np.random.randn(6, 2), pd.date_range('20010102', periods=6), columns=['A', 'B'])
In [13]: df['timestamp'] = pd.Timestamp('20010103')
In [14]: df
Out[14]:
   A         B         timestamp
0  0.404705  0.577046  2001-01-03
1 -1.715002 -1.039268  2001-01-03
2 -0.370647 -1.157892  2001-01-03
3 -1.344312  0.844885  2001-01-03
4  1.075770 -0.109050  2001-01-03
5  1.643563 -1.469388  2001-01-03

# datetime64[ns] out of the box
In [15]: df.dtypes.value_counts()
Out[15]:
float64    2
datetime64[ns]    1
dtype: int64

# use the traditional nan, which is mapped to NaT internally
In [16]: df.loc[df.index[2:4], ['A', 'timestamp']] = np.nan
In [17]: df
Out[17]:
   A         B         timestamp
0  0.404705  0.577046  2001-01-03
1 -1.715002 -1.039268  2001-01-03
2   NaN     NaN         NaT
3 -1.344312  0.844885  2001-01-03
4  1.075770 -0.109050  2001-01-03
5  1.643563 -1.469388  2001-01-03

Astype conversion on datetime64[ns] to object, implicitly converts NaT to np.nan
In [18]: s = pd.Series([datetime.datetime(2001, 1, 2, 0, 0) for i in range(3)])

In [19]: s.dtype
Out[19]: dtype('<M8[ns]')

In [20]: s[1] = np.nan

In [21]: s
Out[21]:
0 2001-01-02
1 NaT
2 2001-01-02
dtype: datetime64[ns]

In [22]: s.dtype
Out[22]: dtype('<M8[ns]')

In [23]: s = s.astype('O')

In [24]: s
Out[24]:
0 2001-01-02 00:00:00
1 NaT
2 2001-01-02 00:00:00
dtype: object

In [25]: s.dtype
Out[25]: dtype('O')

API changes

- Added to_series() method to indices, to facilitate the creation of indexers (GH3275)
- HDFStore
  - added the method select_column to select a single column from a table as a Series.
  - deprecated the unique method, can be replicated by select_column(key, column).unique()
  - min_itemsize parameter to append will now automatically create data_columns for passed keys

Enhancements

- Improved performance of df.to_csv() by up to 10x in some cases. (GH3059)
- Numexpr is now a Recommended Dependencies, to accelerate certain types of numerical and boolean operations
- Bottleneck is now a Recommended Dependencies, to accelerate certain types of nan operations
- HDFStore
  - support read_hdf/to_hdf API similar to read_csv/to_csv

In [26]: df = pd.DataFrame({'A': range(5), 'B': range(5)})

In [27]: df.to_hdf('store.h5', 'table', append=True)

In [28]: pd.read_hdf('store.h5', 'table', where=['index > 2'])
Out[28]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>4</td>
<td>4</td>
</tr>
</tbody>
</table>

- Provide dotted attribute access to get from stores, e.g. `store.df == store['df']`
- New keywords `iterator=boolean`, and `chunksize=number_in_a_chunk` are provided to support iteration on `select` and `select_as_multiple` (GH3076)

- You can now select timestamps from an unordered timeseries similarly to an ordered timeseries (GH2437)
- You can now select with a string from a DataFrame with a datelike index, in a similar way to a Series (GH3070)

```python
In [29]: idx = pd.date_range("2001-10-1", periods=5, freq='M')
In [30]: ts = pd.Series(np.random.rand(len(idx)), index=idx)
In [31]: ts['2001']
Out[31]:
          2001-10-31 0.117967
          2001-11-30 0.702184
          2001-12-31 0.414034
Freq: M, dtype: float64
In [32]: df = pd.DataFrame({'A': ts})
In [33]: df['2001']
Out[33]:
          A
2001-10-31 0.117967
2001-11-30 0.702184
2001-12-31 0.414034
```

- Squeeze to possibly remove length 1 dimensions from an object.

```python
>>> p = pd.Panel(np.random.randn(3, 4, 4), items=['ItemA', 'ItemB', 'ItemC'],
...               major_axis=pd.date_range('20010102', periods=4),
...               minor_axis=['A', 'B', 'C', 'D'])
>>> p
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 4 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2001-01-02 00:00:00 to 2001-01-05 00:00:00
Minor_axis axis: A to D
>>> p.reindex(items=['ItemA']).squeeze()
                   A   B   C   D
2001-01-02 0.926089 -2.026458 0.501277 0.204683
2001-01-03 -0.076524 1.081161 1.141361 0.479243
2001-01-04 0.641817 -0.185352 1.824568 0.809152
2001-01-05 0.575237 0.669934 1.398014 -0.399338
```

```
>>> p.reindex(items=['ItemA'], minor=['B']).squeeze()
2001-01-02 -2.026458
2001-01-03  1.081161
2001-01-04 -0.185352
```
In `pd.io.data.Options`,

- Fix bug when trying to fetch data for the current month when already past expiry.
- Now using lxml to scrape html instead of BeautifulSoup (lxml was faster).
- New instance variables for calls and puts are automatically created when a method that creates them is called. This works for current month where the instance variables are simply `calls` and `puts`. Also works for future expiry months and save the instance variable as `callsMMYY` or `putsMMYY`, where `MMYY` are, respectively, the month and year of the option’s expiry.
- `Options.get_near_stock_price` now allows the user to specify the month for which to get relevant options data.
- `Options.get_forward_data` now has optional kwargs `near` and `above_below`. This allows the user to specify if they would like to only return forward looking data for options near the current stock price. This just obtains the data from `Options.get_near_stock_price` instead of `Options.get_xxx_data()` (GH2758).

- Cursor coordinate information is now displayed in time-series plots.
- added option `display.max_seq_items` to control the number of elements printed per sequence pprinting it. (GH2979)
- added option `display.chop_threshold` to control display of small numerical values. (GH2739)
- added option `display.max_info_rows` to prevent `verbose_info` from being calculated for frames above 1M rows (configurable). (GH2807, GH2918)
- `value_counts()` now accepts a “normalize” argument, for normalized histograms. (GH2710).
- `DataFrame.from_records` now accepts not only dicts but any instance of the collections.Mapping ABC.
- added option `display.mpl_style` providing a sleeker visual style for plots. Based on https://gist.github.com/huyng/816622 (GH3075).
- Treat boolean values as integers (values 1 and 0) for numeric operations. (GH2641)
- `to_html()` now accepts an optional “escape” argument to control reserved HTML character escaping (enabled by default) and escapes `&`, in addition to `<` and `>`. (GH2919)

See the full release notes or issue tracker on GitHub for a complete list.

Contributors

A total of 50 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Adam Greenhall +
- Alvaro Tejero-Cantero +
- Andy Hayden
- Brad Buran +
- Chang She
- Chapman Siu +
- Chris Withers +
- Christian Geier +
- Christopher Whelan
- Damien Garaud
- Dan Birken
- Dan Davison +
- Dieter Vandenbussche
- Drazen Lucanin +
- Dražen Lučanin +
- Garrett Drapala
- Illia Polosukhin +
- James Casbon +
- Jeff Reback
- Jeremy Wagner +
- Jonathan Chambers +
- K.-Michael Aye
- Karmel Allison +
- Loïc Estève +
- Nicholaus E. Halecky +
- Peter Prettenhofer +
- Phillip Cloud +
- Robert Gieseke +
- Skipper Seabold
- Spencer Lyon
- Stephen Lin +
- Thierry Moisan +
- Thomas Kluyver
- Tim Akinbo +
- Vytautas Janciauskas
- Vytautas Jančiauskas +
- Wes McKinney
- Will Furnass +
- Wouter Overmeire
- anomrake +
- davidjameshumphreys +
- dengemann +
• dieterv77 +
• jreback
• lexual +
• stephenwlin +
• thauck +
• vytas +
• waitingkuo +
• y·p

5.18 Version 0.10

5.18.1 Version 0.10.1 (January 22, 2013)

This is a minor release from 0.10.0 and includes new features, enhancements, and bug fixes. In particular, there is substantial new HDFStore functionality contributed by Jeff Reback.

An undesired API breakage with functions taking the `inplace` option has been reverted and deprecation warnings added.

### API changes

- Functions taking an `inplace` option return the calling object as before. A deprecation message has been added
- Groupby aggregations Max/Min no longer exclude non-numeric data (GH2700)
- Resampling an empty DataFrame now returns an empty DataFrame instead of raising an exception (GH2640)
- The file reader will now raise an exception when NA values are found in an explicitly specified integer column instead of converting the column to float (GH2631)
- `DatetimeIndex.unique` now returns a `DatetimeIndex` with the same name and timezone instead of an array (GH2563)

### New features

- MySQL support for database (contribution from Dan Allan)

### HDFStore

You may need to upgrade your existing data files. Please visit the compatibility section in the main docs.

You can designate (and index) certain columns that you want to be able to perform queries on a table, by passing a list to `data_columns`

```python
In [1]: store = pd.HDFStore('store.h5')
In [2]: df = pd.DataFrame(np.random.randn(8, 3),
                      index=pd.date_range('1/1/2000', periods=8),
                      columns=['A', 'B', 'C'])
```

(continues on next page)
In [3]: df['string'] = 'foo'
In [4]: df.loc[df.index[4:6], 'string'] = np.nan
In [5]: df.loc[df.index[7:9], 'string'] = 'bar'
In [6]: df['string2'] = 'cool'

In [7]: df
Out[7]:
   A    B    C   string  string2
0  2000-01-01  0.469112 -0.282863   foo        cool
1  2000-01-02 -1.135632  1.212112  -0.173215   foo        cool
2  2000-01-03   0.119209 -1.044236  -0.861849   foo        cool
3  2000-01-04  -2.104569 -0.494929  1.071804   foo        cool
4  2000-01-05   0.721555 -0.706771 -1.039575  NaN        cool
5  2000-01-06   0.271860 -0.424972  0.567020  NaN        cool
6  2000-01-07   0.276232 -1.087401 -0.673690   foo        cool
7  2000-01-08   0.113648 -1.478427  0.524988  bar        cool

# on-disk operations
In [8]: store.append('df', df, data_columns=['B', 'C', 'string', 'string2'])

In [9]: store.select('df', 'B>0 and string==\'foo\''
Out[9]:
   A    B    C   string  string2
0  2000-01-02 -1.135632  1.212112  -0.173215   foo        cool

# this is in-memory version of this type of selection
In [10]: df[(df.B > 0) & (df.string == 'foo')]
Out[10]:
   A    B    C   string  string2
0  2000-01-02 -1.135632  1.212112  -0.173215   foo        cool

Retrieving unique values in an indexable or data column.

# note that this is deprecated as of 0.14.0
# can be replicated by: store.select_column('df','index').unique()
store.unique('df', 'index')
store.unique('df', 'string')

You can now store datetime64 in data columns

In [11]: df_mixed = df.copy()

In [12]: df_mixed['datetime64'] = pd.Timestamp('20010102')

In [13]: df_mixed.loc[df_mixed.index[3:4], ['A', 'B']] = np.nan

In [14]: store.append('df_mixed', df_mixed)

In [15]: df_mixed1 = store.select('df_mixed')

In [16]: df_mixed1
Out[16]:
You can pass `columns` keyword to select to filter a list of the return columns, this is equivalent to passing a Term('columns',list_of_columns_to_filter)

HDFStore now serializes MultiIndex dataframes when appending tables.

In [19]: index = pd.MultiIndex(levels=[['foo', 'bar', 'baz', 'qux'],
                           ....: ['one', 'two', 'three'],
                           ....: labels=[[0, 0, 0, 1, 1, 2, 2, 3, 3, 3],
                           ....: [0, 1, 2, 0, 1, 1, 2, 0, 1, 2]],
                           ....: names=['foo', 'bar'])
In [20]: df = pd.DataFrame(np.random.randn(10, 3), index=index,
                          columns=['A', 'B', 'C'])
In [21]: df

foo bar
foo one -0.116619 0.295575 -1.047704
two 1.640556 1.905836 2.772115
three 0.088787 -1.144197 -0.633372
bar one 0.925372 -0.006438 -0.820408
two -0.600874 -1.039266 0.824758
baz two -0.824095 -0.337730 -0.927764
three -0.840123 0.248505 -0.109250

(continues on next page)
qux one  0.431977 -0.460710  0.336505  
  two  -3.207595 -1.535854  0.409769  
  three -0.673145 -0.741113 -0.110891  

In [22]: store.append('mi', df)  

In [23]: store.select('mi')  
Out[23]:  
          A    B    C  
foo bar  
foo one -0.116619 0.295575 -1.047704  
two  1.640556 1.905836  2.772115  
  three 0.088787 -1.144197 -0.633372  
bar one 0.925372 -0.006438 -0.820408  
two -0.600874 -1.039266  0.824758  
  three 0.840123  0.248505 -0.109250  
baz two -0.824095 -0.337730 -0.927764  
  three -0.840123  0.248505 -0.109250  
qux one 0.431977 -0.460710  0.336505  
two -3.207595 -1.535854  0.409769  
  three -0.673145 -0.741113 -0.110891  

# the levels are automatically included as data columns  
In [24]: store.select('mi', "foo='bar'")  
Out[24]:  
          A    B    C  
foo bar  
bar one 0.925372 -0.006438 -0.820408  
two -0.600874 -1.039266  0.824758  

Multi-table creation via *append_to_multiple* and selection via *select_as_multiple* can create/select from multiple tables and return a combined result, by using *where* on a selector table.

In [19]: df_mt = pd.DataFrame(np.random.randn(8, 6),  
                        index=pd.date_range('1/1/2000', periods=8),  
                        columns=['A', 'B', 'C', 'D', 'E', 'F'])  

In [20]: df_mt['foo'] = 'bar'  

# you can also create the tables individually  
In [21]: store.append_to_multiple({ 'df1_mt': ['A', 'B'], 'df2_mt': None),  
                               df_mt, selector='df1_mt')  

In [22]: store  
Out[22]:  
<class 'pandas.io.pytables.HDFStore'>  
File path: store.h5  

# individual tables were created  
In [23]: store.select('df1_mt')  
Out[23]:  
          A    B  
2000-01-01  0.404705  0.577046  
2000-01-02 -1.344312  0.844885  
2000-01-03  0.357021 -0.674600  

Enhancements

- **HDFStore** now can read native PyTables table format tables
  
  You can pass `nan_rep = 'my_nan_rep'` to append, to change the default nan representation on disk (which converts to/from `np.nan`), this defaults to `nan`.

- You can pass `index` to `append`. This defaults to `True`. This will automagically create indices on the *indexables* and *data columns* of the table

- You can pass `chunksize=an integer` to `append`, to change the writing chunksize (default is 50000). This will significantly lower your memory usage on writing.

- You can pass `expectedrows=an integer` to the first `append`, to set the TOTAL number of expected rows that PyTables will expected. This will optimize read/write performance.

- `Select` now supports passing `start` and `stop` to provide selection space limiting in selection.

- Greatly improved ISO8601 (e.g., yyyy-mm-dd) date parsing for file parsers (GH2698)

- Allow `DataFrame.merge` to handle combinatorial sizes too large for 64-bit integer (GH2690)

- Series now has unary negation (-series) and inversion (~series) operators (GH2686)

- `DataFrame.plot` now includes a `logx` parameter to change the x-axis to log scale (GH2327)

- Series arithmetic operators can now handle constant and ndarray input (GH2574)

- ExcelFile now takes a `kind` argument to specify the file type (GH2613)

- A faster implementation for Series.str methods (GH2602)

**Bug Fixes**
• **HDFStore** tables can now store `float32` types correctly (cannot be mixed with `float64` however)

• Fixed Google Analytics prefix when specifying request segment (GH2713).

• Function to reset Google Analytics token store so users can recover from improperly setup client secrets (GH2687).

• Fixed groupby bug resulting in segfault when passing in MultiIndex (GH2706)

• Fixed bug where passing a Series with datetime64 values into `to_datetime` results in bogus output values (GH2699)

• Fixed bug in pattern in HDFStore expressions when pattern is not a valid regex (GH2694)

• Fixed performance issues while aggregating boolean data (GH2692)

• When given a boolean mask key and a Series of new values, Series `__setitem__` will now align the incoming values with the original Series (GH2686)

• Fixed MemoryError caused by performing counting sort on sorting MultiIndex levels with a very large number of combinatorial values (GH2684)

• Fixed bug that causes plotting to fail when the index is a DatetimeIndex with a fixed-offset timezone (GH2683)

• Corrected business day subtraction logic when the offset is more than 5 bdays and the starting date is on a weekend (GH2680)

• Fixed C file parser behavior when the file has more columns than data (GH2668)

• Fixed file reader bug that misaligned columns with data in the presence of an implicit column and a specified `usecols` value

• DataFrames with numerical or datetime indices are now sorted prior to plotting (GH2609)

• Fixed DataFrame.from_records error when passed columns, index, but empty records (GH2633)

• Several bug fixed for Series operations when dtype is datetime64 (GH2689, GH2629, GH2626)

See the [full release notes](https://github.com/pandas-dev/pandas/releases) or issue tracker on GitHub for a complete list.

### Contributors

A total of 17 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

• Andy Hayden +

• Anton I. Sipos +

• Chang She

• Christopher Whelan

• Damien Garaud +

• Dan Allan +

• Dieter Vandenbussche

• Garrett Drapala +

• Jay Parlar +

• Thouis (Ray) Jones +

• Vincent Arel-Bundock +
5.18.2 Version 0.10.0 (December 17, 2012)

This is a major release from 0.9.1 and includes many new features and enhancements along with a large number of bug fixes. There are also a number of important API changes that long-time pandas users should pay close attention to.

**File parsing new features**

The delimited file parsing engine (the guts of `read_csv` and `read_table`) has been rewritten from the ground up and now uses a fraction the amount of memory while parsing, while being 40% or more faster in most use cases (in some cases much faster).

There are also many new features:

- Much-improved Unicode handling via the `encoding` option.
- Column filtering (`usecols`)
- Dtype specification (`dtype` argument)
- Ability to specify strings to be recognized as True/False
- Ability to yield NumPy record arrays (`as_recarray`)
- High performance `delim_whitespace` option
- Decimal format (e.g. European format) specification
- Easier CSV dialect options: `escapechar`, `lineterminator`, `quotechar`, etc.
- More robust handling of many exceptional kinds of files observed in the wild

**API changes**

**Deprecated DataFrame BINOP TimeSeries special case behavior**

The default behavior of binary operations between a DataFrame and a Series has always been to align on the DataFrame’s columns and broadcast down the rows, **except** in the special case that the DataFrame contains time series. Since there are now method for each binary operator enabling you to specify how you want to broadcast, we are phasing out this special case (Zen of Python: Special cases aren’t special enough to break the rules). Here’s what I’m talking about:

```
In [1]: import pandas as pd

In [2]: df = pd.DataFrame(np.random.randn(6, 4),
                      index=pd.date_range('1/1/2000', periods=6))
   ...:
```

(continues on next page)
In [3]: df
Out[3]:
      0   1   2   3
2000-01-01 0.469112 -0.282863 -1.509059 -1.135632
2000-01-02 1.212112 -0.173215  0.119209 -1.044236
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804
2000-01-04  0.721555 -0.706771 -1.039575  0.271860
2000-01-05 -0.424972  0.567020  0.276232 -1.087401
2000-01-06 -0.673690  0.113648 -1.478427  0.524988

# deprecated now
In [4]: df - df[0]
Out[4]:
      0   1   2   3
2000-01-01 NaN NaN NaN
2000-01-02 NaN NaN NaN
2000-01-03 NaN NaN NaN
2000-01-04 NaN NaN NaN
2000-01-05 NaN NaN NaN
2000-01-06 NaN NaN NaN

[6 rows x 10 columns]

# Change your code to
In [5]: df.sub(df[0], axis=0)  # align on axis 0 (rows)
Out[5]:
      0   1   2   3
2000-01-01 0.0 -0.751976 -1.978171 -1.604745
2000-01-02 0.0 -1.385327 -1.092903 -2.256348
2000-01-03 0.0 -1.428326 -1.761130 -0.449695
2000-01-04 0.0  0.991993  0.701204 -0.662428
2000-01-05 0.0  0.787338 -0.804737  1.198677

You will get a deprecation warning in the 0.10.x series, and the deprecated functionality will be removed in 0.11 or later.

**Altered resample default behavior**

The default time series resample binning behavior of daily D and higher frequencies has been changed to closed='left', label='left'. Lower frequencies are unaffected. The prior defaults were causing a great deal of confusion for users, especially resampling data to daily frequency (which labeled the aggregated group with the end of the interval: the next day).

In [1]: dates = pd.date_range('1/1/2000', '1/5/2000', freq='4h')
In [2]: series = pd.Series(np.arange(len(dates)), index=dates)
In [3]: series
Out[3]:
      0   1   2   3
2000-01-01 1.0  2.0  3.0  4.0
2000-01-02 1.0  2.0  3.0  4.0
2000-01-03 1.0  2.0  3.0  4.0
2000-01-04 1.0  2.0  3.0  4.0
2000-01-05 1.0  2.0  3.0  4.0
2000-01-01 00:00:00 0
2000-01-01 04:00:00 1
2000-01-01 08:00:00 2
2000-01-01 12:00:00 3
2000-01-01 16:00:00 4
2000-01-01 20:00:00 5
2000-01-02 00:00:00 6
2000-01-02 04:00:00 7
2000-01-02 08:00:00 8
2000-01-02 12:00:00 9
2000-01-02 16:00:00 10
2000-01-02 20:00:00 11
2000-01-03 00:00:00 12
2000-01-03 04:00:00 13
2000-01-03 08:00:00 14
2000-01-03 12:00:00 15
2000-01-03 16:00:00 16
2000-01-03 20:00:00 17
2000-01-04 00:00:00 18
2000-01-04 04:00:00 19
2000-01-04 08:00:00 20
2000-01-04 12:00:00 21
2000-01-04 16:00:00 22
2000-01-04 20:00:00 23
2000-01-05 00:00:00 24
Freq: 4H, dtype: int64

In [4]: series.resample('D', how='sum')
Out[4]:
2000-01-01  15
2000-01-02  51
2000-01-03  87
2000-01-04 123
2000-01-05  24
Freq: D, dtype: int64

In [5]: # old behavior
In [6]: series.resample('D', how='sum', closed='right', label='right')
Out[6]:
2000-01-01    0
2000-01-02    21
2000-01-03    57
2000-01-04    93
2000-01-05   129
Freq: D, dtype: int64

- Infinity and negative infinity are no longer treated as NA by isnull and notnull. That they ever were was a relic of early pandas. This behavior can be re-enabled globally by the mode.use_inf_as_null option:

In [6]: s = pd.Series([1.5, np.inf, 3.4, -np.inf])

In [7]: pd.isnull(s)
Out[7]:
0   False
1   False
2   False

(continues on next page)
3  False
Length: 4, dtype: bool

In [8]: s.fillna(0)
Out[8]:
   0 1.500000
   1      inf
   2  3.400000
   3     -inf
Length: 4, dtype: float64

In [9]: pd.set_option('use_inf_as_null', True)

In [10]: pd.isnull(s)
Out[10]:
   0  False
   1   True
   2  False
   3   True
Length: 4, dtype: bool

In [11]: s.fillna(0)
Out[11]:
   0  1.5
   1   0.0
   2  3.4
   3   0.0
Length: 4, dtype: float64

In [12]: pd.reset_option('use_inf_as_null')

• Methods with the inplace option now all return None instead of the calling object. E.g. code written like
df = df.fillna(0, inplace=True) may stop working. To fix, simply delete the unnecessary variable assignment.

• pandas.merge no longer sorts the group keys (sort=False) by default. This was done for performance reasons: the group-key sorting is often one of the more expensive parts of the computation and is often unnecessary.

• The default column names for a file with no header have been changed to the integers 0 through N − 1. This is to create consistency with the DataFrame constructor with no columns specified. The v0.9.0 behavior (names X0, X1,...) can be reproduced by specifying prefix='X':

In [6]: import io
   
In [7]: data = ('a,b,c
                   ...
                   ...
                   ...
                   '1,Yes,2
                   ...
                   '3,No,4')
                   ...

In [8]: print(data)
a,b,c
1,Yes,2
3,No,4

In [9]: pd.read_csv(io.StringIO(data), header=None)
Out[9]:

(continues on next page)
In [10]: pd.read_csv(io.StringIO(data), header=None, prefix='X')
Out[10]:
<table>
<thead>
<tr>
<th>X0</th>
<th>X1</th>
<th>X2</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>b</td>
<td>c</td>
</tr>
<tr>
<td>1 1</td>
<td>Yes</td>
<td>2</td>
</tr>
<tr>
<td>2 3</td>
<td>No</td>
<td>4</td>
</tr>
</tbody>
</table>

- Values like 'Yes' and 'No' are not interpreted as boolean by default, though this can be controlled by new `true_values` and `false_values` arguments:

```python
In [11]: print(data)
a,b,c
1,Yes,2
3,No,4
In [12]: pd.read_csv(io.StringIO(data))
Out[12]:
<table>
<thead>
<tr>
<th>a</th>
<th>b</th>
<th>c</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>Yes 2</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>No 4</td>
</tr>
</tbody>
</table>
In [13]: pd.read_csv(io.StringIO(data), true_values=['Yes'], false_values=['No'])
Out[13]:
<table>
<thead>
<tr>
<th>a</th>
<th>b</th>
<th>c</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>True 2</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>False 4</td>
</tr>
</tbody>
</table>
```

- The file parsers will not recognize non-string values arising from a converter function as NA if passed in the `na_values` argument. It’s better to do post-processing using the `replace` function instead.

- Calling `fillna` on Series or DataFrame with no arguments is no longer valid code. You must either specify a fill value or an interpolation method:

```python
In [14]: s = pd.Series([np.nan, 1., 2., np.nan, 4])
In [15]: s
Out[15]:
0    NaN
1    1.0
2    2.0
3    NaN
4    4.0
dtype: float64
In [16]: s.fillna(0)
Out[16]:
0    0.0
1    1.0
2    2.0
3    0.0
4    4.0
dtype: float64
```

(continues on next page)
In [17]: s.fillna(method='pad')
Out[17]:
0  NaN
1  1.0
2  2.0
3  2.0
4  4.0
dtype: float64

Convenience methods `ffill` and `bfill` have been added:

In [18]: s.ffill()
Out[18]:
0  NaN
1  1.0
2  2.0
3  2.0
4  4.0
dtype: float64

- `Series.apply` will now operate on a returned value from the applied function, that is itself a series, and possibly upcast the result to a DataFrame

In [19]: def f(x):
    ....:     return pd.Series([x, x**2], index=['x', 'x^2'])
    ....:

In [20]: s = pd.Series(np.random.rand(5))
In [21]: s
Out[21]:
0  0.340445
1  0.984729
2  0.919540
3  0.037772
4  0.861549
dtype: float64
In [22]: s.apply(f)
Out[22]:
        x    x^2
0  0.340445  0.115903
1  0.984729  0.969691
2  0.919540  0.845555
3  0.037772  0.001427
4  0.861549  0.742267

- New API functions for working with pandas options (GH2097):
  - `get_option` / `set_option` - get/set the value of an option. Partial names are accepted. - `reset_option` - reset one or more options to their default value. Partial names are accepted. - `describe_option` - print a description of one or more options. When called with no arguments, print all registered options.

Note: `set_printoptions`/`reset_printoptions` are now deprecated (but functioning), the print options now live under “display.XYZ”. For example:
**New features**

**Wide DataFrame printing**

Instead of printing the summary information, pandas now splits the string representation across multiple rows by default:

```python
In [24]: wide_frame = pd.DataFrame(np.random.randn(5, 16))

In [25]: wide_frame
```

The old behavior of printing out summary information can be achieved via the `expand_frame_repr` print option:

```python
In [26]: pd.set_option('expand_frame_repr', False)
```

The width of each line can be changed via `line_width` (80 by default):

```python
pd.set_option('line_width', 40)
```

```
pandas: powerful Python data analysis toolkit, Release 1.1.1

In [23]: pd.get_option("display.max_rows")
Out[23]: 15

• to_string() methods now always return unicode strings (GH2224).

New features

**Wide DataFrame printing**

Instead of printing the summary information, pandas now splits the string representation across multiple rows by default:

```python
In [24]: wide_frame = pd.DataFrame(np.random.randn(5, 16))

In [25]: wide_frame
```

The old behavior of printing out summary information can be achieved via the `expand_frame_repr` print option:

```python
In [26]: pd.set_option('expand_frame_repr', False)
```

The width of each line can be changed via `line_width` (80 by default):

```python
pd.set_option('line_width', 40)
```

```
pandas: powerful Python data analysis toolkit, Release 1.1.1

In [23]: pd.get_option("display.max_rows")
Out[23]: 15

• to_string() methods now always return unicode strings (GH2224).

New features

**Wide DataFrame printing**

Instead of printing the summary information, pandas now splits the string representation across multiple rows by default:

```python
In [24]: wide_frame = pd.DataFrame(np.random.randn(5, 16))

In [25]: wide_frame
```

The old behavior of printing out summary information can be achieved via the `expand_frame_repr` print option:

```python
In [26]: pd.set_option('expand_frame_repr', False)
```

The width of each line can be changed via `line_width` (80 by default):

```python
pd.set_option('line_width', 40)
```
Updated PyTables support

Docs for PyTables Table format & several enhancements to the API. Here is a taste of what to expect.

```
In [41]: store = pd.HDFStore('store.h5')

In [42]: df = pd.DataFrame(np.random.randn(8, 3),
       index=pd.date_range('1/1/2000', periods=8),
       columns=['A', 'B', 'C'])

In [43]: df
Out[43]:
          A       B       C
2000-01-01 -2.036047  0.000830 -0.955697
2000-01-02 -0.898872 -0.725411  0.059904
2000-01-03 -0.449644  1.082900 -1.221265
2000-01-04  0.361078  1.330704  0.855932
2000-01-05 -1.216718  1.488887  0.018993
2000-01-06 -0.877046  0.045976  0.437274
2000-01-07 -0.567182 -0.888657 -0.556383
2000-01-08  0.655457  1.117949 -2.782376
```

# appending data frames

```
In [44]: df = df[0:4]

In [45]: df2 = df[4:]

In [46]: store.append('df', df)

In [47]: store.append('df', df2)

In [48]: store
Out[48]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df    frame_table (typ->appendable,nrows->8,ncols->3,indexers->[index])
```

# selecting the entire store

```
In [49]: store.select('df')
Out[49]:
          A       B       C
2000-01-01 -2.036047  0.000830 -0.955697
2000-01-02 -0.898872 -0.725411  0.059904
2000-01-03 -0.449644  1.082900 -1.221265
2000-01-04  0.361078  1.330704  0.855932
2000-01-05 -1.216718  1.488887  0.018993
2000-01-06 -0.877046  0.045976  0.437274
2000-01-07 -0.567182 -0.888657 -0.556383
2000-01-08  0.655457  1.117949 -2.782376
```

In [50]: wp = pd.Panel(np.random.randn(2, 5, 4), items=['Item1', 'Item2'],
       index=[pd.date_range('1/1/2000', periods=5),
               'A', 'B', 'C', 'D'])
```
In [51]: wp  
Out[51]:  
<class 'pandas.core.panel.Panel'>  
Dimensions: 2 (items) x 5 (major_axis) x 4 (minor_axis)  
Items axis: Item1 to Item2  
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00  
Minor_axis axis: A to D  

# storing a panel  
In [52]: store.append('wp', wp)  

# selecting via A QUERY  
In [53]: store.select('wp', [pd.Term('major_axis>20000102'),  
....:   pd.Term('minor_axis', '=', ['A', 'B'])])  
....:  
Out[53]:  
<class 'pandas.core.panel.Panel'>  
Dimensions: 2 (items) x 3 (major_axis) x 2 (minor_axis)  
Items axis: Item1 to Item2  
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-05 00:00:00  
Minor_axis axis: A to B  

# removing data from tables  
In [54]: store.remove('wp', pd.Term('major_axis>20000103'))  
Out[54]: 8  

In [55]: store.select('wp')  
Out[55]:  
<class 'pandas.core.panel.Panel'>  
Dimensions: 2 (items) x 3 (major_axis) x 4 (minor_axis)  
Items axis: Item1 to Item2  
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-03 00:00:00  
Minor_axis axis: A to D  

# deleting a store  
In [56]: del store['df']  
In [57]: store  
Out[57]:  
<class 'pandas.io.pytables.HDFStore'>  
File path: store.h5  
/wp __wide_table (typ->appendable,nrows->12,ncols->2,indexers->[major_axis,  
˓→minor_axis])  

Enhancements  
- added ability to hierarchical keys  

In [58]: store.put('foo/bar/bah', df)  
In [59]: store.append('food/orange', df)  
In [60]: store.append('food/apple', df)  
In [61]: store  
Out[61]:  
(continues on next page)
• added mixed-dtype support!

In [64]: df['string'] = 'string'

In [65]: df['int'] = 1

In [66]: store.append('df', df)

In [67]: df1 = store.select('df')

In [68]: df1

Out[68]:

A   B     C        string int
2000-01-01 -2.036047 0.000830 -0.955697 string 1
2000-01-02 -0.898872 -0.725411 0.059904 string 1
2000-01-03 -0.449644 1.082900 -1.221265 string 1
2000-01-04  0.361078 1.330704  0.855932 string 1
2000-01-05 -1.216718 1.488887  0.018993 string 1
2000-01-06 -0.877046 0.045976  0.437274 string 1
2000-01-07 -0.567182 -0.888657 -0.556383 string 1
2000-01-08  0.655457 1.117949 -2.782376 string 1

[8 rows x 5 columns]

In [69]: df1.get_dtype_counts()

Out[69]:

float64 3
int64   1
object  1
dtype: int64

• performance improvements on table writing

• support for arbitrarily indexed dimensions

• SparseSeries now has a density property (GH2384)
• enable `Series.str.strip/lstrip/rstrip` methods to take an input argument to strip arbitrary characters (GH2411)
• implement `value_vars` in `melt` to limit values to certain columns and add `melt` to pandas namespace (GH2412)

**Bug Fixes**

• added `Term` method of specifying where conditions (GH1996).
• `del store['df']` now call `store.remove('df')` for store deletion
• deleting of consecutive rows is much faster than before
• `min_itemsize` parameter can be specified in table creation to force a minimum size for indexing columns (the previous implementation would set the column size based on the first append)
• indexing support via `create_table_index` (requires PyTables >= 2.3) (GH698).
• appending on a store would fail if the table was not first created via `put`
• fixed issue with missing attributes after loading a pickled dataframe (GH2431)
• minor change to select and remove: require a table ONLY if where is also provided (and not None)

**Compatibility**

0.10 of `HDFStore` is backwards compatible for reading tables created in a prior version of pandas, however, query terms using the prior (undocumented) methodology are unsupported. You must read in the entire file and write it out using the new format to take advantage of the updates.

**N dimensional panels (experimental)**

Adding experimental support for Panel4D and factory functions to create n-dimensional named panels. Here is a taste of what to expect.

```python
In [58]: p4d = Panel4D(np.random.randn(2, 2, 5, 4),
                  labels=['Label1','Label2'],
                  items=['Item1', 'Item2'],
                  major_axis=date_range('1/1/2000', periods=5),
                  minor_axis=['A', 'B', 'C', 'D'])
In [59]: p4d
Out[59]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 2 (labels) x 2 (items) x 5 (major_axis) x 4 (minor_axis)
Labels axis: Label1 to Label2
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D
```

See the [full release notes](https://github.com/pandas-dev/pandas/releases) or issue tracker on GitHub for a complete list.
Contributors

A total of 26 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- A. Flaxman +
- Abraham Flaxman
- Adam Obeng +
- Brenda Moon +
- Chang She
- Chris Mulligan +
- Dieter Vandenbussche
- Donald Curtis +
- Jay Bourque +
- Jeff Reback +
- Justin C Johnson +
- K.-Michael Aye
- Keith Hughitt +
- Ken Van Haren +
- Laurent Gautier +
- Luke Lee +
- Martin Blais
- Tobias Brandt +
- Wes McKinney
- Wouter Overmeire
- alex arsenovic +
- jreback +
- locojaydev +
- timmie
- y-p
- zach powers +
5.19 Version 0.9

5.19.1 Version 0.9.1 (November 14, 2012)

This is a bug fix release from 0.9.0 and includes several new features and enhancements along with a large number of bug fixes. The new features include by-column sort order for DataFrame and Series, improved NA handling for the rank method, masking functions for DataFrame, and intraday time-series filtering for DataFrame.

New features

• *Series.sort*, *DataFrame.sort*, and *DataFrame.sort_index* can now be specified in a per-column manner to support multiple sort orders (GH928)

```python
In [2]: df = pd.DataFrame(np.random.randint(0, 2, (6, 3)),
                   columns=['A', 'B', 'C'])
In [3]: df.sort(['A', 'B'], ascending=[1, 0])
```

```
Out[3]:
    A  B  C
0  0  1  1
1  0  1  1
2  0  0  1
3  1  0  0
4  1  0  0
5  1  0  0
```

• *DataFrame.rank* now supports additional argument values for the *na_option* parameter so missing values can be assigned either the largest or the smallest rank (GH1508, GH2159)

```python
In [1]: df = pd.DataFrame(np.random.randn(6, 3), columns=['A', 'B', 'C'])
In [3]: df.rank()
```

```
Out[3]:
    A  B  C
0  3.0 2.0 1.0
1  1.0 3.0 2.0
2  Nan Nan Nan
3  Nan Nan Nan
4  Nan Nan Nan
5  2.0 1.0 3.0
[6 rows x 3 columns]
In [4]: df.rank(na_option='top')
```

```
Out[4]:
    A  B  C
0  6.0 5.0 4.0
1  4.0 6.0 5.0
2  2.0 2.0 2.0
3  2.0 2.0 2.0
4  2.0 2.0 2.0
5  5.0 4.0 6.0
```

(continues on next page)
In [5]: df.rank(na_option='bottom')
Out[5]:
       A    B    C
0   3.0  2.0  1.0
1   1.0  3.0  2.0
2   5.0  5.0  5.0
3   5.0  5.0  5.0
4   5.0  5.0  5.0
5   2.0  1.0  3.0

• DataFrame has new `where` and `mask` methods to select values according to a given boolean mask (GH2109, GH2151)

Dataframe currently supports slicing via a boolean vector the same length as the Dataframe (inside the `[]`). The returned DataFrame has the same number of columns as the original, but is sliced on its index.

In [6]: df = DataFrame(np.random.randn(5, 3), columns=['A','B','C'])
In [7]: df
Out[7]:
       A    B    C
0  0.276232 -1.087401 -0.673690
1  0.113648 -1.478427  0.524988
2  0.404705  0.577046 -1.715002
3 -1.039268 -0.370647 -1.157892
4 -1.344312  0.844885  1.075770

In [8]: df[df['A'] > 0]
Out[8]:
       A    B    C
0  0.276232 -1.087401 -0.673690
1  0.113648 -1.478427  0.524988
2  0.404705  0.577046 -1.715002
3   NaN   NaN   NaN

If a DataFrame is sliced with a DataFrame based boolean condition (with the same size as the original DataFrame), then a DataFrame the same size (index and columns) as the original is returned, with elements that do not meet the boolean condition as `NaN`. This is accomplished via the new method `DataFrame.where`. In addition, `where` takes an optional `other` argument for replacement.

In [9]: df[df>0]
Out[9]:
       A    B    C
0  0.276232   NaN   NaN
1  0.113648   NaN  0.524988
2  0.404705  0.577046   NaN
3   NaN   NaN   NaN

(continues on next page)
Furthermore, `where` now aligns the input boolean condition (ndarray or DataFrame), such that partial selection with setting is possible. This is analogous to partial setting via `.ix` (but on the contents rather than the axis labels).

```
In [12]: df2 = df.copy()

In [13]: df2[ df2[1:4] > 0 ] = 3

In [14]: df2
Out[14]:
   A       B       C
0  0.276232 NaN   NaN
1  0.113648 NaN  0.524988
2  0.404705  0.577046 NaN
3   NaN   NaN   NaN
4   NaN  0.844885  1.075770
```

`DataFrame.mask` is the inverse boolean operation of `where`.

```
In [15]: df.mask(df<=0)
Out[15]:
   A       B       C
0  0.276232 NaN   NaN
1  0.113648 NaN  0.524988
2  0.404705  0.577046 NaN
3   NaN   NaN   NaN
4   NaN  0.844885  1.075770
```
- Enable referencing of Excel columns by their column names (GH1936)

```python
In [16]: xl = pd.ExcelFile('data/test.xls')
In [17]: xl.parse('Sheet1', index_col=0, parse_dates=True,
   ....:     parse_cols='A:D')
   ....:
Out[17]:
      A      B      C      D
   2000-01-03  0.980269  3.685731 -0.364217 -1.159738
   2000-01-04  1.047916 -0.041232 -0.161812  0.212549
   2000-01-05  0.498581  0.731168 -0.537677  1.346270
   2000-01-06  1.120202  1.567621  0.003641  0.675253
   2000-01-07 -0.487094  0.571455 -1.611639  0.103469
   2000-01-08  0.836649  0.246462  0.588543  1.062782
   2000-01-09 -0.157161  1.340307  1.195778 -1.097007
[7 rows x 4 columns]
```

- Added option to disable pandas-style tick locators and formatters using `series.plot(x_compat=True)` or `pandas.plot_params['x_compat'] = True` (GH2205)
- Existing TimeSeries methods `at_time` and `between_time` were added to DataFrame (GH2149)
- DataFrame.dot can now accept ndarrays (GH2042)
- DataFrame.drop now supports non-unique indexes (GH2101)
- Panel.shift now supports negative periods (GH2164)
- DataFrame now support unary ~ operator (GH2110)

### API changes

- Upsampling data with a PeriodIndex will result in a higher frequency TimeSeries that spans the original time window

```python
In [1]: prng = pd.period_range('2012Q1', periods=2, freq='Q')
In [2]: s = pd.Series(np.random.randn(len(prng)), prng)
In [4]: s.resample('M')
Out[4]:
   2012-01  -1.471992
   2012-02   NaN
   2012-03   NaN
   2012-04 -0.493593
   2012-05   NaN
   2012-06   NaN
Freq: M, dtype: float64
```

- Period.end_time now returns the last nanosecond in the time interval (GH2124, GH2125, GH1764)

```python
In [18]: p = pd.Period('2012')
In [19]: p.end_time
Out[19]: Timestamp('2012-12-31 23:59:59.999999999')
```

- File parsers no longer coerce to float or bool for columns that have custom converters specified (GH2184)
In [20]: import io

In [21]: data = ('A,B,C
....:
....:  '00001,001,5
....:  '00002,002,6')

In [22]: pd.read_csv(io.StringIO(data), converters={'A': lambda x: x.strip()})
Out[22]:
    A   B  C
   0  00001  1  5
   1  00002  2  6

[2 rows x 3 columns]

See the full release notes or issue tracker on GitHub for a complete list.

Contributors

A total of 11 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Brenda Moon +
- Chang She
- Jeff Reback +
- Justin C Johnson +
- K.-Michael Aye
- Martin Blais
- Tobias Brandt +
- Wes McKinney
- Wouter Overmeire
- timmie
- y-p

5.19.2 Version 0.9.0 (October 7, 2012)

This is a major release from 0.8.1 and includes several new features and enhancements along with a large number of bug fixes. New features include vectorized unicode encoding/decoding for Series.str, to_latex method to DataFrame, more flexible parsing of boolean values, and enabling the download of options data from Yahoo! Finance.
New features

- Add `encode` and `decode` for unicode handling to vectorized string processing methods in `Series.str` (GH1706)
- Add `DataFrame.to_latex` method (GH1735)
- Add convenient expanding window equivalents of all rolling_* ops (GH1785)
- Add Options class to pandas.io.data for fetching options data from Yahoo! Finance (GH1748, GH1739)
- More flexible parsing of boolean values (Yes, No, TRUE, FALSE, etc) (GH1691, GH1295)
- Add `level` parameter to `Series.reset_index`
- `TimeSeries.between_time` can now select times across midnight (GH1871)
- Series constructor can now handle generator as input (GH1679)
- `DataFrame.dropna` can now take multiple axes (tuple/list) as input (GH924)
- Enable `skip_footer` parameter in ExcelFile.parse (GH1843)

API changes

- The default column names when `header=None` and no columns names passed to functions like `read_csv` has changed to be more Pythonic and amenable to attribute access:

```
In [1]: import io
In [2]: data = ('0,0,1
   ...:  1,1,0
   ...:  0,1,0')
In [3]: df = pd.read_csv(io.StringIO(data), header=None)
In [4]: df
Out[4]:
   0  1  2
0  0  0  1
1  1  1  0
2  0  1  0
[3 rows x 3 columns]
```

- Creating a Series from another Series, passing an index, will cause reindexing to happen inside rather than treating the Series like an ndarray. Technically improper usages like `Series(df[col1], index=df[col2])` that worked before “by accident” (this was never intended) will lead to all NA Series in some cases. To be perfectly clear:

```
In [5]: sl = pd.Series([1, 2, 3])
In [6]: sl
Out[6]:
0  1
1  2
2  3
Length: 3, dtype: int64
```
pandas: powerful Python data analysis toolkit, Release 1.1.1

(continued from previous page)

In [7]: s2 = pd.Series(s1, index=['foo', 'bar', 'baz'])

In [8]: s2
Out[8]:
foo    NaN
bar    NaN
baz    NaN
Length: 3, dtype: float64

- Deprecated `day_of_year` API removed from PeriodIndex, use `dayofyear` (GH1723)
- Don’t modify NumPy suppress printoption to True at import time
- The internal HDF5 data arrangement for DataFrames has been transposed. Legacy files will still be readable by HDFStore (GH1834, GH1824)
- Legacy cruft removed: pandas.stats.misc.quantileTS
- Use ISO8601 format for Period repr: monthly, daily, and on down (GH1776)
- Empty DataFrame columns are now created as object dtype. This will prevent a class of TypeErrors that was occurring in code where the dtype of a column would depend on the presence of data or not (e.g. a SQL query having results) (GH1783)
- Setting parts of DataFrame/Panel using ix now aligns input Series/DataFrame (GH1630)
- `first` and `last` methods in GroupBy no longer drop non-numeric columns (GH1809)
- Resolved inconsistencies in specifying custom NA values in text parser. `na_values` of type dict no longer override default NAs unless `keep_default_na` is set to false explicitly (GH1657)
- `DataFrame.dot` will not do data alignment, and also work with Series (GH1915)

See the full release notes or issue tracker on GitHub for a complete list.

Contributors

A total of 24 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Chang She
- Christopher Whelan +
- Dan Miller +
- Daniel Shapiro +
- Dieter Vandenbussche
- Doug Coleman +
- John-Colvin +
- Johnny +
- Joshua Leahy +
- Lars Buitinck +
- Mark O’Leary +
- Martin Blais
**pandas: powerful Python data analysis toolkit, Release 1.1.1**

- MinRK +
- Paul Ivanov +
- Skipper Seabold
- Spencer Lyon +
- Taavi Burns +
- Wes McKinney
- Wouter Overmeire
- Yaroslav Halchenko
- lenolib +
- tshauck +
- y·p +
- Øystein S. Haaland +

## 5.20 Version 0.8

### 5.20.1 Version 0.8.1 (July 22, 2012)

This release includes a few new features, performance enhancements, and over 30 bug fixes from 0.8.0. New features include notably NA friendly string processing functionality and a series of new plot types and options.

**New features**

- Add *vectorized string processing methods* accessible via Series.str (GH620)
- Add option to disable adjustment in EWMA (GH1584)
- *Radviz plot* (GH1566)
- *Parallel coordinates plot*
- *Bootstrap plot*
- Per column styles and secondary y-axis plotting (GH1559)
- New datetime converters millisecond plotting (GH1599)
- Add option to disable “sparse” display of hierarchical indexes (GH1538)
- Series/DataFrame’s `set_index` method can *append levels* to an existing Index/MultiIndex (GH1569, GH1577)
**Performance improvements**

- Improved implementation of rolling min and max (thanks to Bottleneck !)
- Add accelerated 'median' GroupBy option (GH1358)
- Significantly improve the performance of parsing ISO8601-format date strings with DatetimeIndex or to_datetime (GH1571)
- Improve the performance of GroupBy on single-key aggregations and use with Categorical types
- Significant datetime parsing performance improvements

**Contributors**

A total of 5 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Chang She
- Skipper Seabold
- Todd DeLuca +
- Vytautas Janciauskas
- Wes McKinney

**5.20.2 Version 0.8.0 (June 29, 2012)**

This is a major release from 0.7.3 and includes extensive work on the time series handling and processing infrastructure as well as a great deal of new functionality throughout the library. It includes over 700 commits from more than 20 distinct authors. Most pandas 0.7.3 and earlier users should not experience any issues upgrading, but due to the migration to the NumPy datetime64 dtype, there may be a number of bugs and incompatibilities lurking. Lingering incompatibilities will be fixed ASAP in a 0.8.1 release if necessary. See the full release notes or issue tracker on GitHub for a complete list.

**Support for non-unique indexes**

All objects can now work with non-unique indexes. Data alignment / join operations work according to SQL join semantics (including, if application, index duplication in many-to-many joins)

**NumPy datetime64 dtype and 1.6 dependency**

Time series data are now represented using NumPy’s datetime64 dtype; thus, pandas 0.8.0 now requires at least NumPy 1.6. It has been tested and verified to work with the development version (1.7+) of NumPy as well which includes some significant user-facing API changes. NumPy 1.6 also has a number of bugs having to do with nanosecond resolution data, so I recommend that you steer clear of NumPy 1.6’s datetime64 API functions (though limited as they are) and only interact with this data using the interface that pandas provides.

See the end of the 0.8.0 section for a “porting” guide listing potential issues for users migrating legacy code bases from pandas 0.7 or earlier to 0.8.0.

Bug fixes to the 0.7.x series for legacy NumPy < 1.6 users will be provided as they arise. There will be no more further development in 0.7.x beyond bug fixes.
Time Series changes and improvements

Note: With this release, legacy scikits.timeseries users should be able to port their code to use pandas.

Note: See documentation for overview of pandas timeseries API.

- New datetime64 representation speeds up join operations and data alignment, reduces memory usage, and improve serialization / deserialization performance significantly over datetime.datetime

- High performance and flexible resample method for converting from high-to-low and low-to-high frequency. Supports interpolation, user-defined aggregation functions, and control over how the intervals and result labeling are defined. A suite of high performance Cython/C-based resampling functions (including Open-High-Low-Close) have also been implemented.

- Revamp of frequency aliases and support for frequency shortcuts like ‘15min’, or ‘1h30min’

- New DatetimeIndex class supports both fixed frequency and irregular time series. Replaces now deprecated DateRange class

- New PeriodIndex and Period classes for representing time spans and performing calendar logic, including the 12 fiscal quarterly frequencies <timeseries.quarterly>. This is a partial port of, and a substantial enhancement to, elements of the scikits.timeseries code base. Support for conversion between PeriodIndex and DatetimeIndex

- New Timestamp data type subclasses datetime.datetime, providing the same interface while enabling working with nanosecond-resolution data. Also provides easy time zone conversions.

- Enhanced support for time zones. Add tz_convert and tz_localize methods to TimeSeries and DataFrame. All timestamps are stored as UTC; Timestamps from DatetimeIndex objects with time zone set will be localized to local time. Time zone conversions are therefore essentially free. User needs to know very little about pytz library now; only time zone names as as strings are required. Time zone-aware timestamps are equal if and only if their UTC timestamps match. Operations between time zone-aware time series with different time zones will result in a UTC-indexed time series.

- Time series string indexing conveniences / shortcuts: slice years, year and month, and index values with strings

- Enhanced time series plotting: adaptation of scikits.timeseries matplotlib-based plotting code

- New date_range, bdate_range, and period_range factory functions

- Robust frequency inference function infer_freq and inferred_freq property of DatetimeIndex, with option to infer frequency on construction of DatetimeIndex

- to_datetime function efficiently parses array of strings to DatetimeIndex. DatetimeIndex will parse array or list of strings to datetime64

- Optimized support for datetime64-dtype data in Series and DataFrame columns

- New NaT (Not-a-Time) type to represent NA in timestamp arrays

- Optimize Series.asof for looking up “as of” values for arrays of timestamps

- Milli, Micro, Nano date offset objects

- Can index time series with datetime.time objects to select all data at particular time of day (TimeSeries.at_time) or between two times (TimeSeries.between_time)

- Add tshift method for leading/lagging using the frequency (if any) of the index, as opposed to a naive lead/lag using shift
Other new features

- New `cut` and `qcut` functions (like R’s cut function) for computing a categorical variable from a continuous variable by binning values either into value-based (`cut`) or quantile-based (`qcut`) bins
- Rename `Factor` to `Categorical` and add a number of usability features
- Add `limit` argument to `fillna/reindex`
- More flexible multiple function application in `GroupBy`, and can pass list (name, function) tuples to get result in particular order with given names
- Add flexible `replace` method for efficiently substituting values
- Enhanced `read_csv/read_table` for reading time series data and converting multiple columns to dates
- Add `comments` option to parser functions: `read_csv`, etc.
- Add `dayfirst` option to parser functions for parsing international DD/MM/YYYY dates
- Allow the user to specify the CSV reader `dialect` to control quoting etc.
- Handling `thousands` separators in `read_csv` to improve integer parsing.
- Enable unstacking of multiple levels in one shot. Alleviate `pivot_table` bugs (empty columns being introduced)
- Move to klib-based hash tables for indexing; better performance and less memory usage than Python’s dict
- Add first, last, min, max, and prod optimized GroupBy functions
- New `ordered_merge` function
- Add flexible `comparison` instance methods `eq`, `ne`, `lt`, `gt`, etc. to `DataFrame`, `Series`
- Improve `scatter_matrix` plotting function and add histogram or kernel density estimates to diagonal
- Add ‘kde’ plot option for density plots
- Support for converting `DataFrame` to R `data.frame` through `rpy2`
- Improved support for complex numbers in `Series` and `DataFrame`
- Add `pct_change` method to all data structures
- Add `max_colwidth` configuration option for `DataFrame` console output
- Interpolate `Series` values using index values
- Can select multiple columns from `GroupBy`
- Add `update` methods to `Series/DataFrame` for updating values in place
- Add `any` and `all` method to `DataFrame`

New plotting methods

```python
import pandas as pd
fx = pd.read_pickle('data/fx_prices')
import matplotlib.pyplot as plt

Series.plot now supports a `secondary_y` option:
```
plt.figure()
fx['FR'].plot(style='g')
fx['IT'].plot(style='k--', secondary_y=True)

Vytautas Jancauskas, the 2012 GSOC participant, has added many new plot types. For example, 'kde' is a new option:

```
In [1]: s = pd.Series(np.concatenate((np.random.randn(1000),
    ...
    np.random.randn(1000) * 0.5 + 3)))
    ...
In [2]: plt.figure()
Out[2]: <Figure size 640x480 with 0 Axes>
In [3]: s.hist(density=True, alpha=0.2)
Out[3]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe2782bc670>
In [4]: s.plot(kind='kde')
Out[4]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe2782bc670>
```

See the plotting page for much more.

**Other API changes**

- Deprecation of offset, time_rule, and timeRule arguments names in time series functions. Warnings will be printed until pandas 0.9 or 1.0.

**Potential porting issues for pandas <= 0.7.3 users**

The major change that may affect you in pandas 0.8.0 is that time series indexes use NumPy's datetime64 data type instead of dtype=object arrays of Python's built-in datetime.datetime objects. DateRange has been replaced by DatetimeIndex but otherwise behaved identically. But, if you have code that converts DateRange or Index objects that used to contain datetime.datetime values to plain NumPy arrays, you may have bugs lurking with code using scalar values because you are handing control over to NumPy:

```
In [5]: import datetime
In [6]: rng = pd.date_range('1/1/2000', periods=10)
In [7]: rng[5]
Out[7]: Timestamp('2000-01-06 00:00:00', freq='D')
In [8]: isinstance(rng[5], datetime.datetime)
Out[8]: True
In [9]: rng_asarray = np.asarray(rng)
In [10]: scalar_val = rng_asarray[5]
In [11]: type(scalar_val)
Out[11]: numpy.datetime64
```
pandas’s Timestamp object is a subclass of datetime.datetime that has nanosecond support (the nanosecond field store the nanosecond value between 0 and 999). It should substitute directly into any code that used datetime.datetime values before. Thus, I recommend not casting DatetimeIndex to regular NumPy arrays.

If you have code that requires an array of datetime.datetime objects, you have a couple of options. First, the astype(object) method of DatetimeIndex produces an array of Timestamp objects:

```python
In [12]: stamp_array = rng.astype(object)
In [13]: stamp_array
Out[13]:
Index(['2000-01-01 00:00:00', '2000-01-02 00:00:00', '2000-01-03 00:00:00',
       '2000-01-04 00:00:00', '2000-01-05 00:00:00', '2000-01-06 00:00:00',
       '2000-01-07 00:00:00', '2000-01-08 00:00:00', '2000-01-09 00:00:00',
       '2000-01-10 00:00:00'],
      dtype='object')
In [14]: stamp_array[5]
Out[14]: Timestamp('2000-01-06 00:00:00', freq='D')
```

To get an array of proper datetime.datetime objects, use the to_pydatetime method:

```python
In [15]: dt_array = rng.to_pydatetime()
In [16]: dt_array
Out[16]:
array([datetime.datetime(2000, 1, 1, 0, 0),
       datetime.datetime(2000, 1, 2, 0, 0),
       datetime.datetime(2000, 1, 3, 0, 0),
       datetime.datetime(2000, 1, 4, 0, 0),
       datetime.datetime(2000, 1, 5, 0, 0),
       datetime.datetime(2000, 1, 6, 0, 0),
       datetime.datetime(2000, 1, 7, 0, 0),
       datetime.datetime(2000, 1, 8, 0, 0),
       datetime.datetime(2000, 1, 9, 0, 0),
       datetime.datetime(2000, 1, 10, 0, 0)),
      dtype=object)
In [17]: dt_array[5]
Out[17]: datetime.datetime(2000, 1, 6, 0, 0)
```

matplotlib knows how to handle datetime.datetime but not Timestamp objects. While I recommend that you plot time series using TimeSeries.plot, you can either use to_pydatetime or register a converter for the Timestamp type. See matplotlib documentation for more on this.

```
Warning: There are bugs in the user-facing API with the nanosecond datetime64 unit in NumPy 1.6. In particular, the string version of the array shows garbage values, and conversion to dtype=object is similarly broken.
```

```python
In [18]: rng = pd.date_range('1/1/2000', periods=10)
In [19]: rng
   '2000-01-09', '2000-01-10'],
   dtype='datetime64[ns]', freq='D')
In [20]: np.asarray(rng)
```
Out[20]:
array(['2000-01-01T00:00:00.000000000', '2000-01-02T00:00:00.000000000',
      '2000-01-03T00:00:00.000000000', '2000-01-04T00:00:00.000000000',
      '2000-01-05T00:00:00.000000000', '2000-01-06T00:00:00.000000000',
      '2000-01-07T00:00:00.000000000', '2000-01-08T00:00:00.000000000',
      '2000-01-09T00:00:00.000000000', '2000-01-10T00:00:00.000000000'],
dtype='datetime64[ns]')

In [21]: converted = np.asarray(rng, dtype=object)

In [22]: converted[5]
Out[22]: Timestamp('2000-01-06 00:00:00', freq='D')

Trust me: don’t panic. If you are using NumPy 1.6 and restrict your interaction with `datetime64` values to pandas’s API you will be just fine. There is nothing wrong with the data-type (a 64-bit integer internally); all of the important data processing happens in pandas and is heavily tested. I strongly recommend that you do not work directly with `datetime64` arrays in NumPy 1.6 and only use the pandas API.

Support for non-unique indexes: In the latter case, you may have code inside a `try:`... `catch:` block that failed due to the index not being unique. In many cases it will no longer fail (some method like `append` still check for uniqueness unless disabled). However, all is not lost: you can inspect `index.is_unique` and raise an exception explicitly if it is `False` or go to a different code branch.

Contributors

A total of 27 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Adam Klein
- Chang She
- David Zaslavsky +
- Eric Chlebek +
- Jacques Kvam
- Kamil Kisiel
- Kelsey Jordahl +
- Kieran O’Mahony +
- Lorenzo Bolla +
- Luca Beltrame
- Marc Abramowitz +
- Mark Wiebe +
- Paddy Mullen +
- Peng Yu +
- Roy Hyunjin Han +
- RuiDC +
- Senthil Palanisami +
• Skipper Seabold
• Stefan van der Walt +
• Takafumi Arakaki +
• Thomas Kluyver
• Vytautas Jancauskas +
• Wes McKinney
• Wouter Overmeire
• Yaroslav Halchenko
• thuske +
• timmie +

5.21 Version 0.7

5.21.1 Version 0.7.3 (April 12, 2012)

This is a minor release from 0.7.2 and fixes many minor bugs and adds a number of nice new features. There are also a couple of API changes to note; these should not affect very many users, and we are inclined to call them “bug fixes” even though they do constitute a change in behavior. See the full release notes or issue tracker on GitHub for a complete list.

New features

• New fixed width file reader, read_fwf
• New scatter_matrix function for making a scatter plot matrix

```python
from pandas.tools.plotting import scatter_matrix
scatter_matrix(df, alpha=0.2)  # noqa F821
```

• Add stacked argument to Series and DataFrame’s plot method for stacked bar plots.

```python
df.plot(kind='bar', stacked=True)  # noqa F821
```

```python
df.plot(kind='barh', stacked=True)  # noqa F821
```

• Add log x and y scaling options to DataFrame.plot and Series.plot
• Add kurt methods to Series and DataFrame for computing kurtosis
NA boolean comparison API change

Reverted some changes to how NA values (represented typically as NaN or None) are handled in non-numeric Series:

```python
In [1]: series = pd.Series(['Steve', np.nan, 'Joe'])
In [2]: series == 'Steve'
Out[2]:
0    True
1   False
2   False
Length: 3, dtype: bool
In [3]: series != 'Steve'
Out[3]:
0   False
1    True
2    True
Length: 3, dtype: bool
```

In comparisons, NA / NaN will always come through as False except with != which is True. Be very careful with boolean arithmetic, especially negation, in the presence of NA data. You may wish to add an explicit NA filter into boolean array operations if you are worried about this:

```python
In [4]: mask = series == 'Steve'
In [5]: series[mask & series.notnull()]
Out[5]:
0    Steve
Length: 1, dtype: object
```

While propagating NA in comparisons may seem like the right behavior to some users (and you could argue on purely technical grounds that this is the right thing to do), the evaluation was made that propagating NA everywhere, including in numerical arrays, would cause a large amount of problems for users. Thus, a “practicality beats purity” approach was taken. This issue may be revisited at some point in the future.

Other API changes

When calling apply on a grouped Series, the return value will also be a Series, to be more consistent with the groupby behavior with DataFrame:

```python
In [6]: df = pd.DataFrame({'A': ['foo', 'bar', 'foo', 'bar',
                          'foo', 'bar', 'foo', 'foo'],
                     'B': ['one', 'one', 'two', 'three',
                          'two', 'two', 'one', 'three'],
                     'C': np.random.randn(8),
                     'D': np.random.randn(8))
In [7]: df
Out[7]:
     A    B        C        D
0  foo  one  0.469112 -0.861849
1  bar  one -0.282863  2.104569
2  foo  two -1.509059  0.494929
3  bar  three -1.135632  1.071804
4  foo  two  1.212112  0.721555
```

(continues on next page)
5 bar two -0.173215 -0.706771
6 foo one 0.119209 -1.039575
7 foo three -1.044236 0.271860

[8 rows x 4 columns]

In [8]: grouped = df.groupby('A')['C']

In [9]: grouped.describe()
Out[9]:

<table>
<thead>
<tr>
<th></th>
<th>count</th>
<th>mean</th>
<th>std</th>
<th>min</th>
<th>25%</th>
<th>50%</th>
<th>75%</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>bar</td>
<td>3.0</td>
<td>-0.53057</td>
<td>0.52686</td>
<td>-1.135632</td>
<td>-0.709248</td>
<td>-0.282863</td>
<td>-0.228039</td>
<td>-0.173215</td>
</tr>
<tr>
<td>foo</td>
<td>5.0</td>
<td>-0.150572</td>
<td>1.113308</td>
<td>-1.509059</td>
<td>-1.044236</td>
<td>0.119209</td>
<td>0.469112</td>
<td>1.212112</td>
</tr>
</tbody>
</table>

[2 rows x 8 columns]

In [10]: grouped.apply(lambda x: x.sort_values()[-2:])
# top 2 values
Out[10]:

<p>| | | | | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>bar</td>
<td>1</td>
<td>-0.282863</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>-0.173215</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>foo</td>
<td>0</td>
<td>0.469112</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>1.212112</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Name: C, Length: 4, dtype: float64

Contributors

A total of 15 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Abraham Flaxman +
- Adam Klein
- Andreas H. +
- Chang She
- Dieter Vandenbussche
- Jacques Kvam +
- K.-Michael Aye +
- Kamil Kisiel +
- Martin Blais +
- Skipper Seabold
- Thomas Kluyver
- Wes McKinney
- Wouter Overmeire
- Yaroslav Halchenko
- lgautier +
5.21.2 Version 0.7.2 (March 16, 2012)

This release targets bugs in 0.7.1, and adds a few minor features.

New features

- Add additional tie-breaking methods in DataFrame.rank (GH874)
- Add ascending parameter to rank in Series, DataFrame (GH875)
- Add coerce_float option to DataFrame.from_records (GH893)
- Add sort_columns parameter to allow unsorted plots (GH918)
- Enable column access via attributes on GroupBy (GH882)
- Can pass dict of values to DataFrame.fillna (GH661)
- Can select multiple hierarchical groups by passing list of values in .ix (GH134)
- Add axis option to DataFrame.fillna (GH174)
- Add level keyword to drop for dropping values from a level (GH159)

Performance improvements

- Use khash for Series.value_counts, add raw function to algorithms.py (GH861)
- Intercept __builtin__.__sum in groupby (GH885)

Contributors

A total of 12 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Adam Klein
- Benjamin Gross +
- Dan Birken +
- Dieter Vandenbussche
- Josh +
- Thomas Kluyver
- Travis N. Vaught +
- Wes McKinney
- Wouter Overmeire
- claudiobertoldi +
- elpres +
- joshuaar +
5.21.3 Version 0.7.1 (February 29, 2012)

This release includes a few new features and addresses over a dozen bugs in 0.7.0.

**New features**

- Add `to_clipboard` function to pandas namespace for writing objects to the system clipboard (GH774)
- Add `itertuples` method to DataFrame for iterating through the rows of a dataframe as tuples (GH818)
- Add ability to pass `fill_value` and method to DataFrame and Series align method (GH806, GH807)
- Add `fill_value` option to `reindex`, `align` methods (GH784)
- Enable `concat` to produce DataFrame from Series (GH787)
- Add `between` method to Series (GH802)
- Add HTML representation hook to DataFrame for the IPython HTML notebook (GH773)
- Support for reading Excel 2007 XML documents using openpyxl

**Performance improvements**

- Improve performance and memory usage of `fillna` on DataFrame
- Can concatenate a list of Series along axis=1 to obtain a DataFrame (GH787)

**Contributors**

A total of 9 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Adam Klein
- Brian Granger +
- Chang She
- Dieter Vandenbussche
- Josh Klein
- Steve +
- Wes McKinney
- Wouter Overmeire
- Yaroslav Halchenko
5.21.4 Version 0.7.0 (February 9, 2012)

New features

• New unified *merge function* for efficiently performing full gamut of database / relational-algebra operations. Refactored existing join methods to use the new infrastructure, resulting in substantial performance gains (GH220, GH249, GH267)

• New *unified concatenation function* for concatenating Series, DataFrame or Panel objects along an axis. Can form union or intersection of the other axes. Improves performance of `Series.append` and `DataFrame.append` (GH468, GH479, GH273)

• *Can* pass multiple DataFrames to `DataFrame.append` to concatenate (stack) and multiple Series to `Series.append` too

• *Can* pass list of dicts (e.g., a list of JSON objects) to `DataFrame构造` (GH526)

• You can now *set multiple columns* in a DataFrame via `__getitem__`, useful for transformation (GH342)

• Handle differently-indexed output values in `DataFrame.apply` (GH498)

```python
In [1]: df = pd.DataFrame(np.random.randn(10, 4))
In [2]: df.apply(lambda x: x.describe())
Out[2]:
         0      1      2      3
count 10.0000 10.0000 10.0000 10.0000
mean  0.1909 -0.3951 -0.7319 -0.4031
std   0.7309  0.8133  1.1120  0.9619
min  -0.8618 -2.1046 -1.7769 -1.4694
25%  -0.4114 -0.6987 -1.5014 -1.0766
50%   0.3808 -0.2280 -1.1919 -1.0041
75%   0.6584  0.0579 -0.0343  0.4617
max   1.2121  0.5770  1.6436  1.0718
```

• *Added* `reorder_levels` method to Series and DataFrame (GH534)

• *Added* dict-like get function to `DataFrame` and Panel (GH521)

• *Added* `DataFrame.iterrows` method for efficiently iterating through the rows of a DataFrame

• *Added* `DataFrame.to_panel` with code adapted from `LongPanel.to_long`

• *Added* `reindex_axis` method added to DataFrame

• *Added* level option to binary arithmetic functions on DataFrame and Series

• *Added* level option to the `reindex` and `align` methods on Series and DataFrame for broadcasting values across a level (GH542, GH552, others)

• *Added* attribute-based item access to Panel and add IPython completion (GH563)

• *Added* logy option to `Series.plot` for log-scaling on the Y axis

• *Added* index and header options to `DataFrame.to_string`

• *Can* pass multiple DataFrames to `DataFrame.join` to join on index (GH115)

• *Can* pass multiple Panels to `Panel.join` (GH115)

• *Added* `justify` argument to `DataFrame.to_string` to allow different alignment of column headers
• Add `sort` option to `GroupBy` to allow disabling sorting of the group keys for potential speedups (GH595)

• Can pass `MaskedArray` to `Series` constructor (GH563)

• Add Panel item access via attributes and IPython completion (GH554)

• Implement `DataFrame.lookup`, fancy-indexing analogue for retrieving values given a sequence of row and column labels (GH338)

• Can pass a `list of functions` to aggregate with `groupby` on a `DataFrame`, yielding an aggregated result with hierarchical columns (GH166)

• Can call `cummin` and `cummax` on `Series` and `DataFrame` to get cumulative minimum and maximum, respectively (GH647)

• `value_range` added as utility function to get min and max of a dataframe (GH288)

• Added `encoding` argument to `read_csv`, `read_table`, `to_csv` and `from_csv` for non-ascii text (GH717)

• Added `abs` method to pandas objects

• Added `crosstab` function for easily computing frequency tables

• Added `isin` method to index objects

• Added `level` argument to `xs` method of `DataFrame`.

### API changes to integer indexing

One of the potentially riskiest API changes in 0.7.0, but also one of the most important, was a complete review of how integer indexes are handled with regard to label-based indexing. Here is an example:

```
In [3]: s = pd.Series(np.random.randn(10), index=range(0, 20, 2))

In [4]: s
Out[4]:
0  -1.294524
2   0.413738
4   0.276662
6  -0.472035
8  -0.013960
10 -0.362543
12 -0.006154
14  0.923061
16  0.895717
18  0.805244
Length: 10, dtype: float64

In [5]: s[0]
Out[5]: -1.2945235902555294

In [6]: s[2]
Out[6]: 0.41373810535784006

In [7]: s[4]
Out[7]: 0.2766617129497566
```

This is all exactly identical to the behavior before. However, if you ask for a key not contained in the Series, in versions 0.6.1 and prior, Series would `fall back` on a location-based lookup. This now raises a `KeyError`:
pandas: powerful Python data analysis toolkit, Release 1.1.1

In [2]: s[1]
KeyError: 1

This change also has the same impact on DataFrame:

```
In [3]: df = pd.DataFrame(np.random.randn(8, 4), index=range(0, 16, 2))
In [4]: df
```

```
0 1 2 3
0 0.88427 0.3363 -0.1787 0.03162
2 0.14451 -0.1415 0.2504 0.58374
4 -1.44779 -0.9186 -1.4996 0.27163
6 -0.26598 -2.4184 -0.2658 0.11503
8 -0.58776 0.3144 -0.8566 0.61941
10 0.10940 -0.7175 -1.0108 0.47990
12 -1.16919 -0.3087 -0.6049 -0.43544
14 -0.07337 0.3410 0.0424 -0.16037
```

In [5]: df.ix[3]
KeyError: 3

In order to support purely integer-based indexing, the following methods have been added:

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.iget_value(i)</td>
<td>Retrieve value stored at location i</td>
</tr>
<tr>
<td>Series.iget(i)</td>
<td>Alias for iget_value</td>
</tr>
<tr>
<td>DataFrame.irow(i)</td>
<td>Retrieve the i-th row</td>
</tr>
<tr>
<td>DataFrame.icol(j)</td>
<td>Retrieve the j-th column</td>
</tr>
<tr>
<td>DataFrame.iget_value(i, j)</td>
<td>Retrieve the value at row i and column j</td>
</tr>
</tbody>
</table>

**API tweaks regarding label-based slicing**

Label-based slicing using `ix` now requires that the index be sorted (monotonic) **unless** both the start and endpoint are contained in the index:

```
In [1]: s = pd.Series(np.random.randn(6), index=list('gmkaec'))
In [2]: s
Out[2]:
g -1.182230
m -0.276183
k -0.243550
a  1.628992
e  0.073308
c -0.539890
dtype: float64
```

Then this is OK:

```
In [3]: s.ix['k':'e']
Out[3]:
k -0.243550
a  1.628992
e  0.073308
dtype: float64
```
But this is not:

```
In [12]: s ix['b':'h']
KeyError 'b'
```

If the index had been sorted, the “range selection” would have been possible:

```
In [4]: s2 = s.sort_index()
In [5]: s2
Out[5]:
a 1.628992
c -0.539890
e 0.073308
g -1.182230
k -0.243550
m -0.276183
dtype: float64
In [6]: s2 ix['b':'h']
Out[6]:
c -0.539890
e 0.073308
g -1.182230
dtype: float64
```

### Changes to Series [] operator

As as notational convenience, you can pass a sequence of labels or a label slice to a Series when getting and setting values via [] (i.e. the __getitem__ and __setitem__ methods). The behavior will be the same as passing similar input to ix except in the case of integer indexing:

```
In [8]: s = pd.Series(np.random.randn(6), index=list('acegkm'))
In [9]: s
Out[9]:
a -1.206412
c 2.565646
e 1.431256
g 1.340309
k -1.170299
m -0.226169
Length: 6, dtype: float64
In [10]: s[['m', 'a', 'c', 'e']]
Out[10]:
m -0.226169
a -1.206412
c 2.565646
e 1.431256
Length: 4, dtype: float64
In [11]: s['b':'l']
Out[11]:
c 2.565646
e 1.431256
```

(continues on next page)
In the case of integer indexes, the behavior will be exactly as before (shadowing ndarray):

```python
In [13]: s = pd.Series(np.random.randn(6), index=range(0, 12, 2))
```

```python
In [14]: s[[4, 0, 2]]
```

```python
Out[14]:
4  0.132003
0  0.410835
2  0.813850
Length: 3, dtype: float64
```

```python
In [15]: s[1:5]
```

```python
Out[15]:
2  0.813850
4  0.132003
6 -0.827317
8 -0.076467
Length: 4, dtype: float64
```

If you wish to do indexing with sequences and slicing on an integer index with label semantics, use `ix`.

**Other API changes**

- The deprecated `LongPanel` class has been completely removed
- If `Series.sort` is called on a column of a DataFrame, an exception will now be raised. Before it was possible to accidentally mutate a DataFrame’s column by doing `df[col].sort()` instead of the side-effect free method `df[col].order()` (GH316)
- Miscellaneous renames and deprecations which will (harmlessly) raise `FutureWarning`
- `drop` added as an optional parameter to `DataFrame.reset_index` (GH699)

**Performance improvements**

- `Cythonized GroupBy aggregations` no longer presort the data, thus achieving a significant speedup (GH93). GroupBy aggregations with Python functions significantly sped up by clever manipulation of the ndarray data type in Cython (GH496).
- Better error message in DataFrame constructor when passed column labels don’t match data (GH497)
- Substantially improve performance of multi-GroupBy aggregation when a Python function is passed, reuse ndarray object in Cython (GH496)
- Can store objects indexed by tuples and floats in HDFStore (GH492)
pandas: powerful Python data analysis toolkit, Release 1.1.1

- Don’t print length by default in Series.to_string, add length option (GH489)
- Improve Cython code for multi-groupby to aggregate without having to sort the data (GH93)
- Improve MultiIndex reindexing speed by storing tuples in the MultiIndex, test for backwards unpickling compatibility
- Improve column reindexing performance by using specialized Cython take function
- Further performance tweaking of Series.__getitem__ for standard use cases
- Avoid Index dict creation in some cases (i.e. when getting slices, etc.), regression from prior versions
- Friendlier error message in setup.py if NumPy not installed
- Use common set of NA-handling operations (sum, mean, etc.) in Panel class also (GH536)
- Default name assignment when calling reset_index on DataFrame with a regular (non-hierarchical) index (GH476)
- Use Cythonized groupers when possible in Series/DataFrame stat ops with level parameter passed (GH545)
- Ported skiplist data structure to C to speed up rolling_median by about 5-10x in most typical use cases (GH374)

Contributors

A total of 18 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Adam Klein
- Bayle Shanks +
- Chris Billington +
- Dieter Vandenbussche
- Fabrizio Pollastri +
- Graham Taylor +
- Gregg Lind +
- Josh Klein +
- Luca Beltrame
- Olivier Grisel +
- Skipper Seabold
- Thomas Kluyver
- Thomas Wiecki +
- Wes McKinney
- Wouter Overmeire
- Yaroslav Halchenko
- fabriziop +
- theandygross +
5.22 Version 0.6

5.22.1 Version 0.6.1 (December 13, 2011)

New features

- Can append single rows (as Series) to a DataFrame
- Add Spearman and Kendall rank correlation options to Series.corr and DataFrame.corr (GH428)
- Added get_value and set_value methods to Series, DataFrame, and Panel for very low-overhead access (>2x faster in many cases) to scalar elements (GH437, GH438). set_value is capable of producing an enlarged object.
- Add PyQt table widget to sandbox (GH435)
- DataFrame.align can accept Series arguments and an axis option (GH461)
- Implement new SparseArray and SparseList data structures. SparseSeries now derives from SparseArray (GH463)
- Better console printing options (GH453)
- Implement fast data ranking for Series and DataFrame, fast versions of scipy.stats.rankdata (GH428)
- Implement DataFrame.from_items alternate constructor (GH444)
- DataFrame.convert_objects method for inferring better dtypes for object columns (GH302)
- Add rolling_corr_pairwise function for computing Panel of correlation matrices (GH189)
- Add margins option to pivot_table for computing subgroup aggregates (GH114)
- Add Series.from_csv function (GH482)
- Can pass DataFrame/DataFrame and DataFrame/Series to rolling_corr/rolling_cov (GH #462)
- MultiIndex.get_level_values can accept the level name

Performance improvements

- Improve memory usage of DataFrame.describe (do not copy data unnecessarily) (PR #425)
- Optimize scalar value lookups in the general case by 25% or more in Series and DataFrame
- Fix performance regression in cross-sectional count in DataFrame, affecting DataFrame.dropna speed
- Column deletion in DataFrame copies no data (computes views on blocks) (GH #158)

Contributors

A total of 7 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Dieter Vandenbussche
- Fernando Perez +
- Jev Kuznetsov +
- Joon Ro
• Ralph Bean
• Wes McKinney
• Wouter Overmeire

5.22.2 Version 0.6.0 (November 25, 2011)

New features

• Added melt function to pandas.core.reshape
• Added level parameter to group by level in Series and DataFrame descriptive statistics (GH313)
• Added head and tail methods to Series, analogous to to DataFrame (GH296)
• Added Series.isin function which checks if each value is contained in a passed sequence (GH289)
• Added float_format option to Series.to_string
• Added skip_footer (GH291) and converters (GH343) options to read_csv and read_table
• Added drop_duplicates and duplicated functions for removing duplicate DataFrame rows and checking for duplicate rows, respectively (GH319)
• Implemented operators `&`, `|`, `^`, `-` on DataFrame (GH347)
• Added Series.mad, mean absolute deviation
• Added QuarterEnd DateOffset (GH321)
• Added dot to DataFrame (GH65)
• Added orient option to Panel.from_dict (GH359, GH301)
• Added orient option to DataFrame.from_dict
• Added passing list of tuples or list of lists to DataFrame.from_records (GH357)
• Added multiple levels to groupby (GH103)
• Allow multiple columns in by argument of DataFrame.sort_index (GH92, GH362)
• Added fast get_value and put_value methods to DataFrame (GH360)
• Added cov instance methods to Series and DataFrame (GH194, GH362)
• Added kind=`bar` option to DataFrame.plot (GH348)
• Added idxmin and idxmax to Series and DataFrame (GH286)
• Added read_clipboard function to parse DataFrame from clipboard (GH300)
• Added nunique function to Series for counting unique elements (GH297)
• Made DataFrame constructor use Series name if no columns passed (GH373)
• Support regular expressions in read_table/read_csv (GH364)
• Added DataFrame.to_html for writing DataFrame to HTML (GH387)
• Added support for MaskedArray data in DataFrame, masked values converted to NaN (GH396)
• Added DataFrame.boxplot function (GH368)
• Can pass extra args, kwds to DataFrame.apply (GH376)
• Implement DataFrame.join with vector on argument (GH312)
• **Added** legend boolean flag to `DataFrame.plot` (GH324)
• **Can** pass multiple levels to `stack` and `unstack` (GH370)
• **Can** pass multiple values columns to `pivot_table` (GH381)
• **Use** Series name in `GroupBy` for result index (GH363)
• **Added** `raw` option to `DataFrame.apply` for performance if only need `ndarray` (GH309)
• Added proper, tested weighted least squares to standard and panel OLS (GH303)

**Performance enhancements**

• VBENCH Cythonized `cache_readonly`, resulting in substantial micro-performance enhancements throughout the code base (GH361)
• VBENCH Special Cython matrix iterator for applying arbitrary reduction operations with 3-5x better performance than `np.apply_along_axis` (GH309)
• VBENCH Improved performance of `MultiIndex.from_tuples`
• VBENCH Special Cython matrix iterator for applying arbitrary reduction operations
• VBENCH + DOCUMENT **Add** `raw` option to `DataFrame.apply` for getting better performance when
• VBENCH Faster cythonized count by level in `Series` and `DataFrame` (GH341)
• VBENCH? Significant `GroupBy` performance enhancement with multiple keys with many “empty” combinations
• VBENCH New Cython vectorized function `map_infer` speeds up `Series.apply` and `Series.map` significantly when passed elementwise Python function, motivated by (GH355)
• VBENCH Significantly improved performance of `Series.order`, which also makes `np.unique` called on a `Series` faster (GH327)
• VBENCH Vastly improved performance of `GroupBy` on axes with a `MultiIndex` (GH299)

**Contributors**

A total of 8 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

• Adam Klein +
• Chang She +
• Dieter Vandenbussche
• Jeff Hammerbacher +
• Nathan Pinger +
• Thomas Kluyver
• Wes McKinney
• Wouter Overmeire +
5.23 Version 0.5

5.23.1 Version 0.5.0 (October 24, 2011)

New features

- Added `DataFrame.align` method with standard join options
- Added `parse_dates` option to `read_csv` and `read_table` methods to optionally try to parse dates in the index columns
- Added `nrows`, `chunksize`, and `iterator` arguments to `read_csv` and `read_table`. The last two return a new `TextParser` class capable of lazily iterating through chunks of a flat file (GH242)
- Added ability to join on multiple columns in `DataFrame.join` (GH214)
- Added private `_get_duplicates` function to `Index` for identifying duplicate values more easily (ENH5c)
- Added column attribute access to `DataFrame`.
- Added Python tab completion hook for `DataFrame` columns. (GH233, GH230)
- Implemented `Series.describe` for `Series` containing objects (GH241)
- Added `inner join` option to `DataFrame.join` when joining on key(s) (GH248)
- Implemented selecting `DataFrame` columns by passing a list to `__getitem__` (GH253)
- Implemented `&` and `|` to intersect / union `Index` objects, respectively (GH261)
- Added `pivot_table` convenience function to pandas namespace (GH234)
- Implemented `Panel.rename_axis` function (GH243)
- `DataFrame` will show index level names in console output (GH334)
- Implemented `Panel.take`
- Added `set_eng_float_format` for alternate `DataFrame` floating point string formatting (ENH61)
- Added convenience `set_index` function for creating a `DataFrame` index from its existing columns
- Implemented `groupby` hierarchical index level name (GH223)
- Added support for different delimiters in `DataFrame.to_csv` (GH244)
- TODO: DOCS ABOUT TAKE METHODS

Performance enhancements

- VBENCH Major performance improvements in file parsing functions `read_csv` and `read_table`
- VBENCH Added Cython function for converting tuples to ndarray very fast. Speeds up many MultiIndex-related operations
- VBENCH Refactored merging / joining code into a tidy class and disabled unnecessary computations in the float/object case, thus getting about 10% better performance (GH211)
- VBENCH Improved speed of `DataFrame.xs` on mixed-type `DataFrame` objects by about 5x, regression from 0.3.0 (GH215)
- VBENCH With new `DataFrame.align` method, speeding up binary operations between differently-indexed `DataFrame` objects by 10-25%.
- VBENCH Significantly sped up conversion of nested dict into DataFrame (GH212)
- VBENCH Significantly speed up DataFrame __repr__ and count on large mixed-type DataFrame objects

**Contributors**

A total of 9 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Aman Thakral +
- Luca Beltrame +
- Nick Pentreath +
- Skipper Seabold
- Thomas Kluyver +
- Wes McKinney
- Yaroslav Halchenko +
- lodagro +
- unknown +

**5.24 Version 0.4**

**5.24.1 Versions 0.4.1 through 0.4.3 (September 25 - October 9, 2011)**

**New features**

- Added Python 3 support using 2to3 (GH200)
- Added name attribute to Series, now prints as part of Series.__repr__
- Added instance methods isnull and notnull to Series (GH209, GH203)
- Added Series.align method for aligning two series with choice of join method (ENH56)
- Added method get_level_values to MultiIndex (GH188)
- Set values in mixed-type DataFrame objects via .ix indexing attribute (GH135)
- Added new DataFrame methods get_dtype_counts and property dtypes (ENHdc)
- Added ignore_index option to DataFrame.append to stack DataFrames (ENH1b)
- read_csv tries to sniff delimiters using csv.Sniffer (GH146)
- read_csv can read multiple columns into a MultiIndex; DataFrame’s to_csv method writes out a corresponding MultiIndex (GH151)
- DataFrame.rename has a new copy parameter to rename a DataFrame in place (ENHed)
- Enable unstacking by name (GH142)
- Enable sortlevel to work by level (GH141)
Performance enhancements

- Altered binary operations on differently-indexed SparseSeries objects to use the integer-based (dense) alignment logic which is faster with a larger number of blocks (GH205)
- Wrote faster Cython data alignment / merging routines resulting in substantial speed increases
- Improved performance of isnull and notnull, a regression from v0.3.0 (GH187)
- Refactored code related to DataFrame.join so that intermediate aligned copies of the data in each DataFrame argument do not need to be created. Substantial performance increases result (GH176)
- Substantially improved performance of generic Index.intersection and Index.union
- Implemented BlockManager.take resulting in significantly faster take performance on mixed-type DataFrame objects (GH104)
- Improved performance of Series.sort_index
- Significant groupby performance enhancement: removed unnecessary integrity checks in DataFrame internals that were slowing down slicing operations to retrieve groups
- Optimized _ensure_index function resulting in performance savings in type-checking Index objects
- Wrote fast time series merging / joining methods in Cython. Will be integrated later into DataFrame.join and related functions

Contributors

A total of 2 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Thomas Kluyver +
- Wes McKinney
BIBLIOGRAPHY

[1] https://docs.sqlalchemy.org
[1] https://docs.sqlalchemy.org
pandas, 1