# Contents

1 What’s New
   1.1 v0.17.0 (October 9, 2015) .................................................. 3
   1.2 v0.16.2 (June 12, 2015) .................................................. 28
   1.3 v0.16.1 (May 11, 2015) .................................................. 32
   1.4 v0.16.0 (March 22, 2015) .................................................. 42
   1.5 v0.15.2 (December 12, 2014) ............................................. 58
   1.6 v0.15.1 (November 9, 2014) .............................................. 63
   1.7 v0.15.0 (October 18, 2014) .............................................. 69
   1.8 v0.14.1 (July 11, 2014) .................................................. 96
   1.9 v0.14.0 (May 31, 2014) .................................................. 102
   1.10 v0.13.1 (February 3, 2014) .............................................. 129
   1.11 v0.13.0 (January 3, 2014) .............................................. 136
   1.12 v0.12.0 (July 24, 2013) ................................................. 159
   1.13 v0.11.0 (April 22, 2013) ................................................. 170
   1.14 v0.10.1 (January 22, 2013) .............................................. 179
   1.15 v0.10.0 (December 17, 2012) .......................................... 185
   1.16 v0.9.1 (November 14, 2012) .......................................... 196
   1.17 v0.9.0 (October 7, 2012) .............................................. 200
   1.18 v0.8.1 (July 22, 2012) .................................................. 202
   1.19 v0.8.0 (June 29, 2012) .................................................. 202
   1.20 v.0.7.3 (April 12, 2012) ............................................... 208
   1.21 v.0.7.2 (March 16, 2012) ............................................... 211
   1.22 v.0.7.1 (February 29, 2012) ........................................... 212
   1.23 v.0.7.0 (February 9, 2012) ........................................... 212
   1.24 v.0.6.1 (December 13, 2011) ......................................... 217
   1.25 v.0.6.0 (November 25, 2011) ...................................... 218
   1.26 v.0.5.0 (October 24, 2011) .......................................... 220
   1.27 v.0.4.3 through v0.4.1 (September 25 - October 9, 2011) ....... 221

2 Installation ................................................................. 223
   2.1 Python version support .................................................. 223
   2.2 Installing pandas ....................................................... 223
   2.3 Dependencies ............................................................ 226

3 Contributing to pandas .................................................. 229
   3.1 Where to start? .......................................................... 229
   3.2 Bug Reports/Enhancement Requests ................................... 230
   3.3 Working with the code ................................................... 230
   3.4 Contributing to the documentation .................................... 233
   3.5 Contributing to the code base ........................................... 235
   3.6 Contributing your changes to pandas ................................. 238
4 Frequently Asked Questions (FAQ)
   4.1 DataFrame memory usage ............................................. 241
   4.2 Byte-Ordering Issues ............................................. 242
   4.3 Visualizing Data in Qt applications .............................. 243

5 Package overview
   5.1 Data structures at a glance ........................................ 245
   5.2 Mutability and copying of data .................................... 246
   5.3 Getting Support ................................................... 246
   5.4 Credits .................................................................. 246
   5.5 Development Team .................................................. 246
   5.6 License ................................................................ 246

6 10 Minutes to pandas
   6.1 Object Creation ....................................................... 249
   6.2 Viewing Data ......................................................... 251
   6.3 Selection ................................................................ 252
   6.4 Missing Data .......................................................... 257
   6.5 Operations .............................................................. 257
   6.6 Merge .................................................................. 260
   6.7 Grouping ................................................................. 262
   6.8 Reshaping ............................................................... 263
   6.9 Time Series ............................................................. 265
   6.10 Categoricals ............................................................ 266
   6.11 Plotting ................................................................. 268
   6.12 Getting Data In/Out .................................................. 269
   6.13 Gotchas ................................................................ 271

7 Tutorials
   7.1 Internal Guides .......................................................... 273
   7.2 pandas Cookbook ....................................................... 273
   7.3 Lessons for New pandas Users ....................................... 274
   7.4 Practical data analysis with Python ............................... 274
   7.5 Excel charts with pandas, vincent and xlsxwriter .......... 274
   7.6 Various Tutorials ........................................................ 274

8 Cookbook
   8.1 Idioms .................................................................. 277
   8.2 Selection ................................................................. 280
   8.3 MultiIndexing .......................................................... 284
   8.4 Missing Data ........................................................... 288
   8.5 Grouping ................................................................. 289
   8.6 Timeseries ............................................................... 297
   8.7 Merge .................................................................. 298
   8.8 Plotting ................................................................. 299
   8.9 Data In/Out ............................................................ 300
   8.10 Computation ........................................................... 303
   8.11 Timedeltas .............................................................. 304
   8.12 Aliasing Axis Names ................................................. 305
   8.13 Creating Example Data ............................................. 306

9 Intro to Data Structures
   9.1 Series .................................................................. 307
   9.2 DataFrame .............................................................. 311
   9.3 Panel .................................................................. 326
<table>
<thead>
<tr>
<th>Chapter</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>14</td>
<td>MultiIndex / Advanced Indexing</td>
<td>453</td>
</tr>
<tr>
<td>14.1</td>
<td>Hierarchical indexing (MultiIndex)</td>
<td>453</td>
</tr>
<tr>
<td>14.2</td>
<td>Advanced indexing with hierarchical index</td>
<td>459</td>
</tr>
<tr>
<td>14.3</td>
<td>The need for sortedness with MultiIndex</td>
<td>468</td>
</tr>
<tr>
<td>14.4</td>
<td>Take Methods</td>
<td>470</td>
</tr>
<tr>
<td>14.5</td>
<td>CategoricalIndex</td>
<td>471</td>
</tr>
<tr>
<td>14.6</td>
<td>Float64Index</td>
<td>474</td>
</tr>
<tr>
<td>15</td>
<td>Computational tools</td>
<td>479</td>
</tr>
<tr>
<td>15.1</td>
<td>Statistical functions</td>
<td>479</td>
</tr>
<tr>
<td>15.2</td>
<td>Moving (rolling) statistics / moments</td>
<td>483</td>
</tr>
<tr>
<td>15.3</td>
<td>Expanding window moment functions</td>
<td>491</td>
</tr>
<tr>
<td>15.4</td>
<td>Exponentially weighted moment functions</td>
<td>492</td>
</tr>
<tr>
<td>16</td>
<td>Working with missing data</td>
<td>497</td>
</tr>
<tr>
<td>16.1</td>
<td>Missing data basics</td>
<td>497</td>
</tr>
<tr>
<td>16.2</td>
<td>Datetimes</td>
<td>499</td>
</tr>
<tr>
<td>16.3</td>
<td>Inserting missing data</td>
<td>500</td>
</tr>
<tr>
<td>16.4</td>
<td>Calculations with missing data</td>
<td>501</td>
</tr>
<tr>
<td>16.5</td>
<td>Cleaning / filling missing data</td>
<td>502</td>
</tr>
<tr>
<td>16.6</td>
<td>Missing data casting rules and indexing</td>
<td>516</td>
</tr>
<tr>
<td>17</td>
<td>Group By: split-apply-combine</td>
<td>519</td>
</tr>
<tr>
<td>17.1</td>
<td>Splitting an object into groups</td>
<td>520</td>
</tr>
<tr>
<td>17.2</td>
<td>Iterating through groups</td>
<td>524</td>
</tr>
<tr>
<td>17.3</td>
<td>Selecting a group</td>
<td>525</td>
</tr>
<tr>
<td>17.4</td>
<td>Aggregation</td>
<td>526</td>
</tr>
<tr>
<td>17.5</td>
<td>Transformation</td>
<td>529</td>
</tr>
<tr>
<td>17.6</td>
<td>Filtration</td>
<td>533</td>
</tr>
<tr>
<td>17.7</td>
<td>Dispatching to instance methods</td>
<td>534</td>
</tr>
<tr>
<td>17.8</td>
<td>Flexible apply</td>
<td>536</td>
</tr>
<tr>
<td>17.9</td>
<td>Other useful features</td>
<td>538</td>
</tr>
<tr>
<td>17.10</td>
<td>Examples</td>
<td>545</td>
</tr>
<tr>
<td>18</td>
<td>Merge, join, and concatenate</td>
<td>547</td>
</tr>
<tr>
<td>18.1</td>
<td>Concatenating objects</td>
<td>547</td>
</tr>
<tr>
<td>18.2</td>
<td>Database-style DataFrame joining/merging</td>
<td>558</td>
</tr>
<tr>
<td>19</td>
<td>Reshaping and Pivot Tables</td>
<td>573</td>
</tr>
<tr>
<td>19.1</td>
<td>Reshaping by pivoting DataFrame objects</td>
<td>573</td>
</tr>
<tr>
<td>19.2</td>
<td>Reshaping by stacking and unstacking</td>
<td>574</td>
</tr>
<tr>
<td>19.3</td>
<td>Reshaping by Melt</td>
<td>579</td>
</tr>
<tr>
<td>19.4</td>
<td>Combining with stats and GroupBy</td>
<td>580</td>
</tr>
<tr>
<td>19.5</td>
<td>Pivot tables and cross-tabulations</td>
<td>581</td>
</tr>
<tr>
<td>19.6</td>
<td>Tiling</td>
<td>585</td>
</tr>
<tr>
<td>19.7</td>
<td>Computing indicator / dummy variables</td>
<td>585</td>
</tr>
<tr>
<td>19.8</td>
<td>Factorizing values</td>
<td>588</td>
</tr>
<tr>
<td>20</td>
<td>Time Series / Date functionality</td>
<td>589</td>
</tr>
<tr>
<td>20.1</td>
<td>Overview</td>
<td>590</td>
</tr>
<tr>
<td>20.2</td>
<td>Time Stamps vs. Time Spans</td>
<td>590</td>
</tr>
<tr>
<td>20.3</td>
<td>Converting to Timestamps</td>
<td>591</td>
</tr>
<tr>
<td>20.4</td>
<td>Generating Ranges of Timestamps</td>
<td>594</td>
</tr>
<tr>
<td>20.5</td>
<td>DatetimeIndex</td>
<td>596</td>
</tr>
<tr>
<td>20.6</td>
<td>DateOffset objects</td>
<td>602</td>
</tr>
</tbody>
</table>
# Index

25.1 Yahoo! Finance .............................................. 851
25.2 Yahoo! Finance Options ..................................... 852
25.3 Google Finance ............................................... 854
25.4 FRED .......................................................... 854
25.5 Fama/French ................................................... 855
25.6 World Bank ................................................... 855
25.7 Google Analytics ............................................ 858

26 Enhancing Performance ........................................ 861
  26.1 Cython (Writing C extensions for pandas) .................. 861
  26.2 Using numba .................................................. 865
  26.3 Expression Evaluation via `eval()` (Experimental) .... 867

27 Sparse data structures ......................................... 875
  27.1 SparseArray .................................................. 877
  27.2 SparseList ................................................... 877
  27.3 SparseIndex objects .......................................... 878
  27.4 Interaction with scipy.sparse ................................ 878

28 Caveats and Gotchas ......................................... 883
  28.1 Using If/Truth Statements with pandas .................... 883
  28.2 NaN, Integer NA values and NA type promotions ....... 884
  28.3 Integer indexing ............................................ 886
  28.4 Label-based slicing conventions .......................... 886
  28.5 Miscellaneous indexing gotchas ............................ 887
  28.6 Timestamp limitations ....................................... 889
  28.7 Parsing Dates from Text Files .............................. 889
  28.8 Differences with NumPy ...................................... 890
  28.9 Thread-safety ................................................ 890
  28.10 HTML Table Parsing ......................................... 890
  28.11 Byte-Ordering Issues ....................................... 891

29 rpy2 / R interface ........................................... 893
  29.1 Updating your code to use rpy2 functions ............... 893
  29.2 R interface with rpy2 ....................................... 894
  29.3 Transferring R data sets into Python ..................... 894
  29.4 Converting DataFrames into R objects .................... 894
  29.5 Calling R functions with pandas objects ............... 895
  29.6 High-level interface to R estimators ..................... 895

30 pandas Ecosystem ............................................. 897
  30.1 Statistics and Machine Learning ......................... 897
  30.2 Visualization ............................................... 897
  30.3 IDE .......................................................... 898
  30.4 API .......................................................... 899
  30.5 Domain Specific ............................................. 899
  30.6 Out-of-core ................................................ 899

31 Comparison with R / R libraries ............................. 901
  31.1 Base R ........................................................ 901
  31.2 zoo .......................................................... 907
  31.3 xts .......................................................... 907
  31.4 plyr .......................................................... 907
  31.5 reshape / reshape2 .......................................... 908
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>32</td>
<td>Comparison with SQL</td>
<td>913</td>
</tr>
<tr>
<td>32.1</td>
<td>SELECT</td>
<td>913</td>
</tr>
<tr>
<td>32.2</td>
<td>WHERE</td>
<td>914</td>
</tr>
<tr>
<td>32.3</td>
<td>GROUP BY</td>
<td>916</td>
</tr>
<tr>
<td>32.4</td>
<td>JOIN</td>
<td>918</td>
</tr>
<tr>
<td>32.5</td>
<td>UNION</td>
<td>919</td>
</tr>
<tr>
<td>32.6</td>
<td>UPDATE</td>
<td>921</td>
</tr>
<tr>
<td>32.7</td>
<td>DELETE</td>
<td>921</td>
</tr>
<tr>
<td>33</td>
<td>Comparison with SAS</td>
<td>923</td>
</tr>
<tr>
<td>33.1</td>
<td>Data Structures</td>
<td>923</td>
</tr>
<tr>
<td>33.2</td>
<td>Data Input / Output</td>
<td>924</td>
</tr>
<tr>
<td>33.3</td>
<td>Data Operations</td>
<td>925</td>
</tr>
<tr>
<td>33.4</td>
<td>Merging</td>
<td>929</td>
</tr>
<tr>
<td>33.5</td>
<td>Missing Data</td>
<td>930</td>
</tr>
<tr>
<td>33.6</td>
<td>GroupBy</td>
<td>932</td>
</tr>
<tr>
<td>33.7</td>
<td>Other Considerations</td>
<td>934</td>
</tr>
<tr>
<td>34</td>
<td>API Reference</td>
<td>935</td>
</tr>
<tr>
<td>34.1</td>
<td>Input/Output</td>
<td>935</td>
</tr>
<tr>
<td>34.2</td>
<td>General functions</td>
<td>963</td>
</tr>
<tr>
<td>34.3</td>
<td>Series</td>
<td>1006</td>
</tr>
<tr>
<td>34.4</td>
<td>DataFrame</td>
<td>1180</td>
</tr>
<tr>
<td>34.5</td>
<td>Panel</td>
<td>1373</td>
</tr>
<tr>
<td>34.6</td>
<td>Panel4D</td>
<td>1465</td>
</tr>
<tr>
<td>34.7</td>
<td>Index</td>
<td>1519</td>
</tr>
<tr>
<td>34.8</td>
<td>CategoricalIndex</td>
<td>1552</td>
</tr>
<tr>
<td>34.9</td>
<td>DatetimeIndex</td>
<td>1579</td>
</tr>
<tr>
<td>34.10</td>
<td>TimedeltaIndex</td>
<td>1612</td>
</tr>
<tr>
<td>34.11</td>
<td>GroupBy</td>
<td>1634</td>
</tr>
<tr>
<td>34.12</td>
<td>General utility functions</td>
<td>1656</td>
</tr>
<tr>
<td>35</td>
<td>Internals</td>
<td>1669</td>
</tr>
<tr>
<td>35.1</td>
<td>Indexing</td>
<td>1669</td>
</tr>
<tr>
<td>35.2</td>
<td>Subclassing pandas Data Structures</td>
<td>1670</td>
</tr>
<tr>
<td>36</td>
<td>Release Notes</td>
<td>1675</td>
</tr>
<tr>
<td>36.1</td>
<td>pandas 0.17.0</td>
<td>1675</td>
</tr>
<tr>
<td>36.2</td>
<td>pandas 0.16.2</td>
<td>1679</td>
</tr>
<tr>
<td>36.3</td>
<td>pandas 0.16.1</td>
<td>1680</td>
</tr>
<tr>
<td>36.4</td>
<td>pandas 0.16.0</td>
<td>1682</td>
</tr>
<tr>
<td>36.5</td>
<td>pandas 0.15.2</td>
<td>1684</td>
</tr>
<tr>
<td>36.6</td>
<td>pandas 0.15.1</td>
<td>1686</td>
</tr>
<tr>
<td>36.7</td>
<td>pandas 0.15.0</td>
<td>1687</td>
</tr>
<tr>
<td>36.8</td>
<td>pandas 0.14.1</td>
<td>1689</td>
</tr>
<tr>
<td>36.9</td>
<td>pandas 0.14.0</td>
<td>1691</td>
</tr>
<tr>
<td>36.10</td>
<td>pandas 0.13.1</td>
<td>1694</td>
</tr>
<tr>
<td>36.11</td>
<td>pandas 0.13.0</td>
<td>1697</td>
</tr>
<tr>
<td>36.12</td>
<td>pandas 0.12.0</td>
<td>1711</td>
</tr>
<tr>
<td>36.13</td>
<td>pandas 0.11.0</td>
<td>1718</td>
</tr>
<tr>
<td>36.14</td>
<td>pandas 0.10.1</td>
<td>1724</td>
</tr>
<tr>
<td>36.15</td>
<td>pandas 0.10.0</td>
<td>1726</td>
</tr>
<tr>
<td>36.16</td>
<td>pandas 0.9.1</td>
<td>1731</td>
</tr>
<tr>
<td>36.17</td>
<td>pandas 0.9.0</td>
<td>1733</td>
</tr>
<tr>
<td>36.18</td>
<td>pandas 0.8.1</td>
<td>1738</td>
</tr>
<tr>
<td>Version</td>
<td>Description</td>
<td>Page</td>
</tr>
<tr>
<td>---------</td>
<td>-------------</td>
<td>------</td>
</tr>
<tr>
<td>36.19</td>
<td>pandas 0.8.0</td>
<td>1740</td>
</tr>
<tr>
<td>36.20</td>
<td>pandas 0.7.3</td>
<td>1745</td>
</tr>
<tr>
<td>36.21</td>
<td>pandas 0.7.2</td>
<td>1746</td>
</tr>
<tr>
<td>36.22</td>
<td>pandas 0.7.1</td>
<td>1748</td>
</tr>
<tr>
<td>36.23</td>
<td>pandas 0.7.0</td>
<td>1749</td>
</tr>
<tr>
<td>36.24</td>
<td>pandas 0.6.1</td>
<td>1755</td>
</tr>
<tr>
<td>36.25</td>
<td>pandas 0.6.0</td>
<td>1757</td>
</tr>
<tr>
<td>36.26</td>
<td>pandas 0.5.0</td>
<td>1761</td>
</tr>
<tr>
<td>36.27</td>
<td>pandas 0.4.3</td>
<td>1765</td>
</tr>
<tr>
<td>36.28</td>
<td>pandas 0.4.2</td>
<td>1766</td>
</tr>
<tr>
<td>36.29</td>
<td>pandas 0.4.1</td>
<td>1767</td>
</tr>
<tr>
<td>36.30</td>
<td>pandas 0.4.0</td>
<td>1769</td>
</tr>
<tr>
<td>36.31</td>
<td>pandas 0.3.0</td>
<td>1774</td>
</tr>
</tbody>
</table>

**Python Module Index**

1777
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, moving window linear regressions, date shifting and lagging, etc.
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.**

**Note:** This documentation assumes general familiarity with NumPy. If you haven’t used NumPy much or at all, do invest some time in learning about NumPy first.

See the package overview for more detail about what’s in the library.
CHAPTER ONE

WHAT'S NEW

These are new features and improvements of note in each release.

1.1 v0.17.0 (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 unparsable 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)
What’s new in v0.17.0

• New features
  – Datetime with TZ
  – Releasing the GIL
  – Plot submethods
  – Additional methods for dt accessor
    * strftime
    * 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
  – Changes to bool passed as header in Parsers
  – Other API Changes
  – Deprecations
  – Removal of prior version deprecations/changes
• Performance Improvements
• Bug Fixes

1.1.1 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.

```
In [1]: df = DataFrame({'A' : date_range('20130101',periods=3),
                      'B' : date_range('20130101',periods=3,tz='US/Eastern'),
                      'C' : 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

In [3]: df.dtypes
Out[3]:
A             datetime64[ns]
B       datetime64[ns, US/Eastern]
C      datetime64[ns, CET]
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, 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, 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.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') 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>(...):

```
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:

```
In [12]: df.plot.<TAB>
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

#### strftime

We are now supporting a `Series.dt.strftime` method for datetime-likes to generate a formatted string (GH10110). Examples:

```
# DatetimeIndex
In [13]: s = pd.Series(pd.date_range('20130101', periods=4))
```

```
In [14]: s
Out[14]:
      0  2013-01-01
      1  2013-01-02
      2  2013-01-03
      3  2013-01-04
dtype: datetime64[ns]
```

```
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
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
dtype: object

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
dtype: object

The string format is as the python standard library and details can be found here

**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
dtype: timedelta64[ns]

In [21]: s.dt.total_seconds()
Out[21]:
0    60
1  86460
2 172860
3 259260
dtype: float64

**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 00:00:00')

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='int64', freq='2D')
In [30]: idx + 1
Out[30]: PeriodIndex(['2015-08-03', '2015-08-05', '2015-08-07', '2015-08-09'], dtype='int64', 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)

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, 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.

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([['j'],['l','k']],
   names = ['i1', 'i2']))

In [32]: df
Out[32]:
       col1  col2
    foo bar
    a  b  a  b
    j 1  1  2  3  4
    k 5  6  7  8

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  col2
    foo bar
    a  b  a  b
    j 1  1  2  3  4
    k 5  6  7  8

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>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>idx_name</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>2000-01-07 00:00:00</td>
<td>0.968129</td>
<td>0.906529</td>
<td>0.05343</td>
<td>0.02619</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>2000-01-10 00:00:00</td>
<td>-0.16632</td>
<td>1.981993</td>
<td>1.830939</td>
<td>0.803685</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>2000-01-11 00:00:00</td>
<td>0.121057</td>
<td>0.36946</td>
<td>-0.02888</td>
<td>1.683975</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>2000-01-12 00:00:00</td>
<td>-1.70456</td>
<td>-0.73089</td>
<td>-0.38088</td>
<td>0.020946</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>2000-01-13 00:00:00</td>
<td>-1.20024</td>
<td>1.907733</td>
<td>0.629318</td>
<td>1.507033</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>2000-01-14 00:00:00</td>
<td>-0.66344</td>
<td>0.073188</td>
<td>1.583482</td>
<td>0.735205</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>2000-01-17 00:00:00</td>
<td>0.716635</td>
<td>-2.07952</td>
<td>1.760536</td>
<td>0.970309</td>
<td></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>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>idx_name</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>2000-01-07 00:00:00</td>
<td>0.968129</td>
<td>0.906529</td>
<td>0.05343</td>
<td>0.02619</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>2000-01-10 00:00:00</td>
<td>-0.16632</td>
<td>1.981993</td>
<td>1.830939</td>
<td>0.803685</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>2000-01-11 00:00:00</td>
<td>0.121057</td>
<td>0.36946</td>
<td>-0.02888</td>
<td>1.683975</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>2000-01-12 00:00:00</td>
<td>-1.70456</td>
<td>-0.73089</td>
<td>-0.38088</td>
<td>0.020946</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>2000-01-13 00:00:00</td>
<td>-1.20024</td>
<td>1.907733</td>
<td>0.629318</td>
<td>1.507033</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>2000-01-14 00:00:00</td>
<td>-0.66344</td>
<td>0.073188</td>
<td>1.583482</td>
<td>0.735205</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>2000-01-17 00:00:00</td>
<td>0.716635</td>
<td>-2.07952</td>
<td>1.760536</td>
<td>0.970309</td>
<td></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)

In [36]: df = pd.DataFrame({u'': ['UK', u''], u'': ['Alice', u'']})

In [37]: df;
... pandas: powerful Python data analysis toolkit, Release 0.17.0 ...

In [38]: pd.set_option('display.unicode.east_asian_width', True)

In [39]: df;
>>> pd.set_option('display.unicode.east_asian_width', True)

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>

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]})

In [42]: pd.merge(df1, df2, on='col1', how='outer', indicator=True)

Out[42]:

<table>
<thead>
<tr>
<th>col1</th>
<th>col_left</th>
<th>col_right</th>
<th>_merge</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>a</td>
<td>NaN</td>
<td>left_only</td>
</tr>
<tr>
<td>1</td>
<td>b</td>
<td>2</td>
<td>both</td>
</tr>
<tr>
<td>2</td>
<td>NaN</td>
<td>2</td>
<td>right_only</td>
</tr>
<tr>
<td>3</td>
<td>NaN</td>
<td>2</td>
<td>right_only</td>
</tr>
</tbody>
</table>

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

• 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
2 5
3 7
4 NaN
5 11
6 13
dtype: float64

• Added a DataFrame.round method to round the values to a variable number of decimal places (GH10568).

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 0.179356 0.908835 0.571981
second 0.851401 0.203918 0.105336
third 0.597175 0.113613 0.326599

In [51]: df.round(2)
Out[51]:
   A    B    C
first 0.18 0.91 0.57
second 0.85 0.20 0.11
third 0.60 0.11 0.33

In [52]: df.round({'A': 0, 'C': 2})
Out[52]:
   A    B    C
first 0 0.91 0.57
second 1 0.20 0.11
third 1 0.11 0.33

• drop_duplicates and duplicated now accept a keyword to target first, last, and all duplicates.
The `take_last` keyword is deprecated, see here (GH6511, GH8505)

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
   dtype: object

In [55]: s.drop_duplicates(keep='last')
Out[55]:
   2 C
   3 A
   4 B
   5 D
   dtype: object

In [56]: s.drop_duplicates(keep=False)
Out[56]:
   2 C
   5 D
   dtype: object

- Reindex now has a tolerance argument that allows for finer control of *Limits on filling while reindexing* (GH10411):

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]:
   t    x
   0.1  2000-01-01  0
   1.9  2000-01-03  2
   3.5  NaT          NaN

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:

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

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).
1.1.2 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>DataFrame.sort_index()</td>
<td>DataFrame.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(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 than 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 [3]: pd.to_datetime(['2009-07-31', 'asd'])
   ValueError: Unknown string format

Of course you can coerce this as well.
In [61]: 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]: to_datetime(['2009-07-31', 'asd'], errors='ignore')
Out[62]: array(['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]: Timestamp('2012Q2')
   Traceback
   ...
   ValueError: Unable to parse 2012Q2

   # Results in today's date.
In [2]: 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]: Timestamp('2012Q2')
Out[63]: Timestamp('2012-04-01 00:00:00')

In [64]: Timestamp('2014')
Out[64]: Timestamp('2014-01-01 00:00:00')

In [65]: 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]: Timestamp.now()
Out[67]: Timestamp('2015-10-09 20:59:45.917782')

In [68]: Timestamp.now() + offsets.DateOffset(years=1)
Out[68]: Timestamp('2016-10-09 20:59:45.919984')

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:

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:

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:

In [69]: np.array([1, 2, 3]) == np.array([1])
Out[69]: array([ True, False, False], dtype=bool)

or it can return False if broadcasting can not be done:

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).

In [71]: s = Series(range(3))

In [72]: s.iloc[1] = None
In [73]: s
Out[73]:
0 0
1 NaN
2 2
dtype: float64

Previous Behavior:

In [5]: s==None
TypeError: Could not compare <type 'NoneType'> type with Series

New Behavior:

In [74]: s==None
Out[74]:
0  False
1  False
2  False
dtype: bool

Usually you simply want to know which values are null.

In [75]: s.isnull()
Out[75]:
0  False
1  True
2  False
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.

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    1
In [28]:
df_with_missing.to_hdf('file.h5',
                                 'df_with_missing',
                                 format='table',
                                 mode='w')

pd.read_hdf('file.h5', 'df_with_missing')

Out [28]:
    col1  col2
0     0 1
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
1     NaN  NaN
2     2 NaN

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.

```python
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'])
....:
In [88]: cat
Out[88]:
[C, A, B, C]
Categories (3, object): [A, B, C]

In [89]: cat.unique()
Out[89]:
[C, A, B]
Categories (3, object): [C, A, B]
```

**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`

```python
In [29]: df = pd.read_csv('data.csv', header=False)
TypeError: Passing a bool to header is invalid. Use header=None for no header or header=int or list-like of ints to specify the row(s) making up the column names
```
pandas: powerful Python data analysis toolkit, Release 0.17.0

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).

<table>
<thead>
<tr>
<th>Behavior</th>
<th>Methods</th>
</tr>
</thead>
<tbody>
<tr>
<td>return np.nan</td>
<td>weekday, isoweekday</td>
</tr>
<tr>
<td>return NaT</td>
<td>date, now, replace, to_datetime, today</td>
</tr>
<tr>
<td>return np.datetime64('NaT')</td>
<td>to_datetime64 (unchanged)</td>
</tr>
<tr>
<td>raise ValueError</td>
<td>All other public methods (names not beginning with underscores)</td>
</tr>
</tbody>
</table>

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’) listed in here 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)

In [90]: np.random.seed(1234)

In [91]: df = DataFrame(np.random.randn(5,2),columns=list('AB'),index=date_range('20130101',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

Previously

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 -1.190976
2013-01-02 2.865414 -0.312652
2013-01-03 -0.720589  0.887163
2013-01-04  0.859588 -0.636524
2013-01-05  0.015696 -2.242685

Current

1.1. v0.17.0 (October 9, 2015)
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

• 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)

1.1.3 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)

1.1.4 Bug Fixes

• Bug in incorrection computation of .mean() on timedelta64 [ns] because of overflow (GH9442)
• Bug in `.isin` on older numpycs ([issue: 11232])
• 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 NaN (GH10477)
• Bug in `Series.dt` ops in preserving meta-data (GH10477)
• Bug in preserving NaN 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 NaN. (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 pickling 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 multi-index (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 (issue: 11016)
• 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 `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 `Timedelta` 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)
• 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)

1.2 v0.16.2 (June 12, 2015)

This is a minor bug-fix release from 0.16.1 and includes a a large number of bug fixes along some new features (`pipe()` method), enhancements, and performance improvements.

We recommend that all users upgrade to this version.

Highlights include:

• A new `pipe` method, see [here](#)
• Documentation on how to use `numba` with `pandas`, see [here](#)

What’s new in v0.16.2

• New features
  – `Pipe`
  – Other Enhancements
• API Changes
• Performance Improvements
• Bug Fixes
1.2.1 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)
```

The logic flows from inside out, and function names are separated from their keyword arguments. This can be rewritten as

```python
(df.pipe(h)
 .pipe(g, arg1=1)
 .pipe(f, arg2=2, arg3=3)
)
```

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:

```python
In [1]: import statsmodels.formula.api as sm
In [2]: bb = pd.read_csv('data/baseball.csv', index_col='id')
# sm.poisson takes (formula, data)
In [3]: (bb.query('h > 0')
   ...: .assign(ln_h = lambda df: np.log(df.h))
   ...: .pipe((sm.poisson, 'data'), 'hr ~ ln_h + year + g + C(lg)')
   ...: .fit()
   ...: .summary()
   ...: )
```

Optimization terminated successfully.
Current function value: 2.116284
Iterations 24

```sql
Out[3]: <class 'statsmodels.iolib.summary.Summary'>
```

### Poisson Regression Results

| Coef  | Std. Err | z    | P>|z| | [95.0% Conf. Int.] |
|-------|----------|------|-----|---------------------|
| Intercept | -1267.3636 | 457.867 | -2.768 | 0.006 | -2164.767 | -369.960 |
| C(lg) [T.NL] | -0.2057 | 0.101 | -2.044 | 0.041 | -0.403 | -0.008 |
| ln_h | 0.9280 | 0.191 | 4.866 | 0.000 | 0.554 | 1.302 |
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 here.

- `axis` parameter of DataFrame.quantile now accepts also index and column. (GH9543)

1.2.2 API Changes

- Holiday now raises `NotImplementedError` if both offset and observance are used in the constructor instead of returning an incorrect result (GH10217).

1.2.3 Performance Improvements

- Improved Series.resample performance with `dtype=datetime64[ns]` (GH7754)
- Increase performance of `str.split` when `expand=True` (GH10081)

1.2.4 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 funcs 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 timerule (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 DataFrame’s, 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).

1.3 v0.16.1 (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

Warning: In pandas 0.17.0, the sub-package pandas.io.data will be removed in favor of a separately installable package. See here for details (GH8961)

1.3.1 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.
In [1]: df = DataFrame({'A' : np.arange(6),
                   'B' : Series(list('aabbca')).astype('category',
                      categories=list('cab'))})

In [2]: df
Out[2]:
<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>a</td>
</tr>
<tr>
<td>1</td>
<td>a</td>
</tr>
<tr>
<td>2</td>
<td>b</td>
</tr>
<tr>
<td>3</td>
<td>b</td>
</tr>
<tr>
<td>4</td>
<td>c</td>
</tr>
<tr>
<td>5</td>
<td>a</td>
</tr>
</tbody>
</table>

In [3]: df.dtypes
Out[3]:
A  int32
B  category
dtype: object

In [4]: df.B.cat.categories
Out[4]: Index([u'c', u'a', u'b'], dtype='object')

setting the index, will create create a CategoricalIndex

In [5]: df2 = df.set_index('B')

In [6]: df2.index
Out[6]: CategoricalIndex([u'a', u'a', u'b', u'b', u'c', u'a'], categories=[u'c', u'a', u'b'], ordered=False, name='B', dtype='category')

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.

In [7]: df2.loc['a']
Out[7]:
<table>
<thead>
<tr>
<th>A</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
</tr>
<tr>
<td>a</td>
</tr>
<tr>
<td>a</td>
</tr>
</tbody>
</table>

and preserves the CategoricalIndex

In [8]: df2.loc['a'].index
Out[8]: CategoricalIndex([u'a', u'a'], categories=[u'c', u'a', u'b'], ordered=False, name='B', dtype='category')

sorting will order by the order of the categories

In [9]: df2.sort_index()
Out[9]:
<table>
<thead>
<tr>
<th>A</th>
</tr>
</thead>
<tbody>
<tr>
<td>c</td>
</tr>
<tr>
<td>a</td>
</tr>
<tr>
<td>a</td>
</tr>
<tr>
<td>a</td>
</tr>
<tr>
<td>b</td>
</tr>
<tr>
<td>b</td>
</tr>
</tbody>
</table>
groupby operations on the index will preserve the index nature as well

```python
In [10]: df2.groupby(level=0).sum()
Out[10]:
   A  B
0  4
1  6
2  5
```

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]:
   A  B
0  0
1  1
2  5
3  NaN
```

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 or 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)

```python
In [16]: example_series = Series([0,1,2,3,4,5])
```

# When no arguments are passed, returns 1
```python
In [17]: example_series.sample()
Out[17]:
0    0
Name: 0, dtype: int64
```
# One may specify either a number of rows:
In [18]: example_series.sample(n=3)
Out[18]:
4 4
2 2
0 0
dtype: int64

# Or a fraction of the rows:
In [19]: example_series.sample(frac=0.5)
Out[19]:
4 4
5 5
3 3
dtype: int64

# weights are accepted.
In [20]: example_weights = [0, 0, 0.2, 0.2, 0.2, 0.4]

In [21]: example_series.sample(n=3, weights=example_weights)
Out[21]:
4 4
2 2
5 5
dtype: int64

# weights will also be normalized if they do not sum to one,
# and missing values will be treated as zeros.
In [22]: example_weights2 = [0.5, 0, 0, 0, None, np.nan]

In [23]: example_series.sample(n=1, weights=example_weights2)
Out[23]:
0 0
dtype: int64

When applied to a DataFrame, one may pass the name of a column to specify sampling weights when sampling from rows.

In [24]: df = DataFrame({'col1':[9,8,7,6], 'weight_column':[0.5, 0.4, 0.1, 0]})

In [25]: df.sample(n=3, weights='weight_column')
Out[25]:
    col1  weight_column
0     9 0.5
1     8 0.4
2     7 0.1

**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`.  

1.3. v0.16.1 (May 11, 2015)
In [26]: idx = Index([' jack', 'jill ',' jesse ', 'frank'])

In [27]: idx.str.strip()
Out[27]: Index([u'jack', u'jill', u'jesse', u'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 [28]: idx = Index(['a1', 'a2', 'b1', 'b2'])

In [29]: s = Series(range(4), index=idx)

In [30]: s
Out[30]:
a1 0
a2 1
b1 2
b2 3
dtype: int64

In [31]: idx.str.startswith('a')
Out[31]: array([ True, True, False, False], dtype=bool)

In [32]: s[s.index.str.startswith('a')]
Out[32]:
a1 0
a2 1
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>
</tr>
</thead>
<tbody>
<tr>
<td>capitalize()</td>
</tr>
<tr>
<td>swapcase()</td>
</tr>
<tr>
<td>normalize()</td>
</tr>
<tr>
<td>partition()</td>
</tr>
<tr>
<td>rpartition()</td>
</tr>
</tbody>
</table>

• split now takes expand keyword to specify whether to expand dimensionality. return_type is deprecated. (GH9847)

In [33]: s = Series(['a,b', 'a,c', 'b,c'])

# return Series
In [34]: s.str.split(',')
Out[34]:
0  [a, b]
1  [a, c]
2  [b, c]
dtype: object

# return DataFrame
In [35]: s.str.split(',', expand=True)
Out[35]:
0  a  b
1  a  c
2  b  c

In [36]: idx = Index(['a,b', 'a,c', 'b,c'])
# return Index
In [37]: idx.str.split(',', )
Out[37]: Index([['u'a', 'u'b'], ['u'a', 'u'c'], ['u'b', 'u'c']], dtype='object')

# return MultiIndex
In [38]: idx.str.split(',', expand=True)
Out[38]:
MultiIndex(levels=[['u'a', 'u'b'], ['u'b', 'u'c']],
labels=[[0, 0, 1], [0, 1, 1]])

• 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)

In [39]: from pandas.tseries.offsets import BusinessHour
In [40]: Timestamp('2014-08-01 09:00') + BusinessHour()
Out[40]: Timestamp('2014-08-01 10:00:00')

In [41]: Timestamp('2014-08-01 07:00') + BusinessHour()
Out[41]: Timestamp('2014-08-01 10:00:00')

In [42]: Timestamp('2014-08-01 16:30') + BusinessHour()
Out[42]: 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)

In [43]: df = DataFrame(np.random.randn(3, 3), columns=['A', 'B', 'C'])
In [44]: df.drop(['A', 'X'], axis=1, errors='ignore')
Out[44]:
   B  C
0  0.991946  0.953324
1 -0.334077  0.002118
2  0.289092  1.321158

• 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_dtype now returns 'bytes' in Python 3 where appropriate. (GH10032)

1.3.2 API changes

• When passing in an ax to df.plot( ..., ax=ax), the sharex 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 sharex=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 sharex=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)

1.3.3 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, 100, 101, 102, 103], 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]:
New Behavior

In [45]: pd.set_option('display.width', 80)

In [46]: pd.Index(range(4), name='foo')
Out[46]: Int64Index([0, 1, 2, 3], dtype='int64', name='foo')

In [47]: pd.Index(range(30), name='foo')
Out[47]:
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],
dtype='int64', name='foo')

In [48]: pd.Index(range(104), name='foo')
Out[48]:
Int64Index([0, 1, 2, 3, 4, 5, 6, 7, 8, 9,
... 94, 95, 96, 97, 98, 99, 100, 101, 102, 103],
dtype='int64', name='foo', length=104)

In [49]: pd.CategoricalIndex(['a','bb','ccc','dddd'], ordered=True, name='foobar')
Out[49]: CategoricalIndex([u'a', u'bb', u'ccc', u'ddd'], categories=[u'a', u'bb', u'ccc', u'ddd'], ordered=True, name='foobar', dtype='category')

In [50]: pd.CategoricalIndex(['a','bb','ccc','dddd']*10, ordered=True, name='foobar')
Out[50]:
CategoricalIndex([u'a', u'bb', u'ccc', u'ddd', u'a', u'bb', u'ccc', u'ddd', u'a', u'bb', u'ccc', u'ddd', u'a', u'bb', u'ccc', u'ddd', u'a', u'bb', u'ccc', u'ddd', u'a', u'bb', u'ccc', u'ddd', u'a', u'bb', u'ccc', u'ddd',
categories=[u'a', u'bb', u'ccc', u'ddd'], ordered=True, name='foobar', dtype='category')

In [51]: pd.CategoricalIndex(['a','bb','ccc','ddd']*100, ordered=True, name='foobar')
Out[51]:
CategoricalIndex([u'a', u'bb', u'ccc', u'ddd', u'a', u'bb', u'ccc', u'ddd', u'a', u'bb',
... u'ccc', u'ddd', u'a', u'bb', u'ccc', u'ddd', u'a', u'bb', u'ccc', u'ddd'], ordered=True, name='foobar', dtype='category')

In [52]: pd.date_range('20130101', periods=4, name='foo', tz='US/Eastern')
Out[52]:
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', '2013-01-04 00:00:00-05:00'],
dtype='datetime64[ns, US/Eastern]', name='foo', freq='D')

In [53]: pd.date_range('20130101', periods=25, freq='D')
Out[53]:
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
In [54]: pdate_date_range('20130101', periods=104, name='foo', tz='US/Eastern')
Out[54]:
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', '2013-01-04 00:00:00-05:00',
              '2013-01-05 00:00:00-05:00', '2013-01-06 00:00:00-05:00',
              '2013-01-07 00:00:00-05:00', '2013-01-08 00:00:00-05:00',
              '2013-01-09 00:00:00-05:00', '2013-01-10 00:00:00-05:00',
              ... '2013-04-05 00:00:00-04:00', '2013-04-06 00:00:00-04:00',
              '2013-04-07 00:00:00-04:00', '2013-04-08 00:00:00-04:00',
              '2013-04-09 00:00:00-04:00', '2013-04-10 00:00:00-04:00',
              '2013-04-11 00:00:00-04:00', '2013-04-12 00:00:00-04:00',
              '2013-04-13 00:00:00-04:00', '2013-04-14 00:00:00-04:00'],
              dtype='datetime64[ns, US/Eastern]', name='foo', length=104, freq='D')

1.3.4 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)

1.3.5 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_formated_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 whitespace plus one non-space character to be skipped. (GH9710)
• Bug in C csv parser causing spurious NaNs when data started with newline followed by whitespace. (GH10022)
• Bug causing elements with a null group to spill into the final group when grouping by a `Categorical` (GH9603)
• Bug where `.loc` 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 pandas: 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 multi-indexed 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)

1.4 v0.16.0 (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
• Enhancement to the .str accessor to make string operations easier, see here
• The pandas.tools.rplot, pandas.sandbox.qtpandas and pandas.rpy modules are deprecated. We refer users to external packages like seaborn, pandas-qt and rpy2 for similar or equivalent functionality, 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

1.4.1 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.

In [1]: iris = read_csv('data/iris.data')

In [2]: iris.head()

Out[2]:

<table>
<thead>
<tr>
<th>SepalLength</th>
<th>SepalWidth</th>
<th>PetalLength</th>
<th>PetalWidth</th>
<th>Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.1</td>
<td>3.5</td>
<td>1.4</td>
<td>0.2</td>
<td>Iris-setosa</td>
</tr>
<tr>
<td>4.9</td>
<td>3.0</td>
<td>1.4</td>
<td>0.2</td>
<td>Iris-setosa</td>
</tr>
<tr>
<td>4.7</td>
<td>3.2</td>
<td>1.3</td>
<td>0.2</td>
<td>Iris-setosa</td>
</tr>
<tr>
<td>4.6</td>
<td>3.1</td>
<td>1.5</td>
<td>0.2</td>
<td>Iris-setosa</td>
</tr>
<tr>
<td>5.0</td>
<td>3.6</td>
<td>1.4</td>
<td>0.2</td>
<td>Iris-setosa</td>
</tr>
</tbody>
</table>

In [3]: iris.assign(sepal_ratio=iris['SepalWidth'] / iris['SepalLength']).head()

Out[3]:

<table>
<thead>
<tr>
<th>SepalLength</th>
<th>SepalWidth</th>
<th>PetalLength</th>
<th>PetalWidth</th>
<th>Name</th>
<th>sepal_ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.1</td>
<td>3.5</td>
<td>1.4</td>
<td>0.2</td>
<td>Iris-setosa</td>
<td>0.686275</td>
</tr>
<tr>
<td>4.9</td>
<td>3.0</td>
<td>1.4</td>
<td>0.2</td>
<td>Iris-setosa</td>
<td>0.612245</td>
</tr>
<tr>
<td>4.7</td>
<td>3.2</td>
<td>1.3</td>
<td>0.2</td>
<td>Iris-setosa</td>
<td>0.680851</td>
</tr>
<tr>
<td>4.6</td>
<td>3.1</td>
<td>1.5</td>
<td>0.2</td>
<td>Iris-setosa</td>
<td>0.673913</td>
</tr>
<tr>
<td>5.0</td>
<td>3.6</td>
<td>1.4</td>
<td>0.2</td>
<td>Iris-setosa</td>
<td>0.720000</td>
</tr>
</tbody>
</table>

Above was an example of inserting a precomputed value. We can also pass in a function to be evaluated.

In [4]: iris.assign(sepal_ratio = lambda x: (x['SepalWidth'] / x['SepalLength'])).head()

...:

Out[4]:

<table>
<thead>
<tr>
<th>SepalLength</th>
<th>SepalWidth</th>
<th>PetalLength</th>
<th>PetalWidth</th>
<th>sepal_ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
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

```
In [5]: (iris.query('SepalLength > 5')
    ...:   .assign(SepalRatio = lambda x: x.SepalWidth / x.SepalLength,
    ...:             PetalRatio = lambda x: x.PetalWidth / x.PetalLength)
    ...:   .plot(kind='scatter', x='SepalRatio', y='PetalRatio'))
Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0xa993cbcc>
```

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:

```
In [6]: from numpy import nan
In [7]: s = Series([3.0, nan, 1.0, 3.0, nan, nan])
In [8]: s.index = 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 [9]: s
```

```
Out[9]:
 A  B  C  D
1 2 a 0 3
```
1 NaN
1 b 0 1
1 3
2 1 b 0 NaN
1 NaN
dtype: float64

# SparseSeries
In [10]: ss = s.to_sparse()

In [11]: ss
Out[11]:
A B C D
1 2 a 0 3
1 NaN
1 b 0 1
1 3
2 1 b 0 NaN
1 NaN
dtype: float64
BlockIndex
Block locations: array([0, 2])
Block lengths: array([1, 2])

In [12]: A, rows, columns = ss.to_coo(row_levels=['A', 'B'],
....: column_levels=['C', 'D'],
....: sort_labels=False)

In [13]: A
Out[13]:
<3x4 sparse matrix of type '<type 'numpy.float64'>'
with 3 stored elements in COOrdinate format>

In [14]: A.todense()
Out[14]:
matrix([[ 3., 0., 0., 0.],
[ 0., 0., 1., 3.],
[ 0., 0., 0., 0.]]

In [15]: rows
Out[15]: [(1L, 2L), (1L, 1L), (2L, 1L)]

In [16]: columns
Out[16]: [('a', 0L), ('a', 1L), ('b', 0L), ('b', 1L)]

The from_coo method is a convenience method for creating a SparseSeries from a scipy.sparse.coo_matrix:

In [17]: from scipy import sparse

In [18]: A = sparse.coo_matrix(((3.0, 1.0, 2.0), ([1, 0, 0], [0, 2, 3])),
....: shape=(3, 4))

In [19]: A
Out[19]:
<3x4 sparse matrix of type '<type 'numpy.float64'>'>
with 3 stored elements in COOrdinate format>

In [20]: A.todense()
Out[20]:
matrix([[ 0., 0., 1., 2.],
        [ 3., 0., 0., 0.],
        [ 0., 0., 0., 0.]])

In [21]: ss = SparseSeries.from_coo(A)

In [22]: ss
Out[22]:
0 2 1
3 2
1 0 3
dtype: float64
BlockIndex
Block locations: array([0])
Block lengths: array([3])

String Methods Enhancements

- Following new methods are accesible 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>
<th>isdecimal()</th>
</tr>
</thead>
<tbody>
<tr>
<td>find()</td>
<td>rfind()</td>
<td>ljust()</td>
<td>rjust()</td>
<td>zfill()</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In [23]: s = Series(["abcd", "3456", "EFGH"])

In [24]: s.str.isalpha()
Out[24]:
0    True
1   False
2    True
dtype: bool

In [25]: s.str.find('ab')
Out[25]:
0   0
1   -1
2   -1
dtype: int64

- Series.str.pad() and Series.str.center() now accept fillchar option to specify filling character (GH9352)

In [26]: s = Series(['12', '300', '25'])

In [27]: s.str.pad(5, fillchar='_')
Out[27]:
0    __12
1    __300
2    __25
dtype: object
- Added `Series.str.slice_replace()`, which previously raised `NotImplementedError` (GH8888)

  ```python
  In [28]: s = Series(['ABCD', 'EFGH', 'IJK'])
  In [29]: s.str.slice_replace(1, 3, 'X')
  Out[29]:
  0  AXD
  1  EXH
  2   IX
  dtype: object

  # replaced with empty char
  In [30]: s.str.slice_replace(0, 1)
  Out[30]:
  0  BCD
  1  FGH
  2   JK
  dtype: object
  ```

Other enhancements

- Reindex now supports `method='nearest'` for frames or series with a monotonic increasing or decreasing index (GH9258):

  ```python
  In [31]: df = pd.DataFrame({'x': range(5)})
  In [32]: df.reindex([0.2, 1.8, 3.5], method='nearest')
  Out[32]:
  x
  0.2 0
  1.8 2
  3.5 4
  ```

  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 for more (GH9636).

1.4.2 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 * 3600 + 11 * 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)

Previous Behavior

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

New Behavior

In [33]: t = pd.Timedelta('1 day, 10:11:12.100123')
In [34]: t.days
Out[34]: 1L
In [35]: t.seconds
Out[35]: 36672L
In [36]: t.microseconds
Out[36]: 100123L
Using `.components` allows the full component access

```python
In [37]: t.components
Out[37]: Components(days=1L, hours=10L, minutes=11L, seconds=12L, milliseconds=100L, microseconds=123L, nanoseconds=0L)

In [38]: t.components.seconds
Out[38]: 12L
```

### 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 [39]: df = DataFrame(np.random.randn(5,4),
   ....: columns=list('ABCD'),
   ....: index=date_range('20130101',periods=5))

In [40]: df
Out[40]:
   A         B         C         D
2013-01-01 -1.546906 -0.202646 -0.655969  0.193421
2013-01-02  0.553439  1.318152 -0.469305  0.675554
2013-01-03 -1.817027 -0.183109  1.058969 -0.397840
2013-01-04  0.337438  1.047579  1.045938  0.863717
2013-01-05 -0.122092  0.124713 -0.322795  0.841675

In [41]: s = Series(range(5),[-2,-1,1,2,3])

In [42]: s
Out[42]:
-2  0
-1  1
  2
  3
  4
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 [43]: df.loc['2013-01-02':'2013-01-10']
Out[43]:
   A         B         C         D
2013-01-02  0.553439  1.318152 -0.469305  0.675554
2013-01-03 -1.817027 -0.183109  1.058969 -0.397840
2013-01-04  0.337438  1.047579  1.045938  0.863717
```
Allow slicing with float-like values on an integer index for .ix. Previously this was only enabled for .loc:

**Previous Behavior**

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**

In [45]: s.ix[-1.0:2]

Out[45]:

-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**

In [4]: df.loc[2:3]

KeyError: 'start bound [2] is not the [index]'

**New Behavior**

In [4]: df.loc[2:3]

TypeError: Cannot do slice indexing on <class 'pandas.tseries.index.DatetimeIndex'> with <type 'int'>

### 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**

In [3]: s = Series([0,1,2], dtype='category')

In [4]: s

Out[4]:

0  0
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 [46]: s = Series([0,1,2], dtype='category')

In [47]: s
Out[47]:
0 0
1 1
2 2
dtype: category
Categories (3, int64): [0, 1, 2]

In [48]: s.cat.ordered
Out[48]: False

In [49]: s = s.cat.as_ordered()

In [50]: s
Out[50]:
0 0
1 1
2 2
dtype: category
Categories (3, int64): [0 < 1 < 2]

In [51]: s.cat.ordered
Out[51]: True

# you can set in the constructor of the Categorical
In [52]: s = Series(Categorical([0,1,2],ordered=True))

In [53]: s
Out[53]:
0 0
1 1
2 2
dtype: category
Categories (3, int64): [0 < 1 < 2]

In [54]: s.cat.ordered
Out[54]: True

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.

```
In [55]: s = Series(['a','b','c','a']).astype('category',ordered=True)
```

```
In [56]: s
Out[56]:
0   a
1   b
2   c
3   a
dtype: category
Categories (3, object): [a < b < c]
```

```
In [57]: s = Series(['a','b','c','a']).astype('category',categories=list('abcdef'),ordered=False)
```

```
In [58]: s
Out[58]:
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:

```
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:

```
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**

```python
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.

```python
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**

```python
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

```python
In [59]: p = pd.Series([0, 1])

In [60]: p / 0
Out[60]:
     0   NaN
     1   inf
dtype: float64

In [61]: p // 0
Out[61]:
     0   NaN
     1   inf
dtype: float64
```

• **Series.values_counts** and **Series.describe** for categorical data will now put NaN entries at the
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:
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:
In [62]: pd.to_datetime(['2000-01-31', '2000-02-28']).asof('2000-02')
Out[62]: 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 using rplot to seaborn: rplot docs.

- 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 thru 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 substraction 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)

1.4.3 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)

1.4.4 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` `dtype` argument not accepting an instantiated SQLAlchemy type (GH9083).
• Bug in `.loc` partial setting with a 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 multi-index 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 DatetimeIndex 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 thru 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 stubnames 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
   1   1
   2   1
   ... 
  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.

In [1]: df1 = DataFrame({'x': Series(['a','b','c']), 'y': Series(['d','e','f'])})
In [2]: df2 = df1[['x']]
In [3]: df2['y'] = ['g', 'h', 'i']
1.5 v0.15.2 (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

1.5.1 API changes

- Indexing in MultiIndex beyond lex-sort depth is now supported, though a lexically sorted index will have a better performance. (GH2646)

```
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  0.043324
     x  0.561433
1     y  0.502967
     z  0.329668

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  0.329668

# lexically sorting
In [5]: df2 = df.sortlevel()

In [6]: df2
Out[6]:
           jolie
       jim  joe
0     x  0.043324
     x  0.561433
1     y  0.502967
     z  0.329668

In [7]: df2.index.lexsort_depth
Out[7]: 2
In [8]: df2.loc[(1,'z')]
Out[8]:
    jolie
    jim
    joe
  1   z  0.329668

• 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:

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:

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)

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

# this assignment was inconsistent
In [15]: data.y = 5

Old behavior:
In [6]: data.y
Out[6]: 2

In [7]: data['y'].values
Out[7]: array([5, 5, 5])

New behavior:

In [16]: data.y
Out[16]: 5

In [17]: data['y'].values
Out[17]: array([2, 4, 6], dtype=int64)

• 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:

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:

In [18]: s = pd.Series(np.arange(3), ['a', 'b', 'c'])

In [19]: s.loc['c':'a':-1]
Out[19]:
   c 2
   b 1
   a 0
   dtype: int32

1.5.2 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})
```

• `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
dtype: bool
```

• Panel now supports the `all` and `any` aggregation functions. (GH8302):

```python
In [22]: p = pd.Panel(np.random.rand(2, 5, 4) > 0.1)
In [23]: p.all()
Out[23]:
   0
  0    True False
  1    True True
  2    True True
  3    False 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 datatypes of non-NA values for columns that contain NA values and have dtype `object` (GH8778).
1.5.3 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)

1.5.4 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 paramaters 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 multi-index 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 numpy 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 outputing 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 \texttt{.size} attribute across \texttt{NDFrame} objects to provide compat with numpy \(\geq 1.9.1\); buggy with \texttt{np.array_split} (GH8846)
• Skip testing of histogram plots for matplotlib \(\leq 1.2\) (GH8648).
• Bug where \texttt{get\_data\_google} returned object dtypes (GH3995)
• Bug in \texttt{DataFrame.stack(..., dropna=False)} when the \texttt{DataFrame.\texttt{columns\texttt{}} is a \texttt{MultiIndex}} whose \texttt{labels} do not reference all its \texttt{levels}. (GH8844)
• Bug in that \texttt{Option context applied on \texttt{__enter__}} (GH8514)
• Bug in resample that causes a \texttt{ValueError} when resampling across multiple days and the last offset is not calculated from the start of the range (GH8863)
• Bug where \texttt{DataFrame.plot(kind='scatter')} fails when checking if an np.array is in the \texttt{DataFrame} (GH8852)
• Bug in \texttt{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 \texttt{use\_index=False} (GH8558).
• Bugs when trying to stack multiple columns, when some (or all) of the level names are numbers (GH8584).
• Bug in \texttt{MultiIndex} where \texttt{\texttt{__contains__} returns wrong result if index is not lexically sorted or unique} (GH724)
• BUG CSV: fix problem with trailing whitespace in skipped rows, (GH8679), (GH8661), (GH8983)
• Regression in \texttt{Timestamp} does not parse ‘Z’ zone designator for UTC (GH8771)
• Bug in \texttt{StataWriter} the produces writes strings with 244 characters irrespective of actual size (GH8969)
• Fixed \texttt{ValueError} raised by.cummin/cummax when datetime64 Series contains NaT. (GH8965)
• Bug in \texttt{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)

1.6 v0.15.1 (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.

• \textit{Enhancements}

• \textit{API Changes}

• \textit{Bug Fixes}
1.6.1 API changes

- `s.dt.hour` and other `.dt` accessors will now return `np.nan` for missing values (rather than previously -1), (GH8689)

```python
In [1]: s = Series(date_range('20130101', periods=5, freq='D'))
In [2]: s.iloc[2] = np.nan

In [3]: s
Out[3]:
0 2013-01-01
1 2013-01-02
2 NaT
3 2013-01-04
4 2013-01-05
dtype: datetime64[ns]
```

previous behavior:

```python
In [6]: s.dt.hour
Out[6]:
0 0
1 0
2 -1
3 0
4 0
dtype: int64
```

current behavior:

```python
In [4]: s.dt.hour
Out[4]:
0 0
1 0
2 NaN
3 0
4 0
dtype: float64
```

- `groupby` with `as_index=False` will not add erroneous extra columns to result (GH8582):

```python
In [5]: np.random.seed(2718281)

In [6]: df = pd.DataFrame(np.random.randint(0, 100, (10, 2)), columns=['jim', 'joe'])
   ...:
   ...

In [7]: df.head()
Out[7]:
    jim  joe
0   61   81
1   96   49
2   55   65
3   72   51
4   77   12

In [8]: ts = pd.Series(5 * np.random.randint(0, 3, 10))
```

previous behavior:
In [4]: df.groupby(ts, as_index=False).max()
Out[4]:
   NaN  jim  joe
0    0    72    83
1    5    77    84
2   10    96    65

current behavior:

In [9]: df.groupby(ts, as_index=False).max()
Out[9]:
   jim  joe
0    72    83
1    77    84
2    96    65

• groupby will not erroneously exclude columns if the column name conflits 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

In [12]: gr = df.groupby(df['jim'] < 2)

previous behavior (excludes 1st column from output):

In [4]: gr.apply(sum)
Out[4]:
   joe
False 24
True  11

current behavior:

In [13]: gr.apply(sum)
Out[13]:
   jim  joe
   jim
False  9  24
True   1  11

• 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])

In [15]: s
Out[15]:
4    a
3    b
2    c
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
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]:
<table>
<thead>
<tr>
<th>Strike</th>
<th>Expiry</th>
<th>Type</th>
<th>Symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td>60</td>
<td>2015-10-16</td>
<td>call</td>
<td>AAPL151016C00060000</td>
</tr>
<tr>
<td>65</td>
<td>2015-10-16</td>
<td>call</td>
<td>AAPL151016C00065000</td>
</tr>
<tr>
<td>70</td>
<td>2015-10-16</td>
<td>call</td>
<td>AAPL151016C00070000</td>
</tr>
<tr>
<td>75</td>
<td>2015-10-16</td>
<td>call</td>
<td>AAPL151016C00075000</td>
</tr>
<tr>
<td>79</td>
<td>2015-10-16</td>
<td>call</td>
<td>AAPL151016C00079000</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Last</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>51.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>47.84</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>38.68</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>36.65</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>30.80</td>
</tr>
</tbody>
</table>

In [20]: aapl.expiry_dates
Out[20]:
[datetime.date(2015, 10, 16),
 datetime.date(2015, 10, 23),
 datetime.date(2015, 10, 30),
 datetime.date(2015, 11, 6),
 datetime.date(2015, 11, 13),
 datetime.date(2015, 11, 20),]
```python
datetime.date(2015, 12, 18),
datetime.date(2016, 1, 15),
datetime.date(2016, 4, 15),
datetime.date(2016, 6, 17),
datetime.date(2016, 7, 15),
datetime.date(2017, 1, 20),
datetime.date(2018, 1, 19)]
```

```python
In [21]: aapl.get_near_stock_price(expiry=aapl.expiry_dates[0:3]).iloc[0:5,0:1]
Out[21]:
```
<table>
<thead>
<tr>
<th>Strike</th>
<th>Expiry</th>
<th>Type</th>
<th>Symbol</th>
<th>Last</th>
</tr>
</thead>
<tbody>
<tr>
<td>111</td>
<td>2015-10-23</td>
<td>call</td>
<td>AAPL151023C00111000</td>
<td>2.44</td>
</tr>
<tr>
<td></td>
<td>2015-10-30</td>
<td>call</td>
<td>AAPL151030C00111000</td>
<td>4.45</td>
</tr>
<tr>
<td>112</td>
<td>2015-10-16</td>
<td>call</td>
<td>AAPL151016C00112000</td>
<td>1.13</td>
</tr>
<tr>
<td></td>
<td>2015-10-23</td>
<td>call</td>
<td>AAPL151023C00112000</td>
<td>1.85</td>
</tr>
<tr>
<td></td>
<td>2015-10-30</td>
<td>call</td>
<td>AAPL151030C00112000</td>
<td>3.85</td>
</tr>
</tbody>
</table>
```

See the Options documentation in `Remote Data`

- pandas now also registers the `datetime64` dtype in matplotlib's units registry to plot such values as date-times. 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)*.

### 1.6.2 Enhancements

- `concat` permits a wider variety of iterables of pandas objects to be passed as the first parameter *(GH8645)*:

```python
In [22]: from collections import deque
In [23]: df1 = pd.DataFrame([1, 2, 3])
In [24]: df2 = pd.DataFrame([4, 5, 6])
```

previous behavior:

```python
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:

```python
In [25]: pd.concat(deque((df1, df2)))
Out[25]:
```
```
<table>
<thead>
<tr>
<th></th>
<th>0</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.0</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>2</td>
<td>4</td>
<td>5</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 [26]: dfi = 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 [27]: dfi.memory_usage(index=True)
Out[27]:
Index 11020
A 8000
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)

1.6.3 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 (issue: 8703)
• Bug in slicing a multi-index 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 where DataReader'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).

1.7 v0.15.0 (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
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.

```python
In [1]: df = 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, 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, dtype: category
Categories (5, object): [very bad, bad, medium, good, very good]

In [7]: df.sort("grade")
Out[7]:
      id  raw_grade  grade
0       1       a   very good
1       2       b     good
2       3       b     good
3       4       a  very good
4       5       a  very good

In [8]: df.groupby("grade").size()
Out[8]:
grade
       very bad     1
        bad         0
       medium       0
        good       2
     very good  3
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. (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 = 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 whatstnew entry
```

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.

Construct a scalar

```python
In [9]: Timedelta('1 days 06:05:01.00003')
Out[9]: Timedelta('1 days 06:05:01.000030')

In [10]: Timedelta('15.5us')
Out[10]: Timedelta('0 days 00:00:00.000015')

In [11]: Timedelta('1 hour 15.5us')
Out[11]: Timedelta('0 days 01:00:00.000015')

# negative Timedeltas have this string repr
# to be more consistent with datetime.timedelta conventions
In [12]: Timedelta('-1us')
Out[12]: Timedelta('-1 days +23:59:59.999999')

# a NaT
In [13]: Timedelta('nan')
Out[13]: NaT
```

Access fields for a Timedelta

```python
In [14]: td = Timedelta('1 hour 3m 15.5us')

In [15]: td.seconds
Out[15]: 3780L

In [16]: td.microseconds
Out[16]: 15L
```
In [17]: td.nanoseconds
Out[17]: 500L

Construct a TimedeltaIndex

In [18]: TimedeltaIndex(['1 days', '1 days 00:00:05',
                  ....:
                  np.timedelta64(2, 'D'), timedelta(days=2, seconds=2))
                  ....:
Out[18]:
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)

Constructing a TimedeltaIndex with a regular range

In [19]: 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]: 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 = Series(np.arange(5),
                   index=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, dtype: int32

You can select with partial string selections

In [23]: s['1 day 00:00:02']
Out[23]: 2
Finally, the combination of TimedeltaIndex with DatetimeIndex allow certain combination operations that are NaT preserving:

```python
In [25]: tdi = 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 = date_range('20130101', periods=3)
In [28]: dti.tolist()
Out[28]: [Timestamp('2013-01-01 00:00:00', offset='D'),
          Timestamp('2013-01-02 00:00:00', offset='D'),
          Timestamp('2013-01-03 00:00:00', offset='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 = dict({t: np.random.randint(100, size=n).astype(t)  
             for t in dtypes})
In [34]: df = DataFrame(data)
In [35]: df['categorical'] = df['object'].astype('category')
In [36]: df.info()
```

<class 'pandas.core.frame.DataFrame'>
Int64Index: 5000 entries, 0 to 4999
Data columns (total 8 columns):
bool     5000 non-null bool
complex128 5000 non-null complex128
datetime64[ns] 5000 non-null datetime64[ns]
float64 5000 non-null float64
int64 5000 non-null int64
object 5000 non-null object
timedelta64[ns] 5000 non-null timedelta64[ns]
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: 303.5+ KB

Additionally memory_usage() is an available method for a dataframe object which returns the memory usage of each column.

In [37]: df.memory_usage(index=True)
Out[37]:
Index 40000
bool 5000
category 80000
datetime64[ns] 40000
float64 40000
int64 40000
object 20000
timedelta64[ns] 40000
categorical 5800
dtype: int64

.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

# datetime
In [38]: s = Series(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
dtype: datetime64[ns]

In [40]: s.dt.hour
Out[40]:
0 9
1 9
2 9
3 9
dtype: int64

In [41]: s.dt.second
Out[41]:
0 12
1 12
2 12
3 12
dtype: int64
In [42]: s.dt.day
Out[42]:
0  1
1  2
2  3
3  4
dtype: int64

In [43]: s.dt.freq
Out[43]: <Day>

This enables nice expressions like this:

In [44]: s[s.dt.day==2]
Out[44]:
1  2013-01-02 09:10:12
dtype: datetime64[ns]

You can easily produce tz aware transformations:

In [45]: stz = s.dt.tz_localize('US/Eastern')
In [46]: stz
Out[46]:
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 [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
dtype: datetime64[ns, US/Eastern]

The .dt accessor works for period and timedelta dtypes.

# period
In [49]: s = Series(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
dtype: object

In [51]: s.dt.year
Out[51]:
0  2013
In [52]: s.dt.day
Out[52]:
0 1
1 2
2 3
3 4
dtype: int64

# timedelta
In [53]: s = Series(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
dtype: timedelta64[ns]
In [55]: s.dt.days
Out[55]:
0 1
1 1
2 1
3 1
dtype: int64
In [56]: s.dt.seconds
Out[56]:
0 5
1 6
2 7
3 8
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

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 = Timestamp('2014-08-01 09:00', tz='US/Eastern')
In [59]: ts
Out[59]: Timestamp('2014-08-01 09:00:00-0400', tz='US/Eastern')
In [60]: ts.tz_localize(None)
Out[60]: Timestamp('2014-08-01 09:00:00')

In [61]: didx = DatetimeIndex(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='H')

• 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 = Series([10, 11, 12, 13])

In [15]: rolling_min(s, window=10, min_periods=5)
ValueError: min_periods (5) must be <= window (4)

New behavior

In [65]: rolling_min(s, window=10, min_periods=5)
Out[65]:
0  NaN
1  NaN
2  NaN
3  NaN
4  NaN
pandas: powerful Python data analysis toolkit, Release 0.17.0

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):

```python
In [7]: 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])):

```python
In [66]: rolling_sum(Series(range(4)), window=3, min_periods=0, center=True)
Out[66]:
   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)

Behavior prior to 0.15.0:

```python
In [39]: 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

```python
In [68]: rolling_window(s, window=3, win_type='triang', center=True)
Out[68]:
   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)):

In [69]: s = Series([1, None, None, None, 2, 3])

In [51]: ewma(s, com=3., min_periods=2)
Out[51]:
0    NaN
1    NaN
2     1.0
3     1.0
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):

In [70]: ewma(s, com=3., min_periods=2)
Out[70]:
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)

In [71]: ewma(Series([None, 1., 8.]), com=2.)
Out[71]:
0    NaN
1    1.0
2    5.2
dtype: float64

In [72]: ewma(Series([1., None, 8.]), com=2., ignore_na=True) # pre-0.15.0 behavior
Out[72]:

In [73]: ewma(Series([1., None, 8.]), com=2., ignore_na=False)  # new default
Out[73]:
0  1.0
1  1.0
2  5.846154
dtype: float64

**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:

In [74]: s = 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
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):

```python
In [75]: ewmvar(s, com=2., bias=False)
Out[75]:
0   NaN
1   0.500000
2   1.210526
3   4.089069
dtype: float64
```

```python
In [76]: ewmvar(s, com=2., bias=False) / ewmvar(s, com=2., bias=True)
Out[76]:
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')
pd.read_sql_table('table', engine, schema='other_schema')
```
- Added support for writing NaN values with `to_sql` (GH2754).
- Added support for writing datetime64 columns with `to_sql` for all database flavors (GH7103).

**1.7.2 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 [77]: df = DataFrame([['a'], ['b']],index=[1,2])
In [78]: df
Out[78]:
     0
 1   a
 2   b

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 [79]: df.loc[[1,3]]
Out[79]:
     0
 1   a
 3  NaN
In [80]: df.loc[[1,3],:]
Out[80]:
     0
 1   a
 3  NaN

This can also be seen in multi-axis indexing with a Panel.

In [81]: p = Panel(np.arange(2*3*4).reshape(2,3,4),
   ....:     items=['ItemA','ItemB'],
   ....:     major_axis=[1,2,3],
   ....:     minor_axis=['A','B','C','D'])
In [82]: p
The following would raise `KeyError` prior to 0.15.0:

```python
In [83]: p.loc[['ItemA','ItemD'],:,'D']
Out[83]:
     ItemA ItemD
1     3  NaN
2     7  NaN
3    11  NaN
```

Furthermore, `.loc` will raise if no values are found in a multi-index with a list-like indexer:

```python
In [84]: s = Series(np.arange(3,dtype='int64'),
            index=MultiIndex.from_product([['A'],['foo','bar','baz']],
                                          names=['one','two'])).sortlevel()
In [85]: s
Out[85]:
one two
A   bar 1
     baz 2
     foo 0
dtype: int64
In [86]: try:
   ....:   s.loc[['D']]
   ....: except KeyError as e:
   ....:     print("KeyError: " + str(e))
KeyError: 'cannot index a multi-index axis with these keys'
```

- 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 [87]: s = Series([1, 2, 3])
In [88]: s.loc[0] = None
In [89]: s
Out[89]:
0  NaN
1   2
2   3
dtype: float64
```

`NaT` is now used similarly for datetime containers.

For object containers, we now preserve `None` values (previously these were converted to `NaN` values).
In [90]: s = Series(["a", "b", "c"])

In [91]: s.loc[0] = None

In [92]: s
Out[92]:
0    None
1     b
2      c
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)

In [93]: s = Series([1, 2, 3])

In [94]: s2 = s

In [95]: 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 [96]: s
Out[96]:
0   2.5
1   3.5
2   4.5
dtype: float64

# a reference to the original object
In [97]: s2
Out[97]:
0   2.5
1   3.5
2   4.5
dtype: float64

• Made both the C-based and Python engines for read_csv and read_table ignore empty lines in input as well as
whitespace-filled lines, as long as `sep` is not whitespace. 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 [98]: i = date_range('1/1/2011', periods=3, freq='10s', tz = 'US/Eastern')
```

```python
In [99]: i
```

```
Out[99]:
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')
```

```python
In [100]: df = DataFrame( {'a' : i } )
```

```python
In [101]: df
```

```
Out[101]:
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
```

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)

```python
In [1]: df = DataFrame(np.arange(0,9), columns=['count'])
```

```python
In [2]: df['group'] = 'b'
```

```
/usr/local/bin/ipython:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
See the the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
```

- `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):

    In [103]: df = DataFrame([[True, 1],[False, 2]],
                           columns=["female","fitness"])
    .....:

    In [104]: df
    Out[104]:
    female fitness
       0   True    1
       1  False    2

    In [105]: df.dtypes
    Out[105]:
    female   bool
    fitness  int64
    dtype: object

    # dtypes are now preserved

    In [107]: df
    Out[107]:
    female fitness
       0   True    1
       1  False    2
       2  False    2

    In [108]: df.dtypes
    Out[108]:
    female   bool
    fitness  int64
    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](GH7943).

**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)

```
# +
Index(["a","b","c"]) + Index(["b","c","d"])

# should be replaced by
Index(["a","b","c"]).union(Index(["b","c","d"]))

# −
Index(["a","b","c"]) − Index(["b","c","d"])

# should be replaced by
Index(["a","b","c"]).difference(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`

**1.7.3 Enhancements**

Enhancements in the importing/exporting of Stata files:

- Added support for bool, uint8, uint16 and uint32 datatypes 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).

```python
In [109]: df = DataFrame({'catA': ['foo', 'foo', 'bar'] * 8,
                        'catB': ['a', 'b', 'c', 'd'] * 6,
                        'numC': np.arange(24),
                        'numD': np.arange(24.) + .5})

In [110]: df.describe(include=['object'])
Out[110]:
           catA  catB
count    24    24
unique   2     4
top      foo   d
freq     16     6

In [111]: df.describe(include=['number', 'object'], exclude=['float'])
Out[111]:
           catA  catB  numC
count    24    24  24.000000
unique   2     4   NaN
top      foo   d   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
```

Requesting all columns is possible with the shorthand ‘all’

```python
In [112]: df.describe(include='all')
Out[112]:
```

1.7. v0.15.0 (October 18, 2014)
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 [113]: df = DataFrame({'A': ['a', 'b', 'a'], 'B': ['c', 'c', 'b'],
   .....:  'C': [1, 2, 3]})
   .....:

In [114]: pd.get_dummies(df)
```

```
Out[114]:
   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
```

- **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)

```
In [115]: business_dates = date_range(start='4/1/2014', end='6/30/2014', freq='B')

In [116]: df = DataFrame(1, index=business_dates, columns=['a', 'b'])

# get the first, 4th, and last date index for each month
In [117]: df.groupby((df.index.year, df.index.month)).nth([0, 3, -1])
```

```
Out[117]:
    a   b
2014-04-01  1  1
2014-04-04  1  1
2014-04-30  1  1
2014-05-01  1  1
2014-05-06  1  1
2014-05-30  1  1
2014-06-02  1  1
2014-06-05  1  1
2014-06-30  1  1
```

- **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.

```
In [118]: idx = pd.period_range('2014-07-01 09:00', periods=5, freq='H')

In [119]: idx
Out[119]:
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='int64', freq='H')
```

```
In [120]: idx + pd.offsets.Hour(2)
Out[120]:
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='int64', freq='H')
```

```
In [121]: idx + Timedelta('120m')
Out[121]:
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='int64', freq='H')
```

```
In [122]: idx = pd.period_range('2014-07', periods=5, freq='M')

In [123]:  idx
                      dtype='int64', freq='M')
```

```
In [124]: idx + pd.offsets.MonthEnd(3)
                      dtype='int64', 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 [125]: idx = MultiIndex.from_product([['a'], range(3), list('pqr')], names=['foo', 'bar', 'baz'])

In [126]: idx.set_names('qux', level=0)
Out[126]:
MultiIndex(levels=[['u'a'], [0, 1, 2], ['p', 'q', 'r']],
          labels=[[0, 0, 0, 0, 0, 0, 0, 0, 0], [0, 0, 1, 1, 1, 2, 2, 2, 2], [0, 1, 2, 0, 1, 2, 0, 1, 2],
                  names=['qux', 'bar', 'baz'])
```

```
In [127]: idx.set_names(['qux', 'baz'], level=[0,1])
Out[127]:
MultiIndex(levels=[['u'a'], [0, 1, 2], ['p', 'q', 'r']],
          labels=[[0, 0, 0, 0, 0, 0, 0, 0, 0], [0, 0, 1, 1, 1, 2, 2, 2, 2], [0, 1, 2, 0, 1, 2, 0, 1, 2],
                  names=['u'qux', 'u'baz', 'u'baz'])
```

```
In [128]: idx.set_levels(['a','b','c'], level='bar')
```
Index.isin now supports a level argument to specify which index level to use for membership tests (GH7892, GH7890)

Index now supports duplicated and drop_duplicates. (GH4060)

add copy=True argument to pd.concat to enable pass thru of complete blocks (GH8252)

Added support for numpy 1.8+ data types (bool, int, float, string) for conversion to R dataframe (GH8400)

1.7.4 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)*

### 1.7.5 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 multiindexes dtypes getting mixed up when DataFrame is saved to SQL table** *(GH8021)*
• **Bug in Series 0-division with a float and integer operand dtypes** *(GH7785)*
• **Bug in `Series.astype("unicode")` not calling unicode on the values correctly** *(GH7758)*
• **Bug in DataFrame.as_matrix() with mixed `datetime64[ns]` and `timedelta64[ns]` dtypes** *(GH7778)*
• **Bug in HDFStore.select_column() not preserving UTC timezone info when selecting a `DateTimeIndex`** *(GH7777)*
• **Bug in to_datetime when format='\%Y\%m\%d' and coerce=True are specified**, where previously an object array was returned (rather than a coerced time-series with NaT), *(GH7930)*
• **Bug in `DateTimeIndex` and `PeriodIndex` in-place addition and subtraction cause different result from normal one** *(GH6527)*
• **Bug in adding and subtracting `PeriodIndex` with `PeriodIndex` raise TypeError** *(GH7741)*
• **Bug in `combine_first` with `PeriodIndex` data raises TypeError** *(GH3367)*
• **Bug in multi-index slicing with missing indexers** *(GH7866)*
• **Bug in multi-index slicing with various edge cases** *(GH8132)*
• **Regression in multi-index 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 multi-index 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 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 in to_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 multi-index 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.

1.8 v0.14.1 (July 11, 2014)

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.

- Enhancements
- API Changes
- Performance Improvements
• Experimental Changes

• Bug Fixes

1.8.1 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]: 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, (regresion 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)

1.8.2 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):

In [3]: import pandas.tseries.offsets as offsets
In [4]: day = offsets.Day()
In [5]: day.apply(Timestamp('2014-01-01 09:00'))
Out[5]: Timestamp('2014-01-02 09:00:00')

In [6]: day = offsets.Day(normalize=True)

In [7]: day.apply(Timestamp('2014-01-01 09:00'))
Out[7]: Timestamp('2014-01-02 00:00:00')

• 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 [8]: rng = date_range('3/6/2012 00:00', periods=10, freq='D',
...:                     tz='dateutil/Europe/London')

...:

In [9]: rng.tz
Out[9]: 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 whitelist, 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)

1.8.3 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)

1.8.4 Experimental

• pandas.io.data.Options has a new method, get_all_data method, and now consistently returns a multi-indexed DataFrame, see the docs. (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 httplib2 and the Google apiclient and oauth2client API client libraries which should be more stable and, therefore, reliable than bq.py. See the docs. (GH6937).

1.8.5 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 multi-index 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 timeops 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.get 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 subplots displays ticklabels and labels in different rule (GH5897)
• Bug in Panel.apply with a multi-index as an axis (GH7469)
• Bug in DatetimeIndex.insert doesn’t preserve name and tz (GH7299)
• Bug in DatetimeIndex.asobject doesn’t preserve name (GH7299)
• Bug in multi-index slicing with datetimelike ranges (strings and Timestamps), (GH7429)
• Bug in Index.min and max doesn’t handle nan and NaT properly (GH7261)
• Bug in PeriodIndex.min/max results in int (GH7609)
• Bug in resample where fill_method was ignored if you passed how (GH2073)
• Bug in TimeGrouper doesn’t exclude column specified by key (GH7227)
• Bug in DataFrame and Series bar and barh plot raises TypeError when bottom and left keyword is specified (GH7226)
• Bug in DataFrame.hist raises TypeError when it contains non numeric column (GH7277)
• 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 .ixgetitem should always return a Series (GH7150)
• Bug in multi-index slicing with incomplete indexers (GH7399)
• Bug in multi-index 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 (issue’7306’)
• 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).
1.9  v0.14.0 (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 multi-indexed 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 NDFrame 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)

1.9.1 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 = DataFrame(np.random.randn(5,2),columns=list('AB'))

In [2]: df1
Out[2]:
```
A   B
0  1.583584 -0.438313
1 -0.402537 -0.780572
2 -0.141685  0.542241
3  0.370966 -0.251642
4  0.787484  1.666563

In [3]: df.iloc[:,2:3]
Out[3]:
Empty DataFrame
Columns: []
Index: [0, 1, 2, 3, 4]

In [4]: df.iloc[:,1:3]
Out[4]:
   B
0 -0.438313
1 -0.780572
2  0.542241
3 -0.251642
4  1.666563

In [5]: df.iloc[4:6]
Out[5]:
   A   B
4  0.787484  1.666563

These are out-of-bounds selections

df.iloc[[4,5,6]]
IndexError: positional indexers are out-of-bounds

df.iloc[:,:]
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='int32')
```

- `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
In [10]: tuple_ind
Out[10]: Index([(u'a', u'c'), (u'a', u'd'), (u'b', u'c'), (u'b', u'd')], dtype='object')
```
```
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
```

```
# New behavior
In [12]: mi
Out[12]: MultiIndex(levels=[[u'a', u'b'], [u'c', u'd']],
labels=[[0, 0, 1, 1], [0, 1, 0, 1]])
```
```
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

This also applies when passing multiple indices to set_index:

# 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

# New output, 4-level MultiIndex
In [15]: df_multi.set_index([df_multi.index, df_multi.index])
Out[15]:
     0   1
   a c a c 0.471435 -1.190976
    d a d 1.432707 -0.312652
   b c b c -0.720589 0.887163
   d b d 0.859588 -0.636524

• pairwise keyword was added to the statistical moment functions rolling_cov, rolling_corr, ewmcoy, 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 [16]: df = DataFrame(np.random.randn(10,4),columns=list('ABCD'))

In [17]: covs = rolling_cov(df[['A','B','C']], df[['B','C','D']], 5, pairwise=True)

In [18]: covs[df.index[-1]]
Out[18]:
          B   C   D
A  0.128104 0.183628 -0.047358
B  0.856265 0.058945 0.145447
C  0.058945 0.335350 0.390637

• 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)

```python
x = pd.Series(np.random.rand(10) > 0.5)
y = True
x + y  # warning generated: should do x | y 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)

### 1.9.2 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.
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.

In [24]: pd.DataFrame(np.arange(10*10).reshape((10,10)), index=index)

Out[24]:
   0  1  2 ...
2001-01-01  0  1  2 ...
2001-01-02 10 11 12 ...
2001-01-03 20 21 22 ...
... ...
2001-01-08 70 71 72 ...
2001-01-09 80 81 82 ...
2001-01-10 90 91 92 ...

[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.

In [19]: 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 [20]: with pd.option_context('display.max_rows', 2, 'display.max_columns', 2, 'display.show_dimensions', 'truncate'):
    ....:     print(dfd)
    ....:
    0 ... 4
    0 0 ... 4
In [21]: with pd.option_context('display.max_rows', 10, 'display.max_columns', 40, 'display.show_dimensions', 'truncate'):
   ....:    print(dfd)
   ....:    0  1  2  3  4
    0  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)

1.9.3 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)

1.9.4 Groupby API Changes

More consistent behaviour for some groupby methods:

• groupby head and tail now act more like filter rather than an aggregation:

In [22]: df = pd.DataFrame([[1, 2], [1, 4], [5, 6]], columns=['A', 'B'])

In [23]: g = df.groupby('A')
In [24]: g.head(1)  # filters DataFrame
Out[24]:
   A  B
0  1  2
2  5  6

In [25]: g.apply(lambda x: x.head(1))  # used to simply fall-through
Out[25]:
   A  B
     A
    1  0  1  2
      5  2  5  6

• groupby head and tail respect column selection:

In [26]: g[['B']].head(1)
Out[26]:
   B
0  2
2  6

• 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

In [27]: df = DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=['A', 'B'])
In [28]: g = df.groupby('A')
In [29]: g.nth(0)
Out[29]:
   B
A
1  NaN
5  6

# this is equivalent to g.first()
In [30]: g.nth(0, dropna='any')
Out[30]:
   B
A
1  4
5  6

# this is equivalent to g.last()
In [31]: g.nth(-1, dropna='any')
Out[31]:
   B
A
1  4
5  6

Filtering

In [32]: gf = df.groupby('A',as_index=False)
In [33]: gf.nth(0)
Out[33]:
   A  B
     A
    1  0  1  2
      5  2  5  6

1.9. v0.14.0 (May 31, 2014)
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In [34]: gf.nth(0, dropna='any')
Out[34]:
   A
0  1
1  4
2  5
3  6

• groupby will now not return the grouped column for non-cython functions (GH5610, GH5614, GH6732), as its already the index

In [35]: df = DataFrame([[1, np.nan], [1, 4], [5, 6], [5, 8]], columns=['A', 'B'])
In [36]: g = df.groupby('A')
In [37]: g.count()
Out[37]:
   B
A  
  1  1
  5  2

In [38]: g.describe()
Out[38]:
   A
   count 1.000000
   mean  4.000000
   std   NaN
   min  4.000000
   25%  4.000000
   50%  4.000000
   75%  4.000000
   ... ...
   5  mean  7.000000
   std  1.414214
   min  6.000000
   25%  6.500000
   50%  7.000000
   75%  7.500000
   max  8.000000

[16 rows x 1 columns]

• passing as_index will leave the grouped column in-place (this is not change in 0.14.0)

In [39]: df = DataFrame([[1, np.nan], [1, 4], [5, 6], [5, 8]], columns=['A', 'B'])
In [40]: g = df.groupby('A',as_index=False)
In [41]: g.count()
Out[41]:
   A  B
0  1  1
1  5  2

In [42]: g.describe()
Out[42]:

<table>
<thead>
<tr>
<th></th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>2.0</td>
</tr>
<tr>
<td>1</td>
<td>1.0</td>
</tr>
<tr>
<td>2</td>
<td>4.0</td>
</tr>
<tr>
<td>3</td>
<td>7.0</td>
</tr>
<tr>
<td>4</td>
<td>8.0</td>
</tr>
</tbody>
</table>

[16 rows x 2 columns]

- 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.

1.9.5 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 sqlite3 database:

In [43]: from sqlalchemy import create_engine

# Create your connection.
In [44]: engine = create_engine('sqlite:///::memory:')</code>

This engine can then be used to write or read data to/from this database:
In [45]: df = pd.DataFrame({'A': [1,2,3], 'B': ['a', 'b', 'c']})

In [46]: df.to_sql('db_table', engine, index=False)

You can read data from a database by specifying the table name:

In [47]: pd.read_sql_table('db_table', engine)
Out[47]:
   A  B
0  1  a
1  2  b
2  3  c

or by specifying a sql query:

In [48]: pd.read_sql_query('SELECT * FROM db_table', engine)
Out[48]:
   A  B
0  1  a
1  2  b
2  3  c

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).

1.9.6 MultiIndexing Using Slicers

In 0.14.0 we added a new way to slice multi-indexed objects. You can slice a multi-index 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:

```
df.loc[(slice('A1','A3'),.....),:]
```

rather than this:

```
df.loc[(slice('A1','A3'),.....)]
```

Warning: You will need to make sure that the selection axes are fully lexsorted!

```
In [49]: def mklbl(prefix,n):
   ....:     return ["%s%s" % (prefix,i) for i in range(n)]
   ....:

In [50]: index = MultiIndex.from_product([mklbl('A',4),
   ....:     mklbl('B',2),
   ....:     mklbl('C',4),
   ....:     mklbl('D',2)])
   ....:

In [51]: columns = MultiIndex.from_tuples([('a','foo'),('a','bar'),
   ....:     ('b','foo'),('b','bah')],
   ....:     names=['lvl0', 'lvl1'])
   ....:

In [52]: df = DataFrame(np.arange(len(index)*len(columns)).reshape((len(index),len(columns))),
   ....:     index=index,
   ....:     columns=columns).sortlevel().sortlevel(axis=1)
   ....:

In [53]: df
```

```
Out[53]:
   lvl0  lvl1  a  b
  A0  B0  C0  D0  1  0  3  2
  D1  5  4  7  6
  C1  D0  9  8 11 10
  D1  13 12 15 14
  C2  D0 17 16 19 18
  D1  21 20 23 22
  C3  D0 25 24 27 26
   ...  ...  ...  ...  ...
  A3  B1  C0  D1 229 228 231 230
  C1  D0 233 232 235 234
  D1  237 236 239 238
  C2  D0 241 240 243 242
  D1  245 244 247 246
  C3  D0 249 248 251 250
  D1  253 252 255 254
```

Basic multi-index slicing using slices, lists, and labels.
In [54]: df.loc[(slice('A1', 'A3'), slice(None), ['C1', 'C3']), :]
Out[54]:
   lv0  a  b
  lvl0 bar foo bah foo
    A1  B0  C1  D0  73  72  75  74
  D1  77  76  79  78
    C3  D0  89  88  91  90
  D1  93  92  95  94
    B1  C1  D0  105 104 107 106
  D1  109 108 111 110
    C3  D0  121 120 123 122
  ... ... ... ... ...
  A3  B0  C1  D1  205 204 207 206
    C3  D0  217 216 219 218
  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
[24 rows x 4 columns]

You can use a `pd.IndexSlice` to shortcut the creation of these slices

In [55]: idx = pd.IndexSlice

In [56]: df.loc[idx[:,:,['C1','C3']],idx[:,['foo']]]
Out[56]:
   lv0  a  b
  lvl0 foo foo
    A0  B0  C1  D0  8  10
  D1  12  14
    C3  D0  24  26
  D1  28  30
    B1  C1  D0  40  42
  D1  44  46
    C3  D0  56  58
  ... ... ... ...
  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
[32 rows x 2 columns]

It is possible to perform quite complicated selections using this method on multiple axes at the same time.

In [57]: df.loc['A1',(slice(None),'foo')]
In [58]: df.loc[idx[:,:,['C1','C3']],idx[:,'foo']]

Out[58]:

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>A0</td>
<td>B0</td>
<td>C1</td>
</tr>
<tr>
<td>idx0</td>
<td>idx1</td>
<td>idx2</td>
</tr>
<tr>
<td>D1</td>
<td>84</td>
<td>86</td>
</tr>
<tr>
<td>C3</td>
<td>88</td>
<td>90</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>B1</td>
<td>C0</td>
<td>D1</td>
</tr>
<tr>
<td>C1</td>
<td>100</td>
<td>102</td>
</tr>
<tr>
<td>D1</td>
<td>104</td>
<td>106</td>
</tr>
<tr>
<td>C2</td>
<td>108</td>
<td>110</td>
</tr>
<tr>
<td>D1</td>
<td>112</td>
<td>114</td>
</tr>
<tr>
<td>C3</td>
<td>116</td>
<td>118</td>
</tr>
<tr>
<td>D1</td>
<td>120</td>
<td>122</td>
</tr>
<tr>
<td>A3</td>
<td>B3</td>
<td>C1</td>
</tr>
<tr>
<td>idx0</td>
<td>idx1</td>
<td>idx2</td>
</tr>
<tr>
<td>D1</td>
<td>204</td>
<td>206</td>
</tr>
<tr>
<td>C3</td>
<td>216</td>
<td>218</td>
</tr>
<tr>
<td>D1</td>
<td>220</td>
<td>222</td>
</tr>
<tr>
<td>B1</td>
<td>C1</td>
<td>D0</td>
</tr>
<tr>
<td>C3</td>
<td>232</td>
<td>234</td>
</tr>
<tr>
<td>D1</td>
<td>236</td>
<td>238</td>
</tr>
<tr>
<td>C3</td>
<td>248</td>
<td>250</td>
</tr>
<tr>
<td>D1</td>
<td>252</td>
<td>254</td>
</tr>
</tbody>
</table>

[16 rows x 2 columns]

Using a boolean indexer you can provide selection related to the values.

In [59]: mask = df[('a','foo')]>200

In [60]: df.loc[idx[mask,:,['C1','C3']],idx[:,'foo']]

Out[60]:

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>A0</td>
<td>B0</td>
<td>C1</td>
</tr>
<tr>
<td>idx0</td>
<td>idx1</td>
<td>idx2</td>
</tr>
<tr>
<td>D1</td>
<td>8</td>
<td>10</td>
</tr>
<tr>
<td>C3</td>
<td>24</td>
<td>26</td>
</tr>
<tr>
<td>D1</td>
<td>28</td>
<td>30</td>
</tr>
<tr>
<td>B1</td>
<td>C1</td>
<td>D0</td>
</tr>
<tr>
<td>C3</td>
<td>40</td>
<td>42</td>
</tr>
<tr>
<td>D1</td>
<td>44</td>
<td>46</td>
</tr>
<tr>
<td>C3</td>
<td>56</td>
<td>58</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>A3</td>
<td>B0</td>
<td>C1</td>
</tr>
<tr>
<td>C3</td>
<td>204</td>
<td>206</td>
</tr>
<tr>
<td>D1</td>
<td>216</td>
<td>218</td>
</tr>
<tr>
<td>C3</td>
<td>220</td>
<td>222</td>
</tr>
<tr>
<td>B1</td>
<td>C1</td>
<td>D0</td>
</tr>
<tr>
<td>C3</td>
<td>232</td>
<td>234</td>
</tr>
<tr>
<td>D1</td>
<td>236</td>
<td>238</td>
</tr>
<tr>
<td>C3</td>
<td>248</td>
<td>250</td>
</tr>
<tr>
<td>D1</td>
<td>252</td>
<td>254</td>
</tr>
</tbody>
</table>

[32 rows x 2 columns]

You can also specify the axis argument to .loc to interpret the passed slicers on a single axis.

In [61]: df.loc(axis=0)[:,:,['C1','C3']]

Out[61]:

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>A0</td>
<td>B0</td>
<td>C1</td>
<td>D0</td>
</tr>
<tr>
<td>idx0</td>
<td>idx1</td>
<td>idx2</td>
<td>idx3</td>
</tr>
<tr>
<td>D1</td>
<td>9</td>
<td>8</td>
<td>11</td>
</tr>
<tr>
<td>B1</td>
<td>C1</td>
<td>D0</td>
<td>13</td>
</tr>
<tr>
<td>D1</td>
<td>12</td>
<td>15</td>
<td>14</td>
</tr>
</tbody>
</table>
Furthermore you can set the values using these methods

```python
In [62]: df2 = df.copy()

In [63]: df2.loc(axis=0)[:,:,['C1','C3']] = -10

In [64]: df2
Out[64]:
   a  b
0  1  2
1  3  4
2  5  6
3 -10 -10
4 -10 -10
5 17 18
6 21 22
7 -10 -10
8 -10 -10
9 -10 -10
```

You can use a right-hand-side of an alignable object as well.

```python
In [65]: df2 = df.copy()

In [66]: df2.loc[idx[:,:,['C1','C3']],:] = df2*1000

In [67]: df2
Out[67]:
   a  b
0  1  2
1  3  4
2  5  6
3 9000 8000
4 -10 -10
5 17 18
6 21 22
7 -10 -10
8 -10 -10
9 -10 -10
```
1.9.7 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 matplotlib'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)

• The `DataFrame.boxplot()` now supports `layout` keyword (GH6769)

• The `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.

1.9.8 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 functions 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()` (GH391)

• 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)

1.9.9 Deprecations

• The `pivot_table()`/`DataFrame.pivot_table()` and `crosstab()` functions now take arguments `index` and `columns` instead of `rows` and `cols`. A `FutureWarning` is raised to alert that the old `rows` and `cols` arguments will not be supported in a future release (GH5505)

• The `DataFrame.drop_duplicates()` and `DataFrame.duplicated()` methods now take argument `subset` instead of `cols` to better align with `DataFrame.dropna()`. A `FutureWarning` is raised to alert that the old `cols` arguments will not be supported in a future release (GH6680)

• The `DataFrame.to_csv()` and `DataFrame.to_excel()` functions now takes argument `columns` instead of `cols`. A `FutureWarning` is raised to alert that the old `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]: Series(1, np.arange(5))[3.0]
   pandas/core/index.py:469: FutureWarning: scalar indexers for index type Int64Index should
   Out[1]: 1
```
In [2]: Series(1,np.arange(5)).iloc[3.0]
    pandas/core/index.py:469: FutureWarning: scalar indexers for index type Int64Index should be integers.
    Out[2]: 1

In [3]: Series(1,np.arange(5)).iloc[3.0:4]
    pandas/core/index.py:527: FutureWarning: slice indexers when using iloc should be integers.
    Out[3]:
    3  1
    dtype: int64

# these are Float64Indexes, so integer or floating point is acceptable
In [4]: Series(1,np.arange(5.))[3]
Out[4]: 1

In [5]: Series(1,np.arange(5.))[3.0]
Out[6]: 1

• Numpy 1.9 compat w.r.t. deprecation warnings (GH6960)

• Panel.shift() now has a function signature that matches DataFrame.shift(). The old positional argument lags has been changed to a keyword argument periods with a default value of 1. A FutureWarning is raised if the old argument lags is used by name. (GH6910)

• The order keyword argument of factorize() will be removed. (GH6926).

• Remove the copy keyword from DataFrame.xs(), Panel.major_xs(), Panel.minor_xs(). A view will be returned if possible, otherwise a copy will be made. Previously the user could think that copy=False would ALWAYS return a view. (GH6894)

• 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)

• 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.

1.9.10 Known Issues

• OpenPyXL 2.0.0 breaks backwards compatibility (GH7169)

1.9.11 Enhancements

• DataFrame and Series will create a MultiIndex object if passed a tuples dict, See the docs (GH3323)
In [68]: Series({('a', 'b'): 1, ('a', 'a'): 0, ......: ('a', 'c'): 2, ('b', 'a'): 3, ('b', 'b'): 4})
....:
Out[68]:
a  a  0
    b  1
    c  2
   b  a  3
   b  4
dtype: int64

In [69]: 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[69]:
   a b
   A B 4 1 5 8 10
   C 3 2 6 7 NaN
   D NaN NaN NaN NaN 9

- 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 multi-indexed DataFrame (GH3662)

See the docs. Joining multi-index DataFrames on both the left and right is not yet supported ATM.

In [70]: household = DataFrame(dict(household_id = [1,2,3], ......: male = [0,1,0], ......: wealth = [196087.3,316478.7,294750]), ......: columns = ['household_id','male','wealth'])
....:
Out[71]:
   male  wealth
household_id
1     0       196087.3
2     1       316478.7
3     0       294750.0

In [72]: portfolio = DataFrame(dict(household_id = [1,2,2,3,3,3,4], ......: asset_id = ["nl0000301109","nl0000289783","gb00b03m1x29", ......: "gb00b03m1x29","lu0197800237","n10000289965",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'])
.....:                          ).set_index(['household_id', 'asset_id'])
.....:

In [73]: portfolio
Out[73]:

<table>
<thead>
<tr>
<th>household_id</th>
<th>asset_id</th>
<th>name</th>
<th>share</th>
</tr>
</thead>
<tbody>
<tr>
<td>nl0000301109</td>
<td></td>
<td>ABN Amro</td>
<td>1.00</td>
</tr>
<tr>
<td>n10000289783</td>
<td></td>
<td>Robeco</td>
<td>0.40</td>
</tr>
<tr>
<td>gb00b03mlx29</td>
<td></td>
<td>Royal Dutch Shell</td>
<td>0.60</td>
</tr>
<tr>
<td>gb00b03mlx29</td>
<td></td>
<td>Royal Dutch Shell</td>
<td>0.15</td>
</tr>
<tr>
<td>lu197800237</td>
<td></td>
<td>AAB Eastern Europe Equity Fund</td>
<td>0.60</td>
</tr>
<tr>
<td>n10000289965</td>
<td></td>
<td>Postbank BioTech Fonds</td>
<td>0.25</td>
</tr>
<tr>
<td>NaN</td>
<td>NaN</td>
<td>NaN</td>
<td>1.00</td>
</tr>
</tbody>
</table>

In [74]: household.join(portfolio, how='inner')
Out[74]:

<table>
<thead>
<tr>
<th>household_id</th>
<th>asset_id</th>
<th>male</th>
<th>wealth</th>
<th>name</th>
<th>share</th>
</tr>
</thead>
<tbody>
<tr>
<td>n10000301109</td>
<td></td>
<td>0</td>
<td>196087.3</td>
<td>ABN Amro</td>
<td>1.00</td>
</tr>
<tr>
<td>n10000289783</td>
<td></td>
<td>1</td>
<td>316478.7</td>
<td>Robeco</td>
<td>0.40</td>
</tr>
<tr>
<td>gb00b03mlx29</td>
<td></td>
<td>1</td>
<td>316478.7</td>
<td>Royal Dutch Shell</td>
<td>0.60</td>
</tr>
<tr>
<td>gb00b03mlx29</td>
<td></td>
<td>0</td>
<td>294750.0</td>
<td>Royal Dutch Shell</td>
<td>0.15</td>
</tr>
<tr>
<td>lu197800237</td>
<td></td>
<td>0</td>
<td>294750.0</td>
<td>AAB Eastern Europe Equity Fund</td>
<td>0.60</td>
</tr>
<tr>
<td>n10000289965</td>
<td></td>
<td>0</td>
<td>294750.0</td>
<td>Postbank BioTech Fonds</td>
<td>0.25</td>
</tr>
</tbody>
</table>

• quotechar, doublequote, and escapechar can now be specified when using `DataFrame.to_csv` (GH5414, GH4528)

• Partially sort by only the specified levels of a MultiIndex with the `sort_remaining` boolean kwarg. (GH3984)

• Added `to_julian_date` to `TimeStamp` and `DatetimeIndex`. The Julian Date is used primarily in astronomy and represents the number of days from noon, January 1, 4713 BC. Because nanoseconds are used to define the time in pandas the actual range of dates that you can use is 1678 AD to 2262 AD. (GH4041)

• `DataFrame.to_stata` will now check data for compatibility with Stata data types and will upcast when needed. When it is not possible to losslessly upcast, a warning is issued (GH6327)

• `DataFrame.to_stata` and `StataWriter` will accept keyword arguments `time_stamp` and `data_label` which allow the time stamp and dataset label to be set when creating a file. (GH6545)

• `pandas.io.gbq` now handles reading unicode strings properly. (GH5940)

• `Holidays Calendars` are now available and can be used with the `CustomBusinessDay` offset (GH6719)

• `Float64Index` is now backed by a `float64` dtype `ndarray` instead of an `object` dtype array (GH6471).

• Implemented `Panel.pct_change` (GH6904)

• Added `how` option to rolling-moment functions to dictate how to handle resampling: `rolling_max()` defaults to max, `rolling_min()` defaults to min, and all others default to mean (GH6297)
• **CustomBusinessMonthBegin** and **CustomBusinessMonthEnd** are now available (GH6866)

• **Series.quantile()** and **DataFrame.quantile()** now accept an array of quantiles.

• **describe()** now accepts an array of percentiles to include in the summary statistics (GH4196)

• **pivot_table** can now accept **Grouper** by index and columns keywords (GH6913)

```
In [75]: import datetime

In [76]: df = DataFrame({
    ....:     'Branch': 'A A A A A B'.split(),
    ....:     'Buyer': 'Carl Mark Carl Joe Joe'.split(),
    ....:     'Quantity': [1, 3, 5, 1, 8, 1],
    ....:     'Date': [datetime.datetime(2013,11,1,13,0),
                  datetime.datetime(2013,9,1,13,5),
                  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 [77]: df
Out[77]:
Branch  Buyer                Date                  PayDay
0       A       Carl 2013-11-01 13:00:00 2013-10-04 00:00:00 1
1       A       Mark 2013-09-01 13:05:00 2013-10-15 13:05:00 3
2       A       Carl 2013-10-01 20:00:00 2013-09-05 20:00:00 5
3       A       Carl 2013-10-02 10:00:00 2013-11-02 10:00:00 1
4       A       Joe 2013-11-01 20:00:00 2013-10-07 20:00:00 8
5       B       Joe 2013-10-02 10:00:00 2013-09-05 10:00:00 1
```

```
In [78]: pivot_table(df, index=Grouper(freq='M', key='Date'),
    ....:     columns=Grouper(freq='M', key='PayDay'),
    ....:     values='Quantity', aggfunc=np.sum)
```

```
Out[78]:
    PayDay    Date      2013-09-30 2013-10-31 2013-11-30
Date
2013-09-30       NaN       3       NaN
2013-10-31       6       NaN       1
2013-11-30       NaN       9       NaN
```

• 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 [79]: prng = period_range('2013-01-01 09:00', periods=100, freq='H')

In [80]: ps = Series(np.random.randn(len(prng)), index=prng)

In [81]: ps
Out[81]:
2013-01-01 09:00  0.755414
2013-01-01 10:00  0.215269
2013-01-01 11:00  0.841009
2013-01-01 12:00  1.445810
2013-01-01 13:00  1.401973
2013-01-01 14:00  0.100918
```
In [82]: ps['2013-01-02']
Out[82]:
    2013-01-02 00:00   -0.208499
    2013-01-02 01:00    1.033801
    2013-01-02 02:00   -2.400454
    2013-01-02 03:00    2.030604
    2013-01-02 04:00   -1.142631
    2013-01-02 05:00    0.211883
    2013-01-02 06:00    0.704721
    ...
    2013-01-02 17:00    0.464392
    2013-01-02 18:00   -3.563517
    2013-01-02 19:00    1.321106
    2013-01-02 20:00    0.152631
    2013-01-02 21:00    0.164530
    2013-01-02 22:00   -0.430096
    2013-01-02 23:00    0.767369
Freq: H, 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)

1.9.12 Performance

• Performance improvement when converting DatetimeIndex to floating ordinals using DatetimeConverter (GH6636)
• Performance improvement for DataFrame.shift (GH5609)
• Performance improvement in indexing into a multi-indexed 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).

1.9.13 Experimental

There are no experimental changes in 0.14.0

1.9.14 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 zeroes (GH6391)
• Bug in pd.DataFrame.sort_index where mergesort wasn’t stable when ascending=False (GH6399)
• 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 multi-index 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 `nosestests -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).

• Perf issue in concating 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` (NaTType) (GH4606)
- Bug in `DataFrame.replace()` where regex metacharacters were being treated as regexes 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 adding `np.timedelta64` to `DatetimeIndex` with timezone outputs incorrect results (GH6818)
- 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 datetlike 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 whitespace (GH3374)
- Bug in C parser with `delim_whitespace=True` and \r-delimited lines
- Bug in python parser with explicit multi-index 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)
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- 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 `nan`s 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, multi-index 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 multi-index (GH7199)
• Fix a bug where invalid eval/query operations would blow the stack (GH5198)

1.10 v0.13.1 (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 = DataFrame(dict(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 = DataFrame(dict(A = np.array(['foo','bar','bah','foo','bar'])))
In [5]: df.ix[0,'A'] = np.nan

In [6]: df
Out[6]:
   A
0  NaN
1  bar
2  bah
3  foo
4  bar
```
1.10.1 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 = DataFrame(dict(A = np.random.randn(10),
...: B = np.random.randn(10),
...: C = 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'>
Int64Index: 10 entries, 0 to 9
Data columns (total 3 columns):
   A float64
   B float64
   C datetime64[ns]
dtypes: datetime64[ns](1), float64(2)
memory usage: 320.0 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'>
Int64Index: 10 entries, 0 to 9
Data columns (total 3 columns):
   A 7 non-null float64
   B 10 non-null float64
   C 7 non-null datetime64[ns]
dtypes: datetime64[ns](1), float64(2)
memory usage: 320.0 bytes

- Add show_dimensions display option for the new DataFrame repr to control whether the dimensions print.

```python
In [14]: df = DataFrame([[1, 2], [3, 4]])

In [15]: pd.set_option('show_dimensions', False)

In [16]: df
Out[16]:
0 1
0 1 2
1 3 4

In [17]: pd.set_option('show_dimensions', True)

In [18]: df
Out[18]:
0 1
0 1 2
• The `ArrayFormatter` for `datetime` and `timedelta64` now intelligently limit precision based on the values in the array (GH3401)

Previously output might look like:

```
<table>
<thead>
<tr>
<th>age</th>
<th>today</th>
<th>diff</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 2001-01-01 00:00:00</td>
<td>2013-04-19 00:00:00</td>
<td>4491 days, 00:00:00</td>
</tr>
<tr>
<td>1 2004-06-01 00:00:00</td>
<td>2013-04-19 00:00:00</td>
<td>3244 days, 00:00:00</td>
</tr>
</tbody>
</table>
```

Now the output looks like:

```
In [19]: df = DataFrame([Timestamp('20010101'),
                   Timestamp('20040601')], columns=['age'])

In [20]: df['today'] = Timestamp('20130419')

In [21]: df['diff'] = df['today'] - df['age']

In [22]: df
Out[22]:
<table>
<thead>
<tr>
<th>age</th>
<th>today</th>
<th>diff</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 2001-01-01</td>
<td>2013-04-19</td>
<td>4491 days</td>
</tr>
<tr>
<td>1 2004-06-01</td>
<td>2013-04-19</td>
<td>3244 days</td>
</tr>
</tbody>
</table>
```

1.10.2 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 = Series(['a', 'a|b', np.nan, 'a|c'])

In [24]: s.str.get_dummies(sep='|')
Out[24]:
<table>
<thead>
<tr>
<th>a</th>
<th>b</th>
<th>c</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>
```

• 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.

```
In [25]: df = DataFrame({'col':['foo', 0, np.nan]})

In [26]: df2 = DataFrame({'col':[np.nan, 0, 'foo']}, index=[2,1,0])
```
In [27]: df.equals(df2)
Out[27]: False

In [28]: df.equals(df2.sort())
Out[28]: True

In [29]: import pandas.core.common as com

In [30]: com.array_equivalent(np.array([0, np.nan]), np.array([0, np.nan]))
Out[30]: True

In [31]: np.array_equal(np.array([0, np.nan]), np.array([0, np.nan]))
Out[31]: False

• 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([], dtype: float64))
Out[34]:
a  NaN
b  NaN
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
dtype: float64

In [36]: empty.apply(applied_func, reduce=False)
Out[36]:
Empty DataFrame
Columns: [a, b]
Index: []

[0 rows x 2 columns]

1.10.3 Prior Version Deprecations/Changes

There are no announced changes in 0.13 or prior that are taking effect as of 0.13.1
1.10.4 Deprecations

There are no deprecations of prior behavior in 0.13.1

1.10.5 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 @lexual 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.

  
  ```python
  # Try to infer the format for the index column
  df = pd.read_csv('foo.csv', index_col=0, parse_dates=True,
                   infer_datetime_format=True)
  ```

- `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):

  ```
  In [37]: shades = ['light', 'dark']
  In [38]: colors = ['red', 'green', 'blue']
  In [39]: MultiIndex.from_product([shades, colors], names=['shade', 'color'])
  Out[39]:
  MultiIndex(levels=[[u'dark', u'light'], [u'blue', u'green', u'red']],
             labels=[[1, 1, 1, 0, 0, 0], [2, 1, 0, 2, 1, 0]],
             names=['shade', 'color'])
  ```

- `Panel apply()` will work on non-ufuncs. See the docs.

  ```
  In [40]: import pandas.util.testing as tm
  In [41]: panel = tm.makePanel(5)
  In [42]: panel
  ```

  ```
  Out[42]:
  <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 [43]: panel['ItemA']
  ```

  ```
  Out[43]:
  A    B    C    D
  2000-01-03  0.952478 -1.239072 -1.409432 -0.014752
  2000-01-04  0.988138  0.139683  1.422986  1.272395
  2000-01-05  -0.072608 -0.223019 -2.147855 -1.449567
  2000-01-06  -0.550603  2.123692 -1.347533 -1.195524
  2000-01-07  -0.938153  0.122273  0.363565 -0.591863
  [5 rows x 4 columns]
  ```
Specifying an apply that operates on a Series (to return a single element)

In [44]: panel.apply(lambda x: x.dtype, axis='items')

Out[44]:

<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>float64</td>
<td>float64</td>
<td>float64</td>
<td>float64</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>float64</td>
<td>float64</td>
<td>float64</td>
<td>float64</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>float64</td>
<td>float64</td>
<td>float64</td>
<td>float64</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>float64</td>
<td>float64</td>
<td>float64</td>
<td>float64</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>float64</td>
<td>float64</td>
<td>float64</td>
<td>float64</td>
</tr>
</tbody>
</table>

[5 rows x 4 columns]

A similar reduction type operation

In [45]: panel.apply(lambda x: x.sum(), axis='major_axis')

Out[45]:

<table>
<thead>
<tr>
<th></th>
<th>ItemA</th>
<th>ItemB</th>
<th>ItemC</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.379252</td>
<td>-3.696907</td>
<td>3.709335</td>
</tr>
<tr>
<td>B</td>
<td>0.923558</td>
<td>0.504242</td>
<td>4.656781</td>
</tr>
<tr>
<td>C</td>
<td>-3.118269</td>
<td>-1.545718</td>
<td>3.188329</td>
</tr>
<tr>
<td>D</td>
<td>-1.979310</td>
<td>-0.758060</td>
<td>-1.436483</td>
</tr>
</tbody>
</table>

[4 rows x 3 columns]

This is equivalent to

In [46]: panel.sum('major_axis')

Out[46]:

<table>
<thead>
<tr>
<th></th>
<th>ItemA</th>
<th>ItemB</th>
<th>ItemC</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.379252</td>
<td>-3.696907</td>
<td>3.709335</td>
</tr>
<tr>
<td>B</td>
<td>0.923558</td>
<td>0.504242</td>
<td>4.656781</td>
</tr>
<tr>
<td>C</td>
<td>-3.118269</td>
<td>-1.545718</td>
<td>3.188329</td>
</tr>
<tr>
<td>D</td>
<td>-1.979310</td>
<td>-0.758060</td>
<td>-1.436483</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 [47]: result = panel.apply(
   ...:     lambda x: (x-x.mean())/x.std(),
   ...:     axis='major_axis')

In [48]: result

Out[48]:
<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 [49]: result['ItemA']

Out[49]:

<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>1.004994</td>
<td>-1.166509</td>
<td>-0.535027</td>
<td>0.350970</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>1.045875</td>
<td>-0.036892</td>
<td>1.393532</td>
<td>1.536326</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>-0.718186</td>
<td>1.588611</td>
<td>-0.492880</td>
<td>-0.736422</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>-0.718186</td>
<td>1.588611</td>
<td>-0.492880</td>
<td>-0.736422</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>-0.718186</td>
<td>1.588611</td>
<td>-0.492880</td>
<td>-0.736422</td>
</tr>
</tbody>
</table>

Chapter 1. What’s New
Panel `apply()` operating on cross-sectional slabs. (GH1148)

```python
In [50]: def f(x): return (x.T-x.mean(1))/x.std(1).T
In [51]: result = panel.apply(f, axis=['items','major_axis'])
In [52]: result
Out[52]:
<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 [53]: result.loc[:, :, 'ItemA']
Out[53]:
   A     B     C     D
2000-01-03 -0.363770 0.013169 0.392036 -1.123913
2000-01-04  0.650448 -1.114910  0.841527  0.760706
2000-01-05 -0.987433 -0.438897 -1.154468 -0.015033
2000-01-06  0.494000  1.060450 -0.775993  1.140165
2000-01-07 -0.363770 0.013169 0.392036 -1.123913

[5 rows x 4 columns]
```

This is equivalent to the following

```python
In [54]: result = Panel(dict((ax, f(panel.loc[:, :, ax]))
  ....:   for ax in panel.minor_axis )))
  ....:

In [55]: result
Out[55]:
<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 [56]: result.loc[:, :, 'ItemA']
Out[56]:
   A     B     C     D
2000-01-03 -0.363770 0.013169 0.392036 -1.123913
2000-01-04  0.650448 -1.114910  0.841527  0.760706
2000-01-05 -0.987433 -0.438897 -1.154468 -0.015033
2000-01-06  0.494000  1.060450 -0.775993  1.140165
2000-01-07 -0.363770 0.013169 0.392036 -1.123913

[5 rows x 4 columns]
```

1.10.6 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)

1.10.7 Experimental

There are no experimental changes in 0.13.1

1.10.8 Bug Fixes

See V0.13.1 Bug Fixes for an extensive list of bugs that have been fixed in 0.13.1.

See the full release notes or issue tracker on GitHub for a complete list of all API changes, Enhancements and Bug Fixes.

1.11 v0.13.0 (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

### 1.11.1 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
  index.levels = [[1, 2, 3, 4], [1, 2, 4, 4]]

  # now, you use the set_levels or set_labels methods
  index = 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 = index.set_names(['bob', 'cranberry'])

  # and all methods take an inplace kwarg - but return None
  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])
  In [6]: Series(arr) // 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.

    if df:
        ....
df1 and df2
s1 and s2

Added the .bool() method to NDFrame objects to facilitate evaluating of single-element boolean Series:

    In [1]: Series([True]).bool()
    Out[1]: True

    In [2]: Series([False]).bool()
    Out[2]: False

    In [3]: DataFrame([[True]]).bool()
    Out[3]: True

    In [4]: 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.

    In [5]: dfc = 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.

    In [7]: dfc.loc[0]['A'] = 1111
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

Here is the correct method of assignment.

In [8]: dfc.loc[0,'A'] = 11

In [9]: dfc

Out[9]:
     A  B
0  11  1
1  bbb  2
2    ccc  3
[3 rows x 2 columns]

- 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)

1.11.2 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 then None. This activates truncated display ("...") of long sequences in various places. (GH3391)

1.11.3 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.
1.11.4 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 = Series([1,2,3])

In [11]: s
Out[11]:
0  1
1  2
2  3
dtype: int64


In [13]: s
Out[13]:
0  1
1  2
2  3
5  5
dtype: float64

In [14]: dfi = 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
[3 rows x 2 columns]

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
[3 rows x 3 columns]

This is like an append operation.

In [18]: dfi.loc[3] = 5

In [19]: dfi
Out[19]:
   A  B  C
0  0  1  0
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'] = 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
Major_axis axis: 2001-01-12 00:00:00 to 2001-01-15 00:00:00
Minor_axis axis: A to C
```

```
In [24]: p.loc[:,:,'C']
Out[24]:
Item1 Item2
2001-01-12 30 32
2001-01-13 30 32
2001-01-14 30 32
2001-01-15 30 32
```

[4 rows x 2 columns]

1.11.5 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.

```
In [25]: index = Index([1.5, 2, 3, 4.5, 5])
```

```
In [26]: index
Out[26]: Float64Index([1.5, 2.0, 3.0, 4.5, 5.0], dtype='float64')
```

```
In [27]: s = Series(range(5),index=index)
```
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)

```
In [29]: s[3]
Out[29]: 2
```

The only positional indexing is via `iloc`

```
In [32]: s.iloc[3]
Out[32]: 3
```

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`

```
In [33]: s[2:4]
Out[33]:
2  1
3  2
dtype: int64
```

In float indexes, slicing using floats are allowed

```
In [37]: s[2.1:4.6]
Out[37]:
3.0  2
4.5  3
dtype: int64
```
1.11.6 HDFStore API Changes

- Query Format Changes. A much more string-like query format is now supported. See the docs.

```python
In [39]: path = 'test.h5'

In [40]: dfq = DataFrame(randn(10,4),
    ....:     columns=list('ABCD'),
    ....:     index=date_range('20130101',periods=10))
    ....:

In [41]: dfq.to_hdf(path,'dfq',format='table',data_columns=True)

Use boolean expressions, with in-line function evaluation.

```python
In [42]: read_hdf(path,'dfq',
    ....:     where="index>Timestamp('20130104') & columns=['A', 'B']")
    ....:
Out[42]:
   A    B
0  2.12  1.66
1 -0.48 -0.85
2 -0.85 -1.04
3 -0.95 -0.80
4 -0.68  1.25
5  1.13  0.67
6  1.06  1.29
7  0.71  0.60
8 -1.02  0.35
9  1.28 -0.56

[6 rows x 2 columns]

Use an inline column reference

```python
In [43]: read_hdf(path,'dfq',
    ....:     where="A>0 or C>0")
    ....:
Out[43]:
   A    B    C    D
0  1.0  1.2  0.5  0.8
1  0.8  0.5  0.2  0.3
2  1.0  1.2  0.5  0.8
3  0.8  0.5  0.2  0.3
4  1.0  1.2  0.5  0.8
5  0.8  0.5  0.2  0.3
6  1.0  1.2  0.5  0.8
7  0.8  0.5  0.2  0.3
8  1.0  1.2  0.5  0.8
9  0.8  0.5  0.2  0.3

[6 rows x 4 columns]
2013-01-01 1.126386 0.247112 0.121172 0.298984
2013-01-03 0.581073 2.763844 0.399325 0.668488
2013-01-04 -0.275774 0.500483 0.863065 -1.051628
2013-01-05 -1.392054 1.153922 1.181944 0.391371
2013-01-06 -0.881047 0.295080 1.863801 -1.712274
2013-01-07 -1.407085 0.126781 0.003760 -1.268994
2013-01-09 1.529401 0.205455 0.313013 0.866521
2013-01-10 0.299071 1.076541 0.363177 1.893680

[8 rows x 4 columns]

• 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.

In [44]: path = 'test.h5'

In [45]: df = DataFrame(randn(10,2))

In [46]: df.to_hdf(path,'df_table',format='table')

In [47]: df.to_hdf(path,'df_table2',append=True)

In [48]: df.to_hdf(path,'df_fixed')

In [49]: with get_store(path) as store:
   ....:     print(store)
   ....:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5
/df_fixed  frame   (shape->[10,2])
/df_table  frame_table (typ->appendable,nrows->10,ncols->2,indexers->[index])
/df_table2 frame_table (typ->appendable,nrows->10,ncols->2,indexers->[index])

• 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

In [50]: path = 'test.h5'

In [51]: df = DataFrame(randn(10,2))

In [52]: store1 = HDFStore(path)

In [53]: store2 = HDFStore(path)

In [54]: store1.append('df',df)

In [55]: store2.append('df2',df)
In [56]: store1
Out[56]:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5
/df     frame_table  (typ->appendable,nrows->10,ncols->2,indexers->[index])

In [57]: store2
Out[57]:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5
/df     frame_table  (typ->appendable,nrows->10,ncols->2,indexers->[index])
/df2    frame_table  (typ->appendable,nrows->10,ncols->2,indexers->[index])

In [58]: store1.close()

In [59]: store2
Out[59]:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5
/df     frame_table  (typ->appendable,nrows->10,ncols->2,indexers->[index])
/df2    frame_table  (typ->appendable,nrows->10,ncols->2,indexers->[index])

In [60]: store2.close()

In [61]: store2
Out[61]:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5
File is CLOSED

• 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 thru store creation arguments; can be used to support in-memory stores

1.11.7 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.
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')`.

### 1.11.8 Enhancements

- `df.to_clipboard()` learned a new `excel` keyword that lets 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 outtype. Returns an array of column-keyed dictionaries. (GH4936)
- NaN handing in `get_dummies` (GH4446) with `dummy_na`

```
# previously, nan was erroneously counted as 2 here
# now it is not counted at all
In [62]: get_dummies([1, 2, np.nan])
Out[62]:
          1  2
     0   1   0
     1   0   1
     2   0   0
[3 rows x 2 columns]
```

```
# unless requested
In [63]: get_dummies([1, 2, np.nan], dummy_na=True)
Out[63]:
          1  2  NaN
     0   1   0   0
     1   0   1   0
     2   0   0   1
[3 rows x 3 columns]
```

- `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).

```python
In [64]: to_timedelta('1 days 06:05:01.00003')
Out[64]: Timedelta('1 days 06:05:01.000030')

In [65]: to_timedelta('15.5us')
Out[65]: Timedelta('0 days 00:00:00.000015')

In [66]: to_timedelta(['1 days 06:05:01.00003', '15.5us', 'nan'])
Out[66]: TimedeltaIndex(['1 days 06:05:01.000030', '0 days 00:00:00.000015', NaT], dtype='timedelta64[ns]', freq=None)

In [67]: to_timedelta(np.arange(5), unit='s')
Out[67]: TimedeltaIndex(['00:00:00', '00:00:01', '00:00:02', '00:00:03', '00:00:04'], dtype='timedelta64[ns]', freq=None)

In [68]: to_timedelta(np.arange(5), unit='d')
Out[68]: TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'], dtype='timedelta64[ns]', freq=None)
```

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.

```python
In [69]: from datetime import timedelta

In [70]: td = Series(date_range('20130101', periods=4)) - Series(date_range('20121201', periods=4))

In [71]: td[2] += timedelta(minutes=5, seconds=3)

In [72]: td[3] = np.nan

In [73]: td
Out[73]:
0    31 days 00:00:00
1    31 days 00:00:00
2    31 days 00:05:03
3     NaN
dtype: timedelta64[ns]

# to days
In [74]: td / np.timedelta64(1, 'D')
Out[74]:
0    31.000000
1    31.000000
2    31.003507
3   NaN
dtype: float64

In [75]: td.astype('timedelta64[D]')
Out[75]:
0    31
1    31
2    31
3     NaN
dtype: float64

# to seconds
In [76]: td / np.timedelta64(1, 's')
Out[76]:
0  2678400
1  2678400
In [77]: td.astype('timedelta64[s]')
Out[77]:
0  2678400
1  2678400
2  2678703
3    NaN
dtype: float64

Dividing or multiplying a `timedelta64[ns]` Series by an integer or integer Series

In [78]: td * -1
Out[78]:
0 -31 days +00:00:00
1 -31 days +00:00:00
2 -32 days +23:54:57
3    NaN
dtype: timedelta64[ns]

In [79]: td * Series([1,2,3,4])
Out[79]:
0  31 days 00:00:00
1  62 days 00:00:00
2  93 days 00:15:09
3    NaN
dtype: timedelta64[ns]

Absolute `DateOffset` objects can act equivalently to `timedeltas`

In [80]: from pandas import offsets

In [81]: td + offsets.Minute(5) + offsets.Milli(5)
Out[81]:
0  31 days 00:05:00.005000
1  31 days 00:05:00.005000
2  31 days 00:10:03.005000
3    NaN
dtype: timedelta64[ns]

Fillna is now supported for `timedeltas`

In [82]: td.fillna(0)
Out[82]:
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]

In [83]: td.fillna(timedelta(days=1,seconds=5))
Out[83]:
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 [84]: td.mean()
Out[84]: Timedelta('31 days 00:01:41')
```

```python
In [85]: td.quantile(.1)
Out[85]: 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 `str.extract` return regular expression matches more conveniently.

```python
In [86]: Series(['a1', 'b2', 'c3']).str.extract('[ab](\d)')
Out[86]:
0    a
1    b
2    
dtype: object
```

Elements that do not match return NaN. Extracting a regular expression with more than one group returns a DataFrame with one column per group.

```python
In [87]: Series(['a1', 'b2', '3']).str.extract('([ab])(\d)')
Out[87]:
   letter  digit
0     a       1
1     b       2
2    NaN      NaN
```

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

```python
In [88]: Series(['a1', 'b2', 'c3']).str.extract(  ....:     '(?P<letter>[ab])(?P<digit>\d)')
Out[88]:
   letter  digit
0     a       1
1     b       2
2    NaN      NaN
```

and optional groups can also be used.

```python
In [89]: Series(['a1', 'b2', '3']).str.extract(  ....:     '(?P<letter>[ab])?(?P<digit>\d)')
Out[89]:
   letter  digit
0     a       1
1     b       2
```

```
1.11. v0.13.0 (January 3, 2014)   149
```
2   NaN  3
[3 rows x 2 columns]

- **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 [90]: date_range('2013-01-01', periods=5, freq='5N')
Out[90]:
              '2013-01-01'],
       dtype='datetime64[ns]', freq='5N')
```

or with frequency as offset

```
In [91]: date_range('2013-01-01', periods=5, freq=pd.offsets.Nano(5))
Out[91]:
              '2013-01-01'],
       dtype='datetime64[ns]', freq='5N')
```

Timestamps can be modified in the nanosecond range

```
In [92]: t = Timestamp('20130101 09:01:02')
In [93]: t + pd.datetools.Nano(123)
Out[93]: 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:

```
In [94]: dfi = DataFrame({'A': [1, 2, 3, 4], 'B': ['a', 'b', 'f', 'n']})
In [95]: dfi
Out[95]:
   A B
0  1 a
1  2 b
2  3 f
3  4 n
[4 rows x 2 columns]
In [96]: other = DataFrame({'A': [1, 3, 3, 7], 'B': ['e', 'f', 'f', 'e']})
In [97]: mask = dfi.isin(other)
In [98]: mask
```
Out[98]:
    A  B
0  True False
1  False False
2  True  True
3  False False
[4 rows x 2 columns]

In [99]: dfi[mask.any(1)]
Out[99]:
    A  B
0  1  a
2  3  f
[2 rows x 2 columns]

• 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

    # 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)

    In [100]: df = 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 [101]: df.interpolate()
    Out[101]:
       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
[6 rows x 2 columns]
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 to fillna’s limit:

```
In [102]: ser = Series([1, 3, np.nan, np.nan, np.nan, 11])
In [103]: ser.interpolate(limit=2)
Out[103]:
   0  1
   1  3
   2  5
   3  7
   4 NaN
   5 11
dtype: float64
```

- Added `wide_to_long` panel data convenience function. See the docs.

```
In [104]: np.random.seed(123)
In [105]: 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)))
                      ....:})
```

```
In [106]: df["id"] = df.index
In [107]: df
Out[107]:
0      a      d  2.5   3.2 -1.085631    0
1      b      e  1.2   1.3  0.997345    1
2      c      f  0.7   0.1  0.282978    2

[3 rows x 6 columns]
```

```
In [108]: wide_to_long(df, ["A", "B"], i="id", j="year")
Out[108]:
    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
```

- `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)

### 1.11.9 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 [109]: nrows, ncols = 20000, 100

In [110]: df1, df2, df3, df4 = [DataFrame(randn(nrows, ncols))
    ....: for _ in range(4)]

# eval with NumExpr backend
In [111]: %timeit pd.eval('df1 + df2 + df3 + df4')
100 loops, best of 3: 14.9 ms per loop

# pure Python evaluation
In [112]: %timeit df1 + df2 + df3 + df4
10 loops, best of 3: 22.8 ms per loop
```

For more details, see the [docs](https://pandas.pydata.org/pandas-docs/stable/).

- 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 [113]: df = DataFrame(randn(10, 2), columns=['a', 'b'])

In [114]: df.eval('a + b')
Out[114]:
   a    b
0 -0.685204
1  1.589745
2  0.325441
3 -1.784153
4 -0.432893
5  0.171850
6  1.895919
7  3.065587
8 -0.092759
9  1.391365
```

dtype: float64

- `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 [115]: n = 20

In [116]: df = DataFrame(np.random.randint(n, size=(n, 3)), columns=['a', 'b', 'c'])

In [117]: df.query('a < b < c')
Out[117]:
   a  b  c
11  1  5  8
15  8  16  19
```

[2 rows x 3 columns]
selects all the rows of df where \(a < b < c\) evaluates to True. For more details see the the docs.

- \texttt{pd.read_msgpack()} and \texttt{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.

\begin{footnotesize}
\textbf{Warning:} Since this is an EXPERIMENTAL LIBRARY, the storage format may not be stable until a future release.
\end{footnotesize}

\begin{Verbatim}
In [118]: \texttt{df = DataFrame(np.random.rand(5,2),columns=list('AB'))}
In [119]: \texttt{df.to_msgpack('foo.msg')}
In [120]: \texttt{pd.read_msgpack('foo.msg')}
Out[120]:
\begin{verbatim}
   A      B
0 0.251082 0.017357
1 0.347915 0.929879
2 0.546233 0.203368
3 0.064942 0.031722
4 0.355309 0.524575
\end{verbatim}
\end{Verbatim}

\begin{Verbatim}
In [121]: \texttt{s = Series(np.random.rand(5),index=date_range('20130101',periods=5))}
In [122]: \texttt{pd.to_msgpack('foo.msg', df, s)}
In [123]: \texttt{pd.read_msgpack('foo.msg')}
Out[123]:
\begin{verbatim}
   A      B
0 0.251082 0.017357
1 0.347915 0.929879
2 0.546233 0.203368
3 0.064942 0.031722
4 0.355309 0.524575
\end{verbatim}
\end{Verbatim}

\begin{Verbatim}
In [124]: for \texttt{o in pd.read_msgpack('foo.msg',iterator=True)}:
   \begin{verbatim}
      print o
   \end{verbatim}
   \begin{verbatim}
   A      B
0 0.251082 0.017357
1 0.347915 0.929879
2 0.546233 0.203368
3 0.064942 0.031722
4 0.355309 0.524575
\end{verbatim}
\end{Verbatim}

You can pass \texttt{iterator=True} to iterator over the unpacked results.

\begin{Verbatim}
In [124]: for \texttt{o in pd.read_msgpack('foo/msg',iterator=True)}:
   \begin{verbatim}
      print o
   \end{verbatim}
   \begin{verbatim}
      A      B
0 0.251082 0.017357
1 0.347915 0.929879
2 0.546233 0.203368
3 0.064942 0.031722
4 0.355309 0.524575
\end{verbatim}
\end{Verbatim}

154 Chapter 1. What’s New
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- 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://code.google.com/apis/console/b/0/?noredirect
projectid = xxxxxxxx;

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 = pandas.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>-53.336667</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.

1.11.10 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 [125]: s = Series([1,2,3,4])
```

Numpy Usage

```python
In [126]: np.ones_like(s)
Out[126]: array([1, 1, 1, 1], dtype=int64)
```

```python
In [127]: np.diff(s)
Out[127]: array([1, 1, 1], dtype=int64)
```

```python
In [128]: np.where(s>1,s,np.nan)
Out[128]: array([ nan, 2., 3., 4.])
```

Pandonic Usage

```python
In [129]: Series(1,index=s.index)
Out[129]:
0   1
1   1
2   1
3   1
dtype: int64
```

```python
In [130]: s.diff()
Out[130]:
0   NaN
1   1
2   1
3   1
dtype: float64
```

```python
In [131]: s.where(s>1)
Out[131]:
0   NaN
1   2
2   3
3   4
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 in Series update where the parent frame is not updating its cache based on changes (GH4080) or types (GH3217), fillna (GH3386)
• Indexing with dtype conversions fixed (GH4463, GH4204)
• Refactor Series.reindex to core/generic.py (GH4604, GH4618), allow method= in reindexing on a Series to work
• Series.copy no longer accepts the order parameter and is now consistent with NDFrame copy
• Refactor rename methods to core/generic.py; fixes Series.rename for (GH4605), and adds rename with the same signature for Panel

• Refactor clip methods to core/generic.py (GH4798)

• Refactor of _get_numeric_data/_get_bool_data to core/generic.py, allowing Series/Panel functionality

• Series (for index) / Panel (for items) now allow attribute access to its elements (GH1903)

```python
In [132]: s = Series([1,2,3],index=list('abc'))

In [133]: s.b
Out[133]: 2

In [134]: s.a = 5

In [135]: s
Out[135]:
          a  5
          b  2
          c  3
dtype: int64
```

### 1.11.11 Bug Fixes

See [V0.13.0 Bug Fixes](#) for an extensive list of bugs that have been fixed in 0.13.0.

See the [full release notes](#) or issue tracker on GitHub for a complete list of all API changes, Enhancements and Bug Fixes.

### 1.12 v0.12.0 (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 multi-indexes 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.

#### 1.12.1 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

1.12. v0.12.0 (July 24, 2013)
- `read_clipboard`

The corresponding `writer` functions are object methods that are accessed like `df.to_csv()`

- `to_csv`
- `to_excel`
- `to_hdf`
- `to_sql`
- `to_json`
- `to_html`
- `to_stata`
- `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 = 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

[3 rows x 2 columns]

In [3]: p % p
Out[3]:
        first    second
0        0       NaN
1        0       NaN
2        0        0

[3 rows x 2 columns]

In [4]: p / p
Out[4]:
        first    second
0        1       NaN
1        1       NaN
2        1        1

[3 rows x 2 columns]

In [5]: p / 0
Out[5]:
        first    second
0      inf       NaN
1      inf       NaN
2      inf       inf

[3 rows x 2 columns]
```
pandas: powerful Python data analysis toolkit, Release 0.17.0

• 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 [6]: df2 = DataFrame([{"val1": 1, "val2" : 20}, {"val1":1, "val2": 19},
...:
{"val1":1, "val2": 27}, {"val1":1, "val2": 12}])
...:
In [7]: def func(dataf):
...:
return dataf["val2"]
...:

- dataf["val2"].mean()

# squeezing the result frame to a series (because we have unique groups)
In [8]: df2.groupby("val1", squeeze=True).apply(func)
Out[8]:
0
0.5
1
-0.5
2
7.5
3
-7.5
Name: 1, dtype: float64
# no squeezing (the default, and behavior in 0.10.1)
In [9]: df2.groupby("val1").apply(func)
Out[9]:
val2
0
1
2
3
val1
1
0.5 -0.5 7.5 -7.5
[1 rows x 4 columns]

• 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 plently of alternatives. This preserves the iloc API to be purely positional
based.
In [10]: df = DataFrame(lrange(5), list('ABCDE'), columns=['a'])
In [11]: mask = (df.a%2 == 0)
In [12]: mask
Out[12]:
A
True
B
False
C
True
D
False
E
True
Name: a, dtype: bool
# this is what you should use
In [13]: df.loc[mask]
Out[13]:
a
A 0
C 2
E 4
[3 rows x 1 columns]

1.12. v0.12.0 (July 24, 2013)

161


# this will work as well

```python
In [14]: df.iloc[mask.values]
Out[14]:
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 baseclass 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)

1.12.2 I/O 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

In [15]: df = DataFrame({'a': range(3), 'b': list('abc'))

In [16]: print(df)
   a  b
  0  0  a
  1  1  b
  2  2  c

[3 rows x 2 columns]

In [17]: html = df.to_html()

In [18]: alist = pd.read_html(html, index_col=0)

In [19]: print(df == alist[0])
   a  b
  0 True True
  1 True True
  2 True True

[3 rows x 2 columns]

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

1.12. v0.12.0 (July 24, 2013)
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 [20]: from pandas.util.testing import makeCustomDataframe as mkdf
In [21]: df = mkdf(5, 3, r_idx_nlevels=2, c_idx_nlevels=4)
In [22]: df.to_csv('mi.csv', tupleize_cols=False)
```

```
In [23]: 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 [24]: pd.read_csv('mi.csv', header=[0, 1, 2, 3], index_col=[0, 1], tupleize_cols=False)
Out[24]:
   C0   C_l0_g0   C_l0_g1   C_l0_g2
C0   R0C0       R0C1       R0C2
C1   R1C0       R1C1       R1C2
R0   R_l0_g0   R_l0_g1   R_l0_g2
R1   R_l1_g0   R_l1_g1   R_l1_g2
   R_l2_g0   R_l2_g1   R_l2_g2
   R_l3_g0   R_l3_g1   R_l3_g2
```

- 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]: DataFrame(randn(10, 2)).to_hdf(path, 'df', table=True)
In [27]: for df in 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

1.12.3 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 [25]: df = DataFrame({'a': list('ab..'), 'b': [1, 2, 3, 4]})

In [26]: df.replace(regex=r'\s*\s*\.', value=np.nan)
Out[26]:
     a   b
0    a   1
1    b   2
2  NaN  3
3  NaN  4

[4 rows x 2 columns]
```
to replace all occurrences of the string ‘.’ with zero or more instances of surrounding whitespace with NaN.

Regular string replacement still works as expected. For example, you can do

```python
In [27]: df.replace('.', np.nan)
Out[27]:
     a   b
0    a   1
1    b   2
2  NaN  3
3  NaN  4

[4 rows x 2 columns]
```
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:
In [28]: pd.get_option('a.b')
Out[28]: 2

In [29]: pd.get_option('b.c')
Out[29]: 3

In [30]: pd.set_option('a.b', 1, 'b.c', 4)

In [31]: pd.get_option('a.b')
Out[31]: 1

In [32]: pd.get_option('b.c')
Out[32]: 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.

  In [33]: sf = Series([1, 1, 2, 3, 3, 3])

  In [34]: sf.groupby(sf).filter(lambda x: x.sum() > 2)
  Out[34]:
   3  3
   4  3
   5  3
   dtype: int64

  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.

  In [35]: dff = DataFrame({'A': np.arange(8), 'B': list('aabbbbcc')})

  In [36]: dff.groupby('B').filter(lambda x: len(x) > 2)
  Out[36]:
     A  B
    2  2  b
    3  3  b
    4  4  b
    5  5  b
   [4 rows x 2 columns]

  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 [37]: dff.groupby('B').filter(lambda x: len(x) > 2, dropna=False)
  Out[37]:
     A  B
    0  NaN NaN
    1  NaN NaN
    2  2  b
    3  3  b
    4  4  b
    5  5  b
    6  NaN NaN
    7  NaN NaN
   [8 rows x 2 columns]

- 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)

1.12.4 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.

In [38]: from pandas.tseries.offsets import CustomBusinessDay
In [39]: from datetime import datetime

# As an interesting example, let's look at Egypt where 
# a Friday-Saturday weekend is observed.
In [40]: weekmask_egypt = 'Sun Mon Tue Wed Thu'

# They also observe International Workers' Day so let's 
# add that for a couple of years
In [41]: holidays = ['2012-05-01', datetime(2013, 5, 1), np.datetime64('2014-05-01')]
In [42]: bday_egypt = CustomBusinessDay(holidays=holidays, weekmask=weekmask_egypt)
In [43]: dt = datetime(2013, 4, 30)
In [44]: print(dt + 2 * bday_egypt)
2013-05-05 00:00:00
In [45]: dts = date_range(dt, periods=5, freq=bday_egypt)
In [46]: print(Series(dts.weekday, dts).map(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

1.12.5 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 [47]: strs = 'go', 'bow', 'joe', 'slow'

In [48]: ds = Series(strs)

In [49]: for s in ds.str:
   ....:     print(s)
   ....:
0  g
1  b
2  j
3  s
   dtype: object
0  o
1  o
2  o
3  l
   dtype: object
0  NaN
1  w
2  e
3  o
   dtype: object
0  NaN
1  NaN
2  NaN
3  w
   dtype: object

In [50]: s
Out[50]:
     0    NaN
     1    NaN
     2    NaN
     3     w
   dtype: object

In [51]: s.dropna().values.item() == 'w'
Out[51]: True

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)
- Fix to_csv to handle non-unique columns (GH3495)
- Duplicate indexes with getitem 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)
- 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.

1.13 v0.11.0 (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.

1.13.1 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 indicies 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 hierarchial 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.
1.13.2 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.

1.13.3 Dtypes

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.

```
In [1]: df1 = DataFrame(randn(8, 1), columns = ['A'], dtype = 'float32')

In [2]: df1
Out[2]:
          A
0  1.392665
1  0.123497
2 -0.402761
3  0.246604
4 -0.288433
5 -0.763434
6  2.069526
7  2.035690

[8 rows x 1 columns]

In [3]: df1.dtypes
Out[3]:
A    float32
dtype: object

In [4]: df2 = DataFrame(dict( A = Series(randn(8),dtype='float16'),
                         B = Series(randn(8)),
                         C = Series(randn(8),dtype='uint8') ))

In [5]: df2
Out[5]:
          A             B             C
0   0.591797 -0.038605          0
1   0.841309 -0.460478          1
2  -0.500977 -0.310458          0
3  -0.816406  0.866493        254
4  -0.207031  0.245972          0
5   0.664062  0.319442        255
6   0.580566  1.378512          1
7  -0.965820  0.292502        255

[8 rows x 3 columns]

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  1.984462 -0.038605  0
1  0.717812 -0.460478  1
2 -0.903737 -0.310458  0
3 -1.063011  0.866493  254
4 -0.495465  0.245972  0
5 -1.427497  0.319442  1
6  2.650092  1.378512  1
7 -2.169390  0.292502  255
[8 rows x 3 columns]

In [9]: df3.dtypes
Out[9]:
   A    B    C
dtype: object

1.13.4 Dtype Conversion

This is lower-common-denominator upcasting, meaning you get the dtype which can accommodate all of the types

In [10]: df3.values.dtype
Out[10]: dtype('float64')

Conversion

In [11]: df3.astype('float32').dtypes
Out[11]:
   A    B    C
dtype: object

Mixed Conversion

In [12]: df3['D'] = '1.'

In [13]: df3['E'] = '1'

In [14]: df3.convert_objects(convert_numeric=True).dtypes
Out[14]:
   A    B    C
dtype: object
D   float64
E   int64
dtype: object

# same, but specific dtype conversion
In [15]: df3['D'] = df3['D'].astype('float16')

In [16]: df3['E'] = df3['E'].astype('int32')

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)

In [18]: from datetime import datetime

In [19]: s = Series([datetime(2001,1,1,0,0), 'foo', 1.0, 1, 
....:
....:     Timestamp('20010104'), '20010105'],dtype='O')

In [20]: s.convert_objects(convert_dates='coerce')
Out[20]:
0 2001-01-01
1 NaN
2 NaN
3 NaN
4 2001-01-04
5 2001-01-05
dtype: datetime64[ns]

1.13.5 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

In [21]: DataFrame({'a' : [1,2]}).dtypes
Out[21]:
a   int64
dtype: object

In [22]: DataFrame({'a' : [1,2] }).dtypes
Out[22]:
a   int64
dtype: object

In [23]: DataFrame({'a' : 1 }, index=range(2)).dtypes
Out[23]:
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.

In [24]: dfi = df3.astype('int32')

In [25]: dfi['D'] = dfi['D'].astype('int64')

In [26]: dfi
Out[26]:
     A  B  C  D  E
0    1  0  0  1  1
1    0  0  0  1  1
2   -1  0 254  1  1
3    0  0  0  1  1
4    0  0  0  1  1
5   -1  0  1  1  1
6    2  1  1  1  1
7   -2  0 255  1  1

[8 rows x 5 columns]

In [27]: dfi.dtypes
Out[27]:
A   int32
B   int32
C   int32
D   int64
E   int32

dtype: object

In [28]: casted = dfi[dfi>0]

In [29]: casted
Out[29]:
     A  B  C  D  E
0   NaN NaN NaN  1  1
1   NaN NaN NaN  1  1
2   NaN NaN NaN  1  1
3   NaN NaN 254  1  1
4   NaN NaN NaN  1  1
5   NaN NaN  1  1  1
6    2  1  1  1  1
7   NaN NaN 255  1  1

[8 rows x 5 columns]

In [30]: casted.dtypes
Out[30]:
A   float64
B   float64
C   float64
D   int64
E     int32
dtype: object

While float dtypes are unchanged.

In [31]: df4 = df3.copy()

In [32]: df4['A'] = df4['A'].astype('float32')

In [33]: df4.dtypes
Out[33]:
A    float32
B    float64
C    float64
D   float16
E     int32
dtype: object

In [34]: casted = df4[df4>0]

In [35]: casted
Out[35]:
     A      B      C      D      E
0  1.984462 NaN    NaN   1.0   1.0
1  0.717812 NaN    NaN   1.0   1.0
2  NaN    NaN  0.866493 254  1.0
3  NaN    NaN  0.245972  NaN  1.0
4  NaN    NaN  0.319442  NaN  1.0
5  NaN    NaN  2.650092 1.378512 1.0
6  2.650092 1.378512 1.0  1.0
7  NaN    NaN  0.292502 255  1.0
[8 rows x 5 columns]

In [36]: casted.dtypes
Out[36]:
A    float32
B    float64
C    float64
D   float16
E     int32
dtype: object

1.13.6 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 [37]: df = DataFrame(randn(6,2),date_range('20010102',periods=6),columns=['A','B'])

In [38]: df['timestamp'] = Timestamp('20010103')

In [39]: df
Out[39]:
     A      B      timestamp
0  1.984462 NaN  2001-01-02
1  0.717812 NaN  2001-01-02
2  NaN    NaN  2001-01-02
3  NaN    NaN  2001-01-02
4  NaN    NaN  2001-01-02
5  NaN    NaN  2001-01-02
6  2.650092 1.378512 2001-01-03
7  NaN    NaN  2001-01-03

1.13. v0.11.0 (April 22, 2013)
2001-01-02  1.023958  0.660103  2001-01-03
2001-01-03  1.236475  -2.170629  2001-01-03
2001-01-04   -0.270630  -1.685677  2001-01-03
2001-01-05   -0.440747  -0.115070  2001-01-03
2001-01-06   -0.632102  -0.585977  2001-01-03
2001-01-07   -1.444787  -0.201135  2001-01-03

[6 rows x 3 columns]

# datetime64[ns] out of the box
In [40]: df.get_dtype_counts()
Out[40]:
datetime64[ns]   1
float64          2
dtype: int64

# use the traditional nan, which is mapped to NaT internally
In [41]: df.ix[2:4,[\'A\',\'timestamp\']]=np.nan

In [42]: df
Out[42]:
   A       B     timestamp
0  2001-01-02  1.023958  0.660103 2001-01-03
1  2001-01-03  1.236475 -2.170629 2001-01-03
2  NaN        -1.685677 NaN        NaN
3  NaN        -0.115070 NaN        NaN
4  2001-01-06 -0.632102 -0.585977 2001-01-03
5  2001-01-07 -1.444787 -0.201135 2001-01-03

[6 rows x 3 columns]

Astype conversion on datetime64[ns] to object, implicitly converts NaT to np.nan

In [43]: import datetime
In [44]: s = Series([datetime.datetime(2001, 1, 2, 0, 0) for i in range(3)])
In [45]: s.dtype
Out[45]: dtype(\'<M8[ns]\')
In [46]: s[1] = np.nan
In [47]: s
Out[47]:
0  2001-01-02
1  NaN
2  2001-01-02
dtype: datetime64[ns]
In [48]: s.dtype
Out[48]: dtype(\'<M8[ns]\')
In [49]: s = s.astype(\'O\')
In [50]: s
Out[50]:
0  2001-01-02 00:00:00
1  NaN
2 2001-01-02 00:00:00
dtype: object

In [51]: s.dtype
Out[51]: dtype('O')

1.13.7 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

1.13.8 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 [52]: df = DataFrame(dict(A=lr(5), B=lr(5)))
    In [53]: df.to_hdf('store.h5','table',append=True)
    In [54]: read_hdf('store.h5', 'table', where = ['index>2'])
    Out[54]:
       A  B
    1  3  3
    2  4  4
    [2 rows x 2 columns]
  - 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 sup-port 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)
  In [55]: idx = date_range("2001-10-1", periods=5, freq='M')
  In [56]: ts = Series(np.random.rand(len(idx)),index=idx)
  In [57]: ts['2001']
  Out[57]:
     2001-10-31   0.663256
       2001-11-30   0.079126
       2001-12-31   0.587699

1.13. v0.11.0 (April 22, 2013)
Freq: M, dtype: float64

In[58]: df = DataFrame(dict(A = ts))

In[59]: df['2001']
Out[59]:
    A
2001-10-31  0.663256
2001-11-30  0.079126
2001-12-31  0.587699
[3 rows x 1 columns]

• Squeeze to possibly remove length 1 dimensions from an object.

In[60]: p = Panel(randn(3,4,4),items=['ItemA','ItemB','ItemC'],
   ....:     major_axis=date_range('20010102',periods=4),
   ....:     minor_axis=['A','B','C','D'])

In[61]: p.reindex(items=['ItemA']).squeeze()
Out[61]:
    A  B  C  D
2001-01-02 -1.203403  0.425882 -0.436045 -0.982462
2001-01-03  0.348090 -0.969649  0.121731  0.202798
2001-01-04  1.215695 -0.218549 -0.631381 -0.337116
2001-01-05  0.404238  0.907213 -0.865657  0.483186
[4 rows x 4 columns]

In[62]: p.reindex(items=['ItemA'],minor=['B']).squeeze()
Out[62]:
     A     B     C     D
2001-01-02 -1.203403  0.425882 -0.436045 -0.982462
2001-01-03  0.348090 -0.969649  0.121731  0.202798
2001-01-04  1.215695 -0.218549 -0.631381 -0.337116
2001-01-05  0.404238  0.907213 -0.865657  0.483186
FREQ: D, NAME: B, DTYPE: FLOAT64

• 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.
pandas: powerful Python data analysis toolkit, Release 0.17.0

- `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.

### 1.14 v0.10.1 (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.

#### 1.14.1 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)

#### 1.14.2 New features

- MySQL support for database (contribution from Dan Allan)
1.14.3 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

```
In [1]: store = HDFStore('store.h5')

In [2]: df = DataFrame(randn(8, 3), index=date_range('1/1/2000', periods=8),
...:       columns=['A', 'B', 'C'])

In [3]: df['string'] = 'foo'

In [4]: df.ix[4:6,'string'] = np.nan

In [5]: df.ix[7:9,'string'] = 'bar'

In [6]: df['string2'] = 'cool'

In [7]: df
Out[7]:
    A         B         C     string     string2
0  1.885136  -0.183873  2.550850         foo          cool
1  0.180759  -1.117089  0.061462         foo          cool
2 -0.294467  -0.591411 -0.876691         foo          cool
3  3.127110   1.451130  0.045152         foo          cool
4 -0.242846   1.195819  1.533294        NaN          cool
5  0.820521  -0.281201  1.651561        NaN          cool
6 -0.034086   0.252394 -0.498772         foo          cool
7 -2.290958  -1.601262 -0.256718         bar          cool

[8 rows x 5 columns]
```

```
# on-disk operations
In [8]: store.append('df', df, data_columns = ['B','C','string','string2'])

In [9]: store.select('df', ['B > 0', 'string == foo'])
Out[9]:
Empty DataFrame
Columns: [A, B, C, string, string2]
Index: []

[0 rows x 5 columns]
```

```
# 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  3.127110   1.451130  0.045152         foo          cool
1 -0.034086   0.252394 -0.498772         foo          cool

[2 rows x 5 columns]
```

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'] = Timestamp('20010102')

In [13]: df_mixed.ix[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]:
   A         B         C     string     string2   datetime64
0  2000-01-01  1.885136 -0.183873 2.550850     foo      cool 2001-01-02
1  2000-01-02  0.180759 -1.117089 0.061462     foo      cool 2001-01-02
2  2000-01-03 -0.294467  0.591411 -0.876691     foo      cool 2001-01-02
3  2000-01-04     NaN      NaN     NaN      NaN      NaN     NaN
4  2000-01-05 -0.242846  1.195819  1.533294     NaN      NaN 2001-01-02
5  2000-01-06  0.820521 -0.281201  1.651561     NaN      NaN 2001-01-02
6  2000-01-07 -0.034086  0.252394 -0.498772     foo      cool 2001-01-02
7  2000-01-08 -2.290958 -1.601262 -0.256718     bar      cool 2001-01-02

[8 rows x 6 columns]

In [17]: df_mixed1.get_dtype_counts()
Out[17]:
datetime64[ns]    1
float64           3
object            2
dtype: int64

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)

In [18]: store.select('df',columns = ['A','B'])
Out[18]:
   A         B
0  2000-01-01  1.885136 -0.183873
1  2000-01-02  0.180759 -1.117089
2  2000-01-03 -0.294467  0.591411
3  2000-01-04 -2.290958 -1.601262

[8 rows x 2 columns]

HDFStore now serializes multi-index dataframes when appending tables.

In [19]: index = 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]],
In [20]: df = DataFrame(np.random.randn(10, 3), index=index,
                   columns=['A', 'B', 'C'])

In [21]: df
Out[21]:
   A   B   C
foo bar
foo  one 0.239369 0.174122 -1.131794
two  -1.948006 0.980347  0.674429
three -0.361633 -0.761218  1.768215
bar  one 0.152288 -0.862613 -0.210968
two  -0.859278  1.498195  0.462413
baz  two -0.647604  1.511487 -0.727189
three -0.342928 -0.007364  1.427674
qux  one 0.104020  2.052171 -1.230963
two  -0.019240 -1.713238  0.838912
three -0.637855  0.215109 -1.515362

[10 rows x 3 columns]

In [22]: store.append('mi', df)

In [23]: store.select('mi')
Out[23]:
   A   B   C
foo bar
foo  one 0.239369 0.174122 -1.131794
two  -1.948006 0.980347  0.674429
three -0.361633 -0.761218  1.768215
bar  one 0.152288 -0.862613 -0.210968
two  -0.859278  1.498195  0.462413
baz  two -0.647604  1.511487 -0.727189
three -0.342928 -0.007364  1.427674
qux  one 0.104020  2.052171 -1.230963
two  -0.019240 -1.713238  0.838912
three -0.637855  0.215109 -1.515362

[10 rows x 3 columns]

# the levels are automatically included as data columns
In [24]: store.select('mi', Term('foo=bar'))
Out[24]:
Empty DataFrame
Columns: [A, B, C]
Index: []

[0 rows x 3 columns]

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 [25]: df_mt = DataFrame(randn(8, 6), index=date_range('1/1/2000', periods=8),
                   columns=['A', 'B', 'C', 'D', 'E', 'F'])

In [26]: df_mt
Out[26]:
   A     B     C     D     E     F
0 -0.7346 -0.9420  0.3747  1.4230  0.3505 -0.2064
1  0.2681  1.0600  0.7318 -0.9619 -0.7216 -0.4704
2 -0.3109 -1.5515  0.9196  0.4801 -0.4885  0.1238
3  0.6214 -0.1636 -0.8448  0.3448 -1.1504 -0.1063
4 -1.0953  0.4964 -1.6596 -0.8334 -1.3890  0.5440
5 -0.4937  1.1079 -0.6724  0.2320 -0.5948  0.3536
6 -0.3108 -0.0036  0.7716 -0.8458  0.7456  0.2533
7  0.4085 -0.1725 -0.4148 -0.0341 -0.8842  0.4685

[8 rows x 6 columns]
In [26]: df_mt['foo'] = 'bar'

# you can also create the tables individually
In [27]: store.append_to_multiple({'df1_mt': ['A', 'B'], 'df2_mt': None}, df_mt, selector = 'df1_mt')

In [28]: store
Out[28]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df frame_table (typ->appendable,nrows->8,ncols->5,indexers->[index],dc->[B,C,string,string2])
/df1_mt frame_table (typ->appendable,nrows->8,ncols->2,indexers->[index],dc->[A,B])
/df2_mt frame_table (typ->appendable,nrows->8,ncols->5,indexers->[index])
/df_mixed frame_table (typ->appendable,nrows->8,ncols->6,indexers->[index])
/mi frame_table (typ->appendable_multi,nrows->10,ncols->5,indexers->[index],dc->[bar,foo])

# individual tables were created
In [29]: store.select('df1_mt')
Out[29]:
A    B
2000-01-01 1.586924 -0.447974
2000-01-02 -0.102206  0.870302
2000-01-03  1.249874  1.458210
2000-01-04 -0.616293  0.150468
2000-01-05 -0.431163  0.016640
2000-01-06  0.800353 -0.451572
2000-01-07  1.239198  0.185437
2000-01-08 -0.040863  0.290110
[8 rows x 2 columns]

In [30]: store.select('df2_mt')
Out[30]:
C    D    E    F    foo
2000-01-01 -1.573998  0.630925 -0.710542  0.825392  1.557329  1.993441 bar
2000-01-02  1.275280 -1.199212  1.060780  1.673018  1.993441 bar
2000-01-03 -0.710542  0.825392  1.557329  1.993441 bar
2000-01-04  0.132104  0.580923 -0.128750  1.445964 bar
2000-01-05  0.904578 -1.645852 -0.688741  0.228006 bar
2000-01-06  0.831767  0.228760  0.932498 -2.200069 bar
2000-01-07 -0.540770 -0.370038  1.298390  1.662964 bar
2000-01-08 -0.096145  1.717830 -0.462446 -0.112019 bar
[8 rows x 5 columns]

# as a multiple
In [31]: store.select_as_multiple(['df1_mt','df2_mt'], where = ['A>0','B>0'], selector = 'df1_mt')
Out[31]:
A    B    C    D    E    F    foo
2000-01-03  1.249874  1.458210 -0.710542  0.825392  1.557329  1.993441 bar
2000-01-07  1.239198  0.185437 -0.540770 -0.370038  1.298390  1.662964 bar
[2 rows x 7 columns]

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 automatically 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 expectedrows 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 businessday 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 or issue tracker on GitHub for a complete list.
1.15 v0.10.0 (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.

1.15.1 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

1.15.2 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))

In [3]: df

Out[3]:

        0          1          2          3
2000-01-01 -0.134024   -0.205969   1.348944  -1.198246
2000-01-02  -1.626124    0.982041   0.059493  -0.460111
2000-01-03  -1.565401  -0.025706   0.942864   2.502156
2000-01-04  -0.302741   0.261551  -0.066342   0.897097
2000-01-05   0.268766  -1.225092   0.582752  -1.490764
2000-01-06  -0.639757  -0.952750  -0.892402   0.505987

[6 rows x 4 columns]
# deprecated now

```python
In [4]: df - df[0]
```

```
Out[4]:
2000-01-01 00:00:00 2000-01-02 00:00:00 2000-01-03 00:00:00 NaN
2000-01-04 NaN NaN NaN
2000-01-05 NaN NaN NaN
2000-01-06 NaN NaN NaN
```

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).

Note:

```python
In [6]: dates = pd.date_range('1/1/2000', '1/5/2000', freq='4h')
```

```python
In [7]: series = Series(np.arange(len(dates)), index=dates)
```

```python
In [8]: series
```
Out[8]:
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: int32

In [9]: series.resample('D', how='sum')
Out[9]:
2000-01-01 15
2000-01-02 51
2000-01-03 87
2000-01-04 123
2000-01-05 24
Freq: D, dtype: int32

# old behavior
In [10]: series.resample('D', how='sum', closed='right', label='right')
Out[10]:
2000-01-01 0
2000-01-02 21
2000-01-03 57
2000-01-04 93
2000-01-05 129
Freq: D, dtype: int32

- Infinity and negative infinity are no longer treated as NA by isnull and notnull. That they every were was a relic of early pandas. This behavior can be re-enabled globally by the mode.use_inf_as_null option:

In [11]: s = pd.Series([1.5, np.inf, 3.4, -np.inf])

In [12]: pd.isnull(s)
Out[12]:
0   False
1   False
2   False
3   False
dtype: bool

In [13]: s.fillna(0)
Out[13]:
0   1.500000
1    inf
2  3.400000
3   -inf
dtype: float64
In [14]: pd.set_option('use_inf_as_null', True)

In [15]: pd.isnull(s)
Out[15]:
0  False
1  True
2  False
3  True
dtype: bool

In [16]: s.fillna(0)
Out[16]:
0  1.5
1  0.0
2  3.4
3  0.0
dtype: float64

In [17]: 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 unnec-
essary.

• 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 [18]: data= 'a,b,c
1,Yes,2
3,No,4'

In [19]: print(data)
a,b,c
1,Yes,2
3,No,4

In [20]: pd.read_csv(StringIO(data), header=None)
Out[20]:
0 1 2
0 a b c
1 1 Yes 2
2 3 No 4

[3 rows x 3 columns]

In [21]: pd.read_csv(StringIO(data), header=None, prefix='X')
Out[21]:
 X0  X1  X2
0 a  b  c
1 1 Yes 2
2 3  No 4

[3 rows x 3 columns]

• 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:
In [22]: print(data)
a,b,c
1,Yes,2
3,No,4

In [23]: pd.read_csv(StringIO(data))
Out[23]:
a  b  c
0 1  Yes  2
1 3  No  4
[2 rows x 3 columns]

In [24]: pd.read_csv(StringIO(data), true_values=['Yes'], false_values=['No'])
Out[24]:
a  b  c
0 1  True  2
1 3  False 4
[2 rows x 3 columns]

- 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.

- Callingfillna on Series or DataFrame with no arguments is no longer valid code. You must either specify a fill value or an interpolation method:

In [25]: s = Series([np.nan, 1., 2., np.nan, 4])

In [26]: s
Out[26]:
0  NaN
1  1.0
2  2.0
3  NaN
4  4.0
dtype: float64

In [27]: s.fillna(0)
Out[27]:
0  0
1  1
2  2
3  0
4  4

dtype: float64

In [28]: s.fillna(method='pad')
Out[28]:
0  NaN
1  1
2  2
3  2
4  4

dtype: float64

Convenience methodsffill andbfill have been added:
In [29]: s.ffill()
Out[29]:
0   NaN
1    1
2    2
3    2
4    4
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 [30]: def f(x):
   ....:     return Series([ x, x**2 ], index = ['x', 'x^2'])
   ....:

In [31]: s = Series(np.random.rand(5))

In [32]: s
Out[32]:
0  0.717478
1  0.815199
2  0.452478
3  0.848385
4  0.235477
dtype: float64

In [33]: s.apply(f)
Out[33]:
       x    x^2
0  0.717478  0.514775
1  0.815199  0.664550
2  0.452478  0.204737
3  0.848385  0.719757
4  0.235477  0.055449
[5 rows x 2 columns]

- 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:

In [34]: get_option("display.max_rows")
Out[34]: 15

- to_string() methods now always return unicode strings (GH2224).
1.15.3 New features

1.15.4 Wide DataFrame Printing

Instead of printing the summary information, pandas now splits the string representation across multiple rows by default:

```python
In [35]: wide_frame = DataFrame(randn(5, 16))

In [36]: wide_frame
```

```
Out[36]:
0  1  2   3    4     5      6
0 -0.681624 0.191356 1.180274 -0.834179 0.703043 0.166568 -0.583599
1  0.441522 -0.316864 -0.017062 1.570114 -0.360875 -0.880096 0.235532
2 -0.412451 -0.462580 0.422194 0.288403 -0.487393 -0.777639 0.055865
3 -0.277255 1.331263 0.585174 -0.568825 -0.719412 1.191340 -0.456362
4 -1.642511 0.432560 1.218080 -0.564705 -0.581790 0.286071 0.048725

7  8  9  10  11  12  13
0 -1.201796 -1.422811 -0.882554 1.209871 -0.941235 0.863067 -0.336232
1  0.207232 -1.983857 -1.702547 -1.621234 -0.906840 1.014601 -0.475108
2  1.383381 0.085638 0.246392 0.965887 0.246354 -0.727728 -0.094414
3  0.089931 0.776079 0.752889 -1.195795 -1.425911 -0.548829 0.774225
4  1.002440 1.276582 0.054399 0.241963 -0.471786 0.314510 -0.059986

[5 rows x 16 columns]
```

The old behavior of printing out summary information can be achieved via the ‘expand_frame_repr’ print option:

```python
In [37]: pd.set_option('expand_frame_repr', False)

In [38]: wide_frame
```

```
Out[38]:
0  1  2  3  4  5  6  7  8  9
0 -0.681624 0.191356 1.180274 -0.834179 0.703043 0.166568 -0.583599 -1.201796 -1.422811 -0.882554
1  0.441522 -0.316864 -0.017062 1.570114 -0.360875 -0.880096 0.235532 0.207232 -1.983857 -1.702547
2 -0.412451 -0.462580 0.422194 0.288403 -0.487393 -0.777639 0.055865 1.383381 0.085638 0.246392
3 -0.277255 1.331263 0.585174 -0.568825 -0.719412 1.191340 -0.456362 0.089931 0.776079 0.752889
4 -1.642511 0.432560 1.218080 -0.564705 -0.581790 0.286071 0.048725 1.002440 1.276582 0.054399

[5 rows x 16 columns]
```

The width of each line can be changed via ‘line_width’ (80 by default):

```python
In [39]: pd.set_option('line_width', 40)

In [40]: wide_frame
```

```
Out[40]:
0  1  2
0 -0.681624 0.191356 1.180274 -0.834179 0.703043 0.166568 -0.583599
1  0.441522 -0.316864 -0.017062 1.570114 -0.360875 -0.880096 0.235532 0.207232 -1.983857 -1.702547
2 -0.412451 -0.462580 0.422194 0.288403 -0.487393 -0.777639 0.055865 1.383381 0.085638 0.246392
3 -0.277255 1.331263 0.585174 -0.568825 -0.719412 1.191340 -0.456362 0.089931 0.776079 0.752889
4 -1.642511 0.432560 1.218080 -0.564705 -0.581790 0.286071 0.048725 1.002440 1.276582 0.054399

[5 rows x 16 columns]
```

The width of each line can be changed via ‘line_width’ (80 by default):

```python
In [39]: pd.set_option('line_width', 40)
line_width has been deprecated, use display.width instead (currently both are identical)

In [40]: wide_frame
```

```
Out[40]:
0  1  2
```

### 1.15.5 Updated PyTables Support

*Docs* for PyTables *Table* format & several enhancements to the api. Here is a taste of what to expect.

```python
In [41]: store = HDFStore('store.h5')

In [42]: df = DataFrame(randn(8, 3), index=date_range('1/1/2000', periods=8),
   columns=['A', 'B', 'C'])
   ....:
   ....:

In [43]: df
Out[43]:
    A            B            C
0  0.863067 -0.336232 -0.976847
1  1.014601 -0.475108 -0.358944
2 -0.727728 -0.094414 -0.276854
3 -0.548829  0.774225  0.740501
4  0.314510 -0.059986 -2.069319

[5 rows x 16 columns]
```
2000-01-02 0.511936 -0.116412 -0.625256
2000-01-03 -0.550627 1.261433 -0.552429
2000-01-04 1.695803 -1.025917 -0.910942
2000-01-05 0.426805 -0.131749 0.432600
2000-01-06 0.044671 -0.341265 1.844536
2000-01-07 -2.036047 0.000830 -0.955697
2000-01-08 -0.898872 -0.725411 0.059904

[8 rows x 3 columns]

# appending data frames
In [44]: df1 = df[0:4]

In [45]: df2 = df[4:]

In [46]: store.append('df', df1)

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 -0.369325 -1.502617 -0.376280
2000-01-02  0.511936 -0.116412 -0.625256
2000-01-03 -0.550627  1.261433 -0.552429
2000-01-04  1.695803 -1.025917 -0.910942
2000-01-05  0.426805 -0.131749  0.432600
2000-01-06  0.044671 -0.341265  1.844536
2000-01-07 -2.036047  0.000830 -0.955697
2000-01-08 -0.898872 -0.725411  0.059904

[8 rows x 3 columns]

In [50]: wp = Panel(randn(2, 5, 4), items=['Item1', 'Item2'],
   ....:     major_axis=date_range('1/1/2000', periods=5),
   ....:     minor_axis=['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',
.....:  [ Term('major_axis>20000102'), 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', 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]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/foo/bar/bah frame (shape->[8,3])
/foo/food/apple frame_table (typ->appendable,nrows->8,ncols->3,indexers->[index])
/foo/food/orange frame_table (typ->appendable,nrows->8,ncols->3,indexers->[index])
/wp wide_table (typ->appendable,nrows->12,ncols->2,indexers->[major_axis,minor_axis])

# remove all nodes under this level
In [62]: store.remove('food')

In [63]: store
Out[63]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/foo/bar/bah frame (shape->[8,3])
/wp wide_table (typ->appendable,nrows->12,ncols->2,indexers->[major_axis,minor_axis])
• 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 -0.369325 -1.502617 -0.376280 string 1
  2000-01-02 0.511936 -0.116412 -0.625256 string 1
  2000-01-03 -0.550627 1.261433 -0.552429 string 1
  2000-01-04 1.695803 -1.025917 -0.910942 string 1
  2000-01-05 0.426805 -0.131749 0.432600 string 1
  2000-01-06 0.044671 -0.341265 1.844536 string 1
  2000-01-07 -2.036047 0.000830 -0.955697 string 1
  2000-01-08 -0.898872 -0.725411 0.059904 string 1

  [8 rows x 5 columns]

  In [69]: df1.get_dtypes_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 data frame (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.

### 1.15.6 N Dimensional Panels (Experimental)

Adding experimental support for Panel4D and factory functions to create n-dimensional named panels. Docs for NDim. Here is a taste of what to expect.

```python
In [70]: p4d = Panel4D(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'])
```

```python
In [71]: p4d
```

```python
<class 'pandas.core.panel.Panel'
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 or issue tracker on GitHub for a complete list.

### 1.16 v0.9.1 (November 14, 2012)

This is a bugfix 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.

#### 1.16.1 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 [1]: df = DataFrame(np.random.randint(0, 2, (6, 3)), columns=['A', 'B', 'C'])
  In [2]: df.sort(['A', 'B'], ascending=[1, 0])
  Out[2]:
  A B C
  0 0 1 0
  2 0 0 1
  1 1 1 1
  5 1 1 0
  3 1 0 0
  4 1 0 1
  [6 rows x 3 columns]
  ```

- **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)
In [3]: df = DataFrame(np.random.randn(6, 3), columns=['A', 'B', 'C'])

In [4]: df.ix[2:4] = np.nan

In [5]: df.rank()
Out[5]:
   A  B  C
0  3  2  1
1  1  3  3
2  NaN NaN NaN
3  NaN NaN NaN
4  NaN NaN NaN
5  2  1  2
[6 rows x 3 columns]

In [6]: df.rank(na_option='top')
Out[6]:
   A  B  C
0  6  5  4
1  4  6  6
2  2  2  2
3  2  2  2
4  2  2  2
5  5  4  5
[6 rows x 3 columns]

In [7]: df.rank(na_option='bottom')
Out[7]:
   A  B  C
0  3  2  1
1  1  3  3
2  5  5  5
3  5  5  5
4  5  5  5
5  2  1  2
[6 rows x 3 columns]

• DataFrame has new *where* and *mask* methods to select values according to a given boolean mask (GH2109, GH2151)

DataFarme currently supports slicing via a boolean vector the same length as the DataFarme (inside the []). The returned DataFarme has the same number of columns as the original, but is sliced on its index.

In [8]: df = DataFrame(np.random.randn(5, 3), columns=['A','B','C'])

In [9]: df
Out[9]:
   A     B     C
0 -0.187239 -1.703664  0.613136
1 -0.948528  0.505346  0.017228
2 -2.391256  1.207381  0.853174
3  0.124213 -0.625597 -1.211224
4 -0.476548  0.649425  0.004610
[5 rows x 3 columns]
In [10]: df[df['A'] > 0]
Out[10]:
   A          B         C
0    3  0.124213 -0.625597 -1.211224

[1 rows x 3 columns]

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 [11]: df[df>0]
Out[11]:
   A          B         C
0  NaN        NaN   0.613136
1  NaN        NaN   0.505346
2  NaN   1.207381  0.853174
3  NaN   0.124213       NaN
4  NaN   0.649425  0.004610

[5 rows x 3 columns]

In [12]: df.where(df>0)
Out[12]:
   A          B         C
0  NaN        NaN   0.613136
1  NaN        NaN   0.505346
2  NaN   1.207381  0.853174
3  NaN   0.124213       NaN
4  NaN   0.649425  0.004610

[5 rows x 3 columns]

In [13]: df.where(df>0,-df)
Out[13]:
   A          B         C
0  0.187239  1.703664  0.613136
1  0.948528  0.505346  0.017228
2  2.391256  1.207381  0.853174
3  0.124213  0.625597  1.211224
4  0.476548  0.649425  0.004610

[5 rows x 3 columns]

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 [14]: df2 = df.copy()

In [15]: df2[ df2[1:4] > 0 ] = 3

In [16]: df2
Out[16]:
   A          B         C
0  -0.187239 -1.703664  0.613136
1   -0.948528   3.000000   3.000000
pandas: powerful Python data analysis toolkit, Release 0.17.0

2 -2.391256 3.000000 3.000000
3 3.000000 -0.625597 -1.211224
4 -0.476548 0.649425 0.004610

[5 rows x 3 columns]

**DataFrame.mask** is the inverse boolean operation of **where**.

**In [17]:** df.mask(df<=0)
**Out[17]:**

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>NaN</td>
<td>NaN</td>
<td>0.613136</td>
</tr>
<tr>
<td>NaN</td>
<td>0.505346</td>
<td>0.017228</td>
</tr>
<tr>
<td>NaN</td>
<td>1.207381</td>
<td>0.853174</td>
</tr>
<tr>
<td>0.124213</td>
<td>NaN</td>
<td>NaN</td>
</tr>
<tr>
<td>NaN</td>
<td>0.649425</td>
<td>0.004610</td>
</tr>
</tbody>
</table>

[5 rows x 3 columns]

- Enable referencing of Excel columns by their column names (GH1936)

  **In [18]:** x1 = ExcelFile('data/test.xls')

  **In [19]:** x1.parse('Sheet1', index_col=0, parse_dates=True, parse_cols='A:D')

  **Out[19]:**

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-03</td>
<td>0.980269</td>
<td>3.685731</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>1.047916</td>
<td>-0.041232</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>0.498581</td>
<td>0.731168</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>1.120202</td>
<td>1.567621</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>-0.487094</td>
<td>0.571455</td>
</tr>
<tr>
<td>2000-01-10</td>
<td>0.836649</td>
<td>0.246462</td>
</tr>
<tr>
<td>2000-01-11</td>
<td>-0.157161</td>
<td>1.340307</td>
</tr>
</tbody>
</table>

[7 rows x 3 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)

### 1.16.2 API changes

- Upsampling data with a PeriodIndex will result in a higher frequency TimeSeries that spans the original time window

  **In [20]:** prng = period_range('2012Q1', periods=2, freq='Q')

  **In [21]:** s = Series(np.random.randn(len(prng)), prng)
In [22]: s.resample('M')
Out[22]:
2012-01 -0.508759
2012-02 NaN
2012-03 NaN
2012-04 -0.599515
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)

In [23]: p = Period('2012')
In [24]: p.end_time
Out[24]: 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 [25]: data = 'A,B,C
00001,001,5
00002,002,6'
In [26]: read_csv(StringIO(data), converters={'A' : lambda x: x.strip()})
Out[26]:
   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.

1.17 v0.9.0 (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.

1.17.1 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)
1.17.2 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:

```python
In [1]: data = '0,0,1
   ...: 1,1,0
   ...: 0,1,0'

In [2]: df = read_csv(StringIO(data), header=None)

In [3]: df
Out[3]:
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:

```python
In [4]: s1 = Series([1, 2, 3])

In [5]: s1
Out[5]:
0 1
1 2
2 3
dtype: int64

In [6]: s2 = Series(s1, index=['foo', 'bar', 'baz'])

In [7]: s2
Out[7]:
foo  NaN
bar  NaN
baz  NaN
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.

1.18 v0.8.1 (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.

1.18.1 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)

1.18.2 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

1.19 v0.8.0 (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.
1.19.1 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)

1.19.2 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 codebases 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.

1.19.3 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 codebase. 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 localtime. 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`

### 1.19.4 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 :ref:`dayfirst <io.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

### 1.19.5 New plotting methods

Series.plot now supports a secondary_y option:

```
In [1]: plt.figure()
Out[1]: <matplotlib.figure.Figure at 0xa852f34c>

In [2]: fx['FR'].plot(style='g')
Out[2]: <matplotlib.axes._subplots.AxesSubplot at 0xa852f9ac>

In [3]: fx['IT'].plot(style='k--', secondary_y=True)
Out[3]: <matplotlib.axes._subplots.AxesSubplot at 0xa8d702cc>
```

Vytautas Jancauskas, the 2012 GSOC participant, has added many new plot types. For example, `'kde'` is a new option:

```
In [4]: s = Series(np.concatenate((np.random.randn(1000),
   ...:     np.random.randn(1000) * 0.5 + 3)))
   ...

In [5]: plt.figure()
Out[5]: <matplotlib.figure.Figure at 0xaf3dd2ac>

In [6]: s.hist(normed=True, alpha=0.2)
Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0xa862da2c>

In [7]: s.plot(kind='kde')
Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0xa862da2c>
```

See the *plotting page* for much more.
### 1.19.6 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.

### 1.19.7 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:

```python
In [8]: import datetime
In [9]: rng = date_range('1/1/2000', periods=10)
In [10]: rng[5]
Out[10]: Timestamp('2000-01-06 00:00:00', offset='D')
In [11]: isinstance(rng[5], datetime.datetime)
Out[11]: True
In [12]: rng_asarray = np.asarray(rng)
In [13]: scalar_val = rng_asarray[5]
In [14]: type(scalar_val)
Out[14]: 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 `asobject` property of `DatetimeIndex` produces an array of `Timestamp` objects:

```python
In [15]: stamp_array = rng.asobject
In [16]: stamp_array
Out[16]:
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')
```

To get an array of proper `datetime.datetime` objects, use the `to_pydatetime` method:

```python
In [18]: dt_array = rng.to_pydatetime()
In [19]: dt_array
```

```python
Out[19]:
```
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 [20]: dt_array[5]
Out[20]: 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.

In [21]: rng = date_range('1/1/2000', periods=10)
In [22]: rng
Out[22]:
               '2000-01-09', '2000-01-10'],
              dtype='datetime64[ns]', freq='D')

In [23]: np.asarray(rng)
Out[23]:
array(['2000-01-01T01:00:00.000000000+0100',
       '2000-01-02T01:00:00.000000000+0100',
       '2000-01-03T01:00:00.000000000+0100',
       '2000-01-04T01:00:00.000000000+0100',
       '2000-01-05T01:00:00.000000000+0100',
       '2000-01-06T01:00:00.000000000+0100',
       '2000-01-07T01:00:00.000000000+0100',
       '2000-01-08T01:00:00.000000000+0100',
       '2000-01-09T01:00:00.000000000+0100',
       '2000-01-10T01:00:00.000000000+0100'],
      dtype='datetime64[ns]')

In [24]: converted = np.asarray(rng, dtype=object)
In [25]: converted[5]
Out[25]: 947116800000000000L

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.
1.20 v.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.

1.20.1 New features

- New fixed width file reader, read_fwf
- New scatter_matrix function for making a scatter plot matrix

```
from pandas.tools.plotting import scatter_matrix
scatter_matrix(df, alpha=0.2)
```

- Add stacked argument to Series and DataFrame’s plot method for stacked bar plots.

```
df.plot(kind='bar', stacked=True)
```
df.plot(kind='barh', stacked=True)

- Add log x and y scaling options to DataFrame.plot and Series.plot
- Add kurt methods to Series and DataFrame for computing kurtosis

### 1.20.2 NA Boolean Comparison API Change

Reverted some changes to how NA values (represented typically as NaN or None) are handled in non-numeric Series:

```
In [1]: series = Series(['Steve', np.nan, 'Joe'])

In [2]: series == 'Steve'
Out[2]:
0    True
```
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:

In [4]: mask = series == 'Steve'

In [5]: series[mask & series.notnull()]

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.

1.20.3 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:
A
bar  count  3.000000
mean -0.438936
std  0.992521
min -1.581534
25% -0.763153
50%  0.055228
75%  0.132364
...
foo  mean -0.866287
std  0.584196
min -1.631882
25% -1.079181
50% -0.912061
75% -0.675890
max  0.032419
dtype: float64

In [10]: grouped.apply(lambda x: x.order()[-2:]) # top 2 values
Out[10]:
A
bar  5  0.055228
    3  0.209500
foo  4 -0.675890
    0 -0.032419
dtype: float64

1.21 v.0.7.2 (March 16, 2012)

This release targets bugs in 0.7.1, and adds a few minor features.

1.21.1 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)

1.21.2 Performance improvements

• Use khash for Series.value_counts, add raw function to algorithms.py (GH861)
• Intercept __builtins__.sum in groupby (GH885)
1.22 v.0.7.1 (February 29, 2012)

This release includes a few new features and addresses over a dozen bugs in 0.7.0.

1.22.1 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 (GH87)
• 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

1.22.2 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)

1.23 v.0.7.0 (February 9, 2012)

1.23.1 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 constructor (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)

In [1]: df = DataFrame(randn(10, 4))
In [2]: df.apply(lambda x: x.describe())
Out[2]:
   0         1         2         3
count 10.000000 10.000000 10.000000 10.000000
mean   0.058434  0.008207  0.449898 -0.064109
std    0.959629  1.126010  0.784723  0.650405
Add reorder_levels method to Series and DataFrame (GH534)

Add dict-like get function to DataFrame and Panel (GH521)

Add DataFrame.iterrows method for efficiently iterating through the rows of a DataFrame

Add DataFrame.to_panel with code adapted from LongPanel.to_long

Add reindex_axis method added to DataFrame

Add level option to binary arithmetic functions on DataFrame and Series

Add level option to the reindex and align methods on Series and DataFrame for broadcasting values across a level (GH542, GH552, others)

Add attribute-based item access to Panel and add IPython completion (GH563)

Add logy option to Series.plot for log-scaling on the Y axis

Add 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 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.
1.23.2 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 = Series(randn(10), index=range(0, 20, 2))

In [4]: s
Out[4]:
0    0.041867
2    1.503116
4   -0.841265
6   -1.578003
8   -0.273728
10   1.755240
12  -0.705788
14  -0.351950
16   1.507974
18   0.419219
 dtype: float64

In [5]: s[0]
Out[5]: 0.041867372914288915

In [6]: s[2]
Out[6]: 1.5031163945003796

In [7]: s[4]
Out[7]: -0.84126511615728994

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:

In [2]: s[1]
KeyError: 1

This change also has the same impact on DataFrame:

In [3]: df = DataFrame(randn(8, 4), index=range(0, 16, 2))

In [4]: df
Out[4]:
     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>

### 1.23.3 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:

```python
In [8]: s = Series(randn(6), index=list('gmkaec'))
```

```python
In [9]: s
Out[9]:
g  0.647633
m -0.147670
k -0.759803
a -0.757308
e -1.921164
c -1.093529
dtype: float64
```

Then this is OK:

```python
In [10]: s.ix['k':'e']
Out[10]:
k -0.759803
a -0.757308
e -1.921164
dtype: float64
```

But this is not:

```python
In [12]: s.ix['b':'h']
KeyError 'b'
```

If the index had been sorted, the “range selection” would have been possible:

```python
In [11]: s2 = s.sort_index()
```

```python
In [12]: s2
Out[12]:
a -0.757308
c -1.093529
e -1.921164
g  0.647633
k -0.759803
m -0.147670
dtype: float64
```

```python
In [13]: s2.ix['b':'h']
Out[13]:
c -1.093529
e -1.921164
g  0.647633
dtype: float64
```
1.23.4 Changes to Series [] operator

As an 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 [14]: s = Series(randn(6), index=list('acegkm'))

In [15]: s
Out[15]:
  a   -0.592157
  c   -0.715074
  e   -0.616193
  g   -0.335468
  k   -0.392051
  m   -0.189537
       dtype: float64

In [16]: s[['m', 'a', 'c', 'e']]
Out[16]:
  m   -0.189537
  a   -0.592157
  c   -0.715074
  e   -0.616193
       dtype: float64

In [17]: s['c':'k']
Out[17]:
  c   -0.715074
  e   -0.616193
  g   -0.335468
  k   -0.392051
       dtype: float64
```

In the case of integer indexes, the behavior will be exactly as before (shadowing ndarray):

```
In [19]: s = Series(randn(6), index=range(0, 12, 2))

In [20]: s[[4, 0, 2]]
Out[20]:
  4   0.319635
  0   0.886170
  2  -1.125894
       dtype: float64

In [21]: s[1:5]
Out[21]:
  2  -1.125894
  4   0.319635
  6   0.998222
  8   0.091743
```
If you wish to do indexing with sequences and slicing on an integer index with label semantics, use `ix`.

### 1.23.5 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)

### 1.23.6 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)
- 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)

### 1.24 v.0.6.1 (December 13, 2011)

#### 1.24.1 New features

- Can **append single rows** (as Series) to a DataFrame
pandas: powerful Python data analysis toolkit, Release 0.17.0

• 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

1.24.2 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)

1.25 v.0.6.0 (November 25, 2011)

1.25.1 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)

### 1.25.2 Performance Enhancements

• *VBENCH* Cythonized `cache_readonly`, resulting in substantial micro-performance enhancements throughout the codebase (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 \texttt{map\_infer} speeds up \texttt{Series.apply} and \texttt{Series.map} significantly when passed elementwise Python function, motivated by (GH355)
• VBENCH Significantly improved performance of \texttt{Series.order}, which also makes \texttt{np.unique} called on a Series faster (GH327)
• VBENCH Vastly improved performance of GroupBy on axes with a MultiIndex (GH299)

1.26 v.0.5.0 (October 24, 2011)

1.26.1 New Features

• \textit{Added} \texttt{DataFrame.align} method with standard join options
• \textit{Added} \texttt{parse\_dates} option to \texttt{read\_csv} and \texttt{read\_table} methods to optionally try to parse dates in the index columns
• \textit{Added} \texttt{nrows}, \texttt{chunksize}, and \texttt{iterator} arguments to \texttt{read\_csv} and \texttt{read\_table}. The last two return a new \texttt{TextParser} class capable of lazily iterating through chunks of a flat file (GH242)
• \textit{Added} ability to join on multiple columns in \texttt{DataFrame.join} (GH214)
• \textit{Added} private \texttt{\_get\_duplicates} function to \texttt{Index} for identifying duplicate values more easily (ENH5c)
• \textit{Added} column attribute access to \texttt{DataFrame}.
• \textit{Added} Python tab completion hook for \texttt{DataFrame} columns. (GH233, GH230)
• \textit{Implemented} \texttt{Series.describe} for \texttt{Series} containing objects (GH241)
• \textit{Added} inner join option to \texttt{DataFrame.join} when joining on key(s) (GH248)
• \textit{Implemented} selecting \texttt{DataFrame} columns by passing a list to \texttt{\_getitem\_} (GH253)
• \textit{Implemented} \& and | to intersect / union \texttt{Index} objects, respectively (GH261)
• \textit{Added} \texttt{pivot\_table} convenience function to pandas namespace (GH234)
• \textit{Implemented} \texttt{Panel.rename\_axis} function (GH243)
• \texttt{DataFrame} will show index level names in console output (GH334)
• \textit{Implemented} \texttt{Panel.take}
• \textit{Added} \texttt{set\_eng\_float\_format} for alternate \texttt{DataFrame} floating point string formatting (ENH61)
• \textit{Added} convenience \texttt{set\_index} function for creating a \texttt{DataFrame} index from its existing columns
• \textit{Implemented} \texttt{groupby} hierarchical index level name (GH223)
• \textit{Added} support for different delimiters in \texttt{DataFrame.to\_csv} (GH244)
• TODO: DOCS ABOUT TAKE METHODS

1.26.2 Performance Enhancements

• VBENCH Major performance improvements in file parsing functions \texttt{read\_csv} and \texttt{read\_table}
• VBENCH Added Cython function for converting tuples to \texttt{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

1.27 v.0.4.3 through v0.4.1 (September 25 - October 9, 2011)

1.27.1 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)

1.27.2 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
The easiest way for the majority of users 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, various Linux distributions, or a development version are also provided.

2.1 Python version support

Officially Python 2.6, 2.7, 3.3, 3.4, and 3.5

2.2 Installing pandas

2.2.1 Trying out pandas, no installation required!

The easiest way to start experimenting with pandas doesn’t involve installing pandas at all. Wakari is a free service that provides a hosted IPython Notebook service in the cloud. Simply create an account, and have access to pandas from within your browser via an IPython Notebook in a few minutes.

2.2.2 Installing pandas 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 a simple 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.

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.

An additional advantage of installing with Anaconda is that you don’t require admin rights to install it, it will install in the user’s home directory, and this also makes it trivial to delete Anaconda at a later date (just delete that folder).
2.2.3 Installing pandas 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 (these are analogous to a virtualenv but they also allow you to specify precisely which Python version to install also). 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=0.13.1
```

To install other packages, IPython for example:

```
conda install ipython
```

To install the full Anaconda distribution:

```
conda install anaconda
```

If you require any packages that are available to pip but not conda, simply install pip, and use pip to install these packages:

```
conda install pip
pip install django
```

2.2.4 Installing from PyPI

Pandas can be installed via pip from PyPI.

```
pip install pandas
```

This will likely require the installation of a number of dependencies, including NumPy, will require a compiler to compile required bits of code, and can take a few minutes to complete.
### 2.2.5 Installing using your Linux distribution's package manager.

The commands in this table will install pandas for Python 2 from your distribution. To install pandas for Python 3 you may need to use the package `python3-pandas`.

<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><code>sudo apt-get install python-pandas</code></td>
</tr>
<tr>
<td>Debian &amp; Ubuntu</td>
<td>unstable (latest packages)</td>
<td>NeuroDebian</td>
<td><code>sudo apt-get install python-pandas</code></td>
</tr>
<tr>
<td>Ubuntu</td>
<td>stable</td>
<td>official Ubuntu repository</td>
<td><code>sudo apt-get install python-pandas</code></td>
</tr>
<tr>
<td>Ubuntu</td>
<td>unstable (daily builds)</td>
<td>PythonXY PPA; activate by: <code>sudo add-apt-repository ppa:pythonxy/pythonxy-devel &amp;&amp; sudo apt-get update</code></td>
<td><code>sudo apt-get install python-pandas</code></td>
</tr>
<tr>
<td>OpenSuse &amp; Fedora</td>
<td>stable</td>
<td>OpenSuse Repository</td>
<td><code>zypper in python-pandas</code></td>
</tr>
</tbody>
</table>

### 2.2.6 Installing from source

See the contributing documentation 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.

### 2.2.7 Running the test suite

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

```
$ nosetests pandas
..........................................................................
.......................S..................................................
..........................................................................
..........................................................................
..........................................................................
..........................................................................
..........................................................................
..........................................................................
..........................................................................
..........................................................................
.................S........................................................
....
----------------------------------------------------------------------
Ran 818 tests in 21.631s
OK (SKIP=2)
```

2.2. Installing pandas
2.3 Dependencies

- setuptools
- NumPy: 1.7.1 or higher
- python-dateutil 1.5 or higher
- pytz
  - Needed for time zone support

2.3.1 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 2.1 or higher.
- bottleneck: for accelerating certain types of nan evaluations. bottleneck uses specialized cython routines to achieve large speedups.

Note: You are highly encouraged to install these libraries, as they provide large speedups, especially if working with large data sets.

2.3.2 Optional Dependencies

- Cython: Only necessary to build development version. Version 0.19.1 or higher.
- SciPy: miscellaneous statistical functions
- PyTables: necessary for HDF5-based storage. Version 3.0.0 or higher required, Version 3.2.1 or higher highly recommended.
- SQLAlchemy: for SQL database support. Version 0.8.1 or higher recommended.
- matplotlib: for plotting
- statsmodels
  - Needed for parts of pandas.stats
- openpyxl, xlrd/xlwt
  - Needed for Excel I/O
- XlsxWriter
  - Alternative Excel writer
- boto: necessary for Amazon S3 access.
- blosc: for msgpack compression using blosc
- One of PyQt4, PySide, pygtk, xsel, or xclip: necessary to use read_clipboard(). Most package managers on Linux distributions will have xclip and/or xsel immediately available for installation.
- Google’s python-gflags and google-api-python-client * Needed for gbq
- setuptools * Needed for gbq (specifically, it utilizes pkg_resources)
- httplib2 * Needed for gbq
- One of the following combinations of libraries is needed to use the top-level read_html() function:
- BeautifulSoup4 and html5lib (Any recent version of html5lib is okay.)
- BeautifulSoup4 and lxml
- BeautifulSoup4 and html5lib and lxml
- Only lxml, although see HTML reading gotchas 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 reading gotchas. It explains issues surrounding the installation and usage of the above three libraries
- You may need to install an older version of BeautifulSoup4:
  * Versions 4.2.1, 4.1.3 and 4.0.2 have been confirmed for 64 and 32-bit Ubuntu/Debian
- Additionally, if you’re using Anaconda you should definitely read the gotchas about HTML parsing libraries

**Note:**
- if you’re on a system with apt-get you can do

```
sudo apt-get build-dep python-lxml
```

  to get the necessary dependencies for installation of lxml. This will prevent further headaches down the line.

**Note:** Without the optional dependencies, many useful features will not work. Hence, it is highly recommended that you install these. A packaged distribution like Enthought Canopy may be worth considering.
3.1 Where to start?

All contributions, bug reports, bug fixes, documentation improvements, enhancements and ideas are welcome.

If you are simply looking to start working with the pandas codebase, navigate to the GitHub “issues” tab and start looking through interesting issues. There are a number of issues listed under Docs and Difficulty Novice where you
could start out.

Or maybe through using pandas you have an idea of your own or are looking for something in the documentation and thinking ‘this can be improved’...you can do something about it!

Feel free to ask questions on mailing list

3.2 Bug Reports/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. Since many versions of pandas are supported, knowing version information will also identify improvements made since previous versions. Often trying the bug-producing code out on the master branch is 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 have the code formatted nicely by using GitHub Flavored Markdown:

   ```python
   >>> from pandas import DataFrame
   >>> df = DataFrame(...)  
   ...  
   ```

2. Include the full version string of pandas and its dependencies. In recent (>0.12) versions of pandas you can use a built in function:

   ```python
   >>> from pandas.util.print_versions import show_versions
   >>> show_versions()
   ```

   and in 0.13.1 onwards:

   ```python
   >>> 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.

3.3 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.

3.3.1 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 make the process straightforward and will work without much trouble. 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:
3.3.2 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 working seamlessly with your local repository and GitHub.

3.3.3 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:

```
git clone git@github.com:your-user-name/pandas.git pandas-yourname
cd pandas-yourname
git remote add upstream git://github.com/pydata/pandas.git
```

This creates the directory `pandas-yourname` and connects your repository to the upstream (main project) `pandas` repository.

The testing suite will run automatically on Travis-CI 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 Travis-CI needs to be hooked up to your GitHub repository. Instructions are for doing so are here.

3.3.4 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.

To update this branch, you need to retrieve the changes from the master branch:

```
git fetch upstream
git rebase upstream/master
```

This will replay your commits on top of the lastest pandas git master. If this leads to merge conflicts, you must resolve these before submitting your Pull Request. If you have uncommitted changes, you will need to `stash` them prior to updating. This will effectively store your changes and they can be reapplied after updating.

3.3.5 Creating a Development Environment

An easy way to create a `pandas` development environment is as follows.
• Install either Install Anaconda or Install miniconda
• Make sure that you have cloned the repository
• cd to the pandas source directory

Tell conda to create a new environment, named pandas_dev, or any name you would like for this environment by running:

conda create -n pandas_dev --file ci/requirements_dev.txt

For a python 3 environment

conda create -n pandas_dev python=3 --file ci/requirements_dev.txt

If you are on windows, then you will need to install the compiler linkages:

conda install -n pandas_dev libpython

This will create the new environment, and not touch any of your existing environments, nor any existing python installation. It will install all of the basic dependencies of pandas, as well as the development and testing tools. If you would like to install other dependencies, you can install them as follows:

conda install -n pandas_dev -c pandas pytables scipy

To install all pandas dependencies you can do the following:

conda install -n pandas_dev -c pandas --file ci/requirements_all.txt

To work in this environment, activate it as follows:

activate pandas_dev

At which point, the prompt will change to indicate you are in the new development environment.

Note: The above syntax is for windows environments. To work on macosx/linux, use:

source activate pandas_dev

To view your environments:

conda info -e

To return to you home root environment:

deactivate

See the full conda docs here.

At this point you can easily do an in-place install, as detailed in the next section.

3.3.6 Making changes

Before making your code changes, it is often necessary to build the code that was just checked out. There are two primary methods of doing this.

1. The best way to develop pandas is to build the C extensions in-place by running:

   python setup.py build_ext --inplace

   If you startup the Python interpreter in the pandas source directory you will call the built C extensions
2. Another very common option is to do a develop install of pandas:

```
python setup.py develop
```

This makes a symbolic link that tells the Python interpreter to import pandas from your development directory. Thus, you can always be using the development version on your system without being inside the clone directory.

### 3.4 Contributing to the documentation

If you’re not the developer type, contributing to the documentation is still of huge value. You don’t even have to be an expert on pandas to do so! Something as simple as rewriting small passages for clarity as you reference the docs is a simple but effective way to contribute. The next person to read that passage will be in your debt!

Actually, there are sections of the docs that are worse off by 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 simple way to ensure it will help the next person.

#### 3.4.1 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 pandas/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 the Numpy Docstring Standard which is used widely in the Scientific Python community. This standard specifies the format of the different sections of the docstring. See this document for a detailed explanation, or look at some of the existing functions to extend it in a similar manner.

- 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:

  ```ipython:: python
  x = 2
  x**3```

  will be rendered as
In [1]: x = 2
In [2]: x**3
Out[2]: 8

This means that almost all code examples in the docs are always run (and the output saved) during the doc build. This way, they will always be up to date, but it makes the doc building a bit more complex.

The utility script scripts/api_rst_coverage.py can be used to compare the list of methods documented in doc/source/api.rst (which is used to generate the API Reference page) and the actual public methods. It will identify methods documented in doc/source/api.rst that are not actually class methods, and existing methods that are not documented in doc/source/api.rst.

### 3.4.2 How to build the pandas documentation

**Requirements**

To build the pandas docs there are some extra requirements: you will need to have sphinx and ipython installed. numpydoc is used to parse the docstrings that follow the Numpy Docstring Standard (see above), but you don’t need to install this because a local copy of numpydoc is included in the pandas source code.

It is easiest to create a development environment, then install:

```bash
conda install -n pandas_dev sphinx ipython
```

Furthermore, it is recommended to have all optional dependencies installed. This is not strictly necessary, but be aware that you will see some error messages. Because all the code in the documentation is executed during the doc build, the examples using this optional dependencies will generate errors. Run `pd.show_versions()` to get an overview of the installed version of all dependencies.

**Warning:** Sphinx version >= 1.2.2 or the older 1.1.3 is required.

**Building the documentation**

So how do you build the docs? Navigate to your local the folder pandas/doc/ directory in the console and run:

```bash
python make.py html
```

And then you can find the html output in the folder pandas/doc/build/html/.

The first time it will take quite a while, because it has to run all the code examples in the documentation and build all 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:

```bash
python make.py clean
python make.py build
```

Starting with 0.13.1 you can tell make.py to compile only a single section of the docs, greatly reducing the turn-around time for checking your changes. You will be prompted to delete .rst files that aren’t required. This is okay since the prior version can be checked out from git, but make sure to not commit the file deletions.

```bash
#omit autosummary and API section
python make.py clean
python make.py --no-api
```
# compile the docs with only a single section, that which is in indexing.rst
python make.py clean
python make.py --single indexing

For comparison, a full documentation build may take 10 minutes. a `--no-api` build may take 3 minutes and a single section may take 15 seconds. However, subsequent builds only process portions you changed. Now, open the following file in a web browser to see the full documentation you just built:

```
pandas/docs/build/html/index.html
```

And you’ll have the satisfaction of seeing your new and improved documentation!

## Built 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.

### 3.5 Contributing to the code base

**Code Base:**

- Code Standards
- Test-driven Development/Writing Code
  - Writing tests
  - Running the test suite
  - Running the performance test suite
  - Running the vbench performance test suite (phasing out)
- Documenting your code

#### 3.5.1 Code Standards

*pandas* uses the PEP8 standard. There are several tools to ensure you abide by this standard.

We’ve written a tool to check that your commits are PEP8 great, `pip install pep8radius`. Look at PEP8 fixes in your branch vs master with:

```
pep8radius master --diff
```

Alternatively, use `flake8` tool for checking the style of your code. Additional standards are outlined on the code style wiki page.

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.

#### 3.5.2 Test-driven Development/Writing Code

*Pandas* is serious about testing and strongly encourages individuals 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. It is worth getting in the habit of writing tests ahead of time so this is never an issue.

Like many packages, pandas uses the Nose testing system and the convenient extensions in numpy.testing.

**Writing tests**

All tests should go into the tests subdirectory of the specific package. There are probably many examples already there and looking to these for inspiration is suggested. If you test requires working with files or network connectivity there is more information on the testing page of the wiki.

The pandas.util.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)
```

**Running the test suite**

The tests can then be run directly inside your git clone (without having to install pandas) by typing::

```
nosetests 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. This is done using one of the following constructs:

```
nosetests pandas/tests/[test-module].py
nosetests pandas/tests/[test-module].py:[TestClass]
nosetests pandas/tests/[test-module].py:[TestClass].[test_method]
```

**Running the performance test suite**

Performance matters and it is worth considering that your code has not introduced performance regressions. pandas is in the process of migrating to the asv library to enable easy monitoring of the performance of critical pandas operations. These benchmarks are all found in the pandas/asv_bench directory. asv supports both python2 and python3.
Note: The asv benchmark suite was translated from the previous framework, vbench, so many stylistic issues are likely a result of automated transformation of the code.

To use ‘asv’ you will need either ‘conda’ or ‘virtualenv’. For more details please check installation webpage http://asv.readthedocs.org/en/latest/installing.html

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 the following if you have been developing on master:

```
asv continuous master
```

Otherwise, if you are working on another branch, either of the following can be used:

```
asv continuous master HEAD
asv continuous master your_branch
```

This will checkout the master revision and run the suite on both master and your commit. Running the full test suite can take up to one hour and use up to 3GB of RAM. Usually it is sufficient to paste a subset of the results in to 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:

```
asv continuous master -b groupby
```

If you want to run only some specific group of tests from a file you can do it using . as a separator. For example:

```
asv continuous master -b groupby.groupby_agg_builtins1
```

will only run a groupby_agg_builtins1 test defined in a groupby file.

It is also useful to run tests in your current environment. You can simply do it by:

```
asv dev
```

which would be equivalent to asv run --quick --show-stderr --python=same. This will launch every test only once, display stderr from the benchmarks and use your local python that comes from your $PATH.

Information on how to write a benchmark can be found in *asv*’s documentation http://asv.readthedocs.org/en/latest/writing_benchmarks.html.

### Running the vbench performance test suite (phasing out)

Performance matters and it is worth considering that your code has not introduced performance regressions. Historically, pandas used vbench library to enable easy monitoring of the performance of critical pandas operations. These benchmarks are all found in the pandas/vb_suite directory. vbench currently only works on python2.

To install vbench:

```
pip install git+https://github.com/pydata/vbench
```

Vbench also requires sqlalchemy, gitpython, and psutil which can all be installed using pip. If you need to run a benchmark, change your directory to the pandas root and run:

```
./test_perf.sh -b master -t HEAD
```
This will checkout the master revision and run the suite on both master and your commit. Running the full test suite can take up to one hour and use up to 3GB of RAM. Usually it is sufficient to paste a subset of the results in to the Pull Request to show that the committed changes do not cause unexpected performance regressions.

You can run specific benchmarks using the `-r` flag which takes a regular expression.

See the performance testing wiki for information on how to write a benchmark.

### 3.5.3 Documenting your code

Changes should be reflected in the release notes located in `doc/source/whatsnew/vx.y.z.txt`. 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 `GH1234` 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:: 0.17.0
```

This will put the text `New in version 0.17.0` 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).

### 3.6 Contributing your changes to pandas

#### 3.6.1 Committing your code

Keep style fixes to a separate commit to make your PR more readable.

Once you’ve made changes, you can see them by typing:

```
git status
```

If you’ve 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

```bash
# On branch shiny-new-feature
#
# modified: /relative/path/to/file-you-added.py
#
```

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
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:

```bash
git commit -m
```

If you have multiple commits, it is common to want to combine them into one commit, often referred to as “squashing” or “rebasing”. This is a common request by package maintainers when submitting a Pull Request as it maintains a more compact commit history. To rebase your commits:

```bash
git rebase -i HEAD~#
```

Where # is the number of commits you want to combine. Then you can pick the relevant commit message and discard others.

### 3.6.2 Pushing your changes

When you want your changes to appear publicly on your GitHub page, push your forked feature branch’s commits

```bash
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

```bash
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/pydata/pandas.git (fetch)
upstream git://github.com/pydata/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.

### 3.6.3 Review your code

When you’re ready to ask for a code review, you will file a Pull Request. Before you do, again make sure you’ve 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 off of:

1. Navigate to your repository on GitHub–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.
3.6.4 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 appears to the repository maintainers, and they will review the code. If you need to make more changes, you can make them in your branch, push them to GitHub, and the pull request will be automatically updated. Pushing them to GitHub again is done by:

```
git push -f origin shiny-new-feature
```

This will automatically update your Pull Request with the latest code and restart the Travis-CI tests.

3.6.5 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 just 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 DataFrame memory usage

As of pandas version 0.15.0, the memory usage of a dataframe (including the index) is shown when accessing the info method of a dataframe. A configuration option, display.memory_usage (see Options and Settings), 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 df.info():

```python
In [1]: dtypes = ['int64', 'float64', 'datetime64[ns]', 'timedelta64[ns]',
            'complex128', 'object', 'bool']

In [2]: n = 5000

In [3]: data = dict((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'>
Int64Index: 5000 entries, 0 to 4999
Data columns (total 8 columns):
bool      5000 non-null bool
complex128 5000 non-null complex128
datetime64[ns] 5000 non-null datetime64[ns]
float64   5000 non-null float64
int64     5000 non-null int64
object    5000 non-null object
timedelta64[ns] 5000 non-null timedelta64[ns]
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: 303.5+ KB
```

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.

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 of the dataframe can be found with the memory_usage method:

```
In [7]: df.memory_usage()
Out[7]:
bool      5000
complex128  80000
datetime64[ns]  40000
float64    40000
int64      40000
object     20000
timedelta64[ns]  40000
categorical  5800
```

dtype: int64

# total memory usage of dataframe
```
In [8]: df.memory_usage().sum()
Out[8]: 270800
```

By default the memory usage of the dataframe’s index is not shown in the returned Series, the memory usage of the index can be shown by passing the index=True argument:

```
In [9]: df.memory_usage(index=True)
Out[9]:
Index     40000
bool      5000
complex128  80000
datetime64[ns]  40000
float64    40000
int64      40000
object     20000
timedelta64[ns]  40000
categorical  5800
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.

### 4.2 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. To deal with this issue you should convert the underlying NumPy array to the native system byte order before passing it to Series/DataFrame/Panel constructors using something similar to the following:

```
In [10]: x = np.array(list(range(10)), '>i4')  # big endian
In [11]: newx = x.byteswap().newbyteorder()  # force native byteorder
In [12]: s = pd.Series(newx)
```

See the NumPy documentation on byte order for more details.
There is experimental support for visualizing DataFrames in PyQt4 and PySide applications. At the moment you can display and edit the values of the cells in the DataFrame. Qt will take care of displaying just the portion of the DataFrame that is currently visible and the edits will be immediately saved to the underlying DataFrame.

To demonstrate this we will create a simple PySide application that will switch between two editable DataFrames. For this we will use the DataFrameModel class that handles the access to the DataFrame, and the DataFrameWidget, which is just a thin layer around the QTableView.

```python
import numpy as np
import pandas as pd
from pandas.sandbox.qtpandas import DataFrameModel, DataFrameWidget
from PySide import QtGui, QtCore

# Or if you use PyQt4:
# from PyQt4 import QtGui, QtCore

class MainWidget(QtGui.QWidget):
    def __init__(self, parent=None):
        super(MainWidget, self).__init__(parent)

        # Create two DataFrames
        self.df1 = pd.DataFrame(np.arange(9).reshape(3, 3),
                                columns=['foo', 'bar', 'baz'])
        self.df2 = pd.DataFrame({
            'int': [1, 2, 3],
            'float': [1.5, 2.5, 3.5],
            'string': ['a', 'b', 'c'],
            'nan': [np.nan, np.nan, np.nan]
        }, index=['AAA', 'BBB', 'CCC'],
                                columns=['int', 'float', 'string', 'nan'])

        # Create the widget and set the first DataFrame
        self.widget = DataFrameWidget(self.df1)

        # Create the buttons for changing DataFrames
        self.button_first = QtGui.QPushButton('First')
        self.button_first.clicked.connect(self.on_first_click)
        self.button_second = QtGui.QPushButton('Second')
        self.button_second clicked.connect(self.on_second_click)

        # Set the layout
        vbox = QtGui.QVBoxLayout()
        vbox.addWidget(self.widget)
        hbox = QtGui.QHBoxLayout()
        hbox.addWidget(self.button_first)
        hbox.addWidget(self.button_second)
        vbox.addLayout(hbox)
        self.setLayout(vbox)

    def on_first_click(self):
        '''Sets the first DataFrame'''
        self.widget.setDataFrame(self.df1)
```

4.3. Visualizing Data in Qt applications
```python
def on_second_click(self):
    '''Sets the second DataFrame'''
    self.widget.setDataFrame(self.df2)

if __name__ == '__main__':
    import sys

    # Initialize the application
    app = QtGui.QApplication(sys.argv)
    mw = MainWidget()
    mw.show()
    app.exec_()
```
pandas consists of the following things

- A set of labeled array data structures, the primary of which are Series and DataFrame
- Index objects enabling both simple axis indexing and multi-level / hierarchical axis indexing
- An integrated group by engine for aggregating and transforming data sets
- Date range generation (date_range) and custom date offsets enabling the implementation of customized frequencies
- Input/Output tools: loading tabular data from flat files (CSV, delimited, Excel 2003), and saving and loading pandas objects from the fast and efficient PyTables/HDF5 format.
- Memory-efficient “sparse” versions of the standard data structures for storing data that is mostly missing or mostly constant (some fixed value)
- Moving window statistics (rolling mean, rolling standard deviation, etc.)
- Static and moving window linear and panel regression

### 5.1 Data structures at a glance

<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></td>
<td>DataFrame</td>
<td>General 2D labeled, size-mutable tabular structure with potentially heterogeneous-typed columns</td>
</tr>
<tr>
<td>2</td>
<td>Panel</td>
<td>General 3D labeled, also size-mutable array</td>
</tr>
</tbody>
</table>

#### 5.1.1 Why more than 1 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 Panel is a container for DataFrame objects. 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. And iterating through the columns of the DataFrame thus results in more readable code:

```python
for col in df.columns:
    series = df[col]
    # do something with series
```

### 5.2 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, though, we like to favor immutability where sensible.

### 5.3 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.

Longer discussions occur on the developer mailing list, and commercial support inquiries for Lambda Foundry should be sent to: support@lambdafoundry.com

### 5.4 Credits

pandas development began at AQR Capital Management in April 2008. It was open-sourced at the end of 2009. AQR continued to provide resources for development through the end of 2011, and continues to contribute bug reports today.

Since January 2012, Lambda Foundry, has been providing development resources, as well as commercial support, training, and consulting for pandas.

pandas is only made possible by a group of people around the world like you who have contributed new code, bug reports, fixes, comments and ideas. A complete list can be found on Github.

### 5.5 Development Team

pandas is a part of the PyData project. The PyData Development Team is a collection of developers focused on the improvement of Python’s data libraries. The core team that coordinates development can be found on Github. If you’re interested in contributing, please visit the project website.

### 5.6 License

=======
License
=======

pandas is distributed under a 3-clause ("Simplified" or "New") BSD license. Parts of NumPy, SciPy, numpydoc, bottleneck, which all have
BSD-compatible licenses, are included. Their licenses follow the pandas license.

**pandas license**

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About the Copyright Holders

AQR Capital Management began pandas development in 2008. Development was led by Wes McKinney. AQR released the source under this license in 2009. Wes is now an employee of Lambda Foundry, and remains the pandas project lead.

The PyData Development Team is the collection of developers of the PyData project. This includes all of the PyData sub-projects, including pandas. The core team that coordinates development on GitHub can be found here: http://github.com/pydata.

Full credits for pandas contributors can be found in the documentation.

Our Copyright Policy

=============

5.6. License
PyData uses a shared copyright model. Each contributor maintains copyright over their contributions to PyData. However, it is important to note that these contributions are typically only changes to the repositories. Thus, the PyData source code, in its entirety, is not the copyright of any single person or institution. Instead, it is the collective copyright of the entire PyData Development Team. If individual contributors want to maintain a record of what changes/contributions they have specific copyright on, they should indicate their copyright in the commit message of the change when they commit the change to one of the PyData repositories.

With this in mind, the following banner should be used in any source code file to indicate the copyright and license terms:

```
# vim: set tw=79:
#-----------------------------------------------------------------------------
# Copyright (c) 2012, PyData Development Team
# All rights reserved.
# Distributed under the terms of the BSD Simplified License.
# The full license is in the LICENSE file, distributed with this software.
#-----------------------------------------------------------------------------

Other licenses can be found in the LICENSES directory.
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 pandas as pd
In [2]: import numpy as np
In [3]: import matplotlib.pyplot as plt
```

### 6.1 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 [4]: s = pd.Series([1,3,5,np.nan,6,8])
```

```
Out[5]:
0   1
1   3
2   5
3  NaN
4   6
5   8
dtype: float64
```

Creating a **DataFrame** by passing a numpy array, with a datetime index and labeled columns:

```
In [6]: dates = pd.date_range('20130101', periods=6)
```

```
In [7]: dates
Out[7]:
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05', '2013-01-06'],
               dtype='datetime64[ns]', freq='D')
```

```
In [8]: df = pd.DataFrame(np.random.randn(6,4), index=dates, columns=list('ABCD'))
```

```
In [9]: df
Out[9]:
        A         B         C         D
0  0.031328  1.076581 -0.790599 -0.659458
1 -1.380495 -0.895836 -0.645884 -0.240664
2  1.182722  1.180555  0.048576  0.093673
3  0.135093  0.942155  0.203480  0.811963
4  1.076881  0.434609 -0.211962 -0.108786
5 -1.574123 -1.596326 -0.364704 -0.260048
```
Creating a DataFrame by passing a dict of objects that can be converted to series-like.

```python
In [10]: 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' })
```

```python
In [11]: df2
Out[11]:
   A     B         C              D             E            F
0  1 2013-01-02  1.0 2013-01-02  3.0          'test'       'foo'
1  1 2013-01-02  1.0 2013-01-02  3.0          'train'      'foo'
2  1 2013-01-02  1.0 2013-01-02  3.0          'test'       'foo'
3  1 2013-01-02  1.0 2013-01-02  3.0          'train'      'foo'
```

Having specific dtypes

```python
In [12]: df2.dtypes
Out[12]:
A float64
B datetime64[ns]
C float32
D int32
E category
F object
dtype: 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:

```python
In [13]: df2.<TAB>
df2.A     df2.boxplot
df2.abs    df2.C
df2.add    df2.clip
df2.add_prefix    df2.clip_lower
df2.add_suffix    df2.clip_upper
df2.align    df2.columns
df2.all     df2.combine
df2.any    df2.combineAdd
df2.append    df2.combine_first
df2.apply    df2.combineMult
df2.applymap    df2.compound
df2.as_blocks    df2.consolidate
df2.asfreq    df2.convert_objects
df2.as_matrix    df2.copy
df2.astype    df2.corr
df2.at    df2.corrwith
df2.at_time    df2.count
df2.axes    df2.cov
```
As you can see, the columns A, B, C, and D are automatically tab completed. E is there as well; the rest of the attributes have been truncated for brevity.

6.2 Viewing Data

See the Basics section

See the top & bottom rows of the frame

```python
In [14]: df.head()
Out[14]:
          A      B      C      D
2013-01-01 0.4691  0.2829 -1.5091 -1.1356
2013-01-02 1.2121  0.1732  0.1192  0.0442
2013-01-03-0.8618 -2.1046 -0.4949  1.0718
2013-01-04 0.7216 -0.7068 -1.0396  0.2719
2013-01-05-0.425  0.567  0.2762 -1.0874
```

```python
In [15]: df.tail(3)
Out[15]:
          A      B      C      D
2013-01-04 0.7216  0.7067 -1.0396  0.2719
2013-01-05-0.4249  0.567  0.2762 -1.0874
2013-01-06-0.6737  0.1136 -1.4784  0.5249
```

Display the index, columns, and the underlying numpy data

```python
In [16]: df.index
Out[16]:
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 [17]: df.columns
Out[17]: Index([u'A', u'B', u'C', u'D'], dtype='object')
```

```python
In [18]: df.values
Out[18]:
array([[ 0.4691, -0.2829, -1.5091, -1.1356],
       [ 1.2121, -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,  0.5249]])
```

Describe shows a quick statistic summary of your data

```python
In [19]: df.describe()
Out[19]:
          A         B         C         D
count 6.000000 6.000000 6.000000 6.000000
```
mean       0.073711 -0.431125 -0.687758 -0.233103  
std        0.843157  0.922818  0.779887  0.973118  
min        -0.861849 -2.104569 -1.509059 -1.135632  
25%        -0.611510 -0.600794 -1.368714 -1.076610  
50%        0.022070 -0.228039 -0.767252 -0.386188  
75%        0.658444  0.041933 -0.034326  0.461706  
max        1.212112  0.567020  0.276232  1.071804  

Transposing your data

In [20]: df.T
Out[20]:

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.469112</td>
<td>1.212112</td>
<td>-0.861849</td>
<td>0.721555</td>
<td>-0.424972</td>
<td>-0.673690</td>
</tr>
<tr>
<td>B</td>
<td>-0.282863</td>
<td>-0.173215</td>
<td>-2.104569</td>
<td>-0.706771</td>
<td>0.567020</td>
<td>0.113648</td>
</tr>
<tr>
<td>C</td>
<td>-1.509059</td>
<td>0.119209</td>
<td>-0.494929</td>
<td>-1.039575</td>
<td>0.276232</td>
<td>-1.478427</td>
</tr>
<tr>
<td>D</td>
<td>-1.135632</td>
<td>-1.044236</td>
<td>1.071804</td>
<td>0.271860</td>
<td>-1.087401</td>
<td>0.524988</td>
</tr>
</tbody>
</table>

Sorting by an axis

In [21]: df.sort_index(axis=1, ascending=False)
Out[21]:

D  C  B  A
2013-01-01 -1.135632 -1.509059 -0.282863 0.469112
2013-01-02 -1.044236 0.119209 -0.173215 1.212112
2013-01-03 1.071804 -0.494929 -2.104569 -0.861849
2013-01-04 0.271860 -1.039575 -0.706771 0.721555
2013-01-05 -1.087401 0.276232 0.567020 -0.424972
2013-01-06 0.524988 -1.478427 0.113648 -0.673690

Sorting by values

In [22]: df.sort_values(by='B')
Out[22]:

A  B  C  D
2013-01-03 -0.861849 -2.104569 -0.494929 1.071804
2013-01-04 0.721555 -0.706771 -1.039575 0.271860
2013-01-01 0.469112 -0.282863 -1.509059 -1.135632
2013-01-02 1.212112 -0.173215 0.119209 -1.044236
2013-01-06 -0.673690 0.113648 -1.478427 0.524988
2013-01-05 -0.424972 0.567020 0.276232 -1.087401

6.3 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, .iloc and .ix.

See the indexing documentation Indexing and Selecting Data and MultiIndex / Advanced Indexing

6.3.1 Getting

Selecting a single column, which yields a Series, equivalent to df.A
In [23]: df['A']
Out[23]:
2013-01-01  0.469112
2013-01-02  1.212112
2013-01-03 -0.861849
2013-01-04  0.721555
2013-01-05 -0.424972
2013-01-06 -0.673690
Freq: D, Name: A, dtype: float64

Selecting via [], which slices the rows.

In [24]: df[0:3]
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

In [25]: df['20130102':'20130104']
Out[25]:
   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

6.3.2 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    B    C    D  
2013-01-01 0.469112 -0.282863 -1.509059 -1.135632
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 0.469112 -0.282863
2013-01-02 1.212112 -0.173215
2013-01-03-0.861849 -2.104569
2013-01-04 0.721555 -0.706771
2013-01-05 -0.424972  0.567020
2013-01-06 -0.673690  0.113648

Showing label slicing, both endpoints are included

In [28]: df.loc['20130102':'20130104',['A','B']]
Out[28]:
   A    B
2013-01-02 1.212112 -0.173215

6.3. Selection
2013-01-03 -0.861849 -2.104569  
2013-01-04 0.721555 -0.706771

Reduction in the dimensions of the returned object

In [29]: df.loc['20130102', ['A', 'B']]  
Out[29]:  
A  1.212112  
B -0.173215  
Name: 2013-01-02 00:00:00, dtype: float64

For getting a scalar value

In [30]: df.loc[dates[0], 'A']  
Out[30]: 0.46911229990718628

For getting fast access to a scalar (equiv to the prior method)

In [31]: df.at[dates[0], 'A']  
Out[31]: 0.46911229990718628

6.3.3 Selection by Position

See more in Selection by Position

Select via the position of the passed integers

In [32]: df.iloc[3]  
Out[32]:  
A 0.721555  
B -0.706771  
C -1.039575  
D 0.271860  
Name: 2013-01-04 00:00:00, dtype: float64

By integer slices, acting similar to numpy/python

In [33]: df.iloc[3:5, 0:2]  
Out[33]:  
A B  
2013-01-04 0.721555 -0.706771  
2013-01-05 -0.424972 0.567020

By lists of integer position locations, similar to the numpy/python style

In [34]: df.iloc[[1, 2, 4], [0, 2]]  
Out[34]:  
A C  
2013-01-02 1.212112 0.119209  
2013-01-03 -0.861849 -0.494929  
2013-01-05 -0.424972 0.276232

For slicing rows explicitly

In [35]: df.iloc[1:3, :]  
Out[35]:  
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
For slicing columns explicitly

```
In [36]: df.iloc[:,1:3]
Out[36]:
          B     C
2013-01-01 -0.282863 -1.509059
2013-01-02  0.119209  0.119209
2013-01-03 -2.104569  0.494929
2013-01-04 -0.706771 -1.039575
2013-01-05  0.567020  0.276232
2013-01-06  0.113648 -1.478427
```

For getting a value explicitly

```
In [37]: df.iloc[1,1]
Out[37]: -0.17321464905330858
```

For getting fast access to a scalar (equiv to the prior method)

```
In [38]: df.iat[1,1]
Out[38]: -0.17321464905330858
```

### 6.3.4 Boolean Indexing

Using a single column’s values to select data.

```
In [39]: df[df.A > 0]
Out[39]:
            A     B     C     D
2013-01-01  0.469112 -0.282863 -1.509059 -1.135632
2013-01-02  1.212112 -0.173215  0.119209 -1.044236
2013-01-03  0.721555 -0.706771 -1.039575  0.271860
```

A `where` operation for getting.

```
In [40]: df[df > 0]
Out[40]:
            A     B     C     D
2013-01-01  0.469112  NaN  NaN  NaN
2013-01-02  1.212112  NaN  0.119209  NaN
2013-01-03  0.721555  NaN  NaN  1.071804
2013-01-04  0.721555  NaN  0.271860  NaN
2013-01-05  0.567020  0.276232  NaN
2013-01-06  0.113648  0.524988  NaN
```

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  0.469112 -0.282863 -1.509059 -1.135632  one
2013-01-02  1.212112 -0.173215  0.119209 -1.044236  one
2013-01-03  0.861849 -2.104569 -0.494929  1.071804  two
2013-01-04  0.721555 -0.706771 -1.039575  0.271860  three
2013-01-05  0.424972  0.567020  0.276232 -1.087401  four
2013-01-06  0.113648  0.113648  0.524988  0.524988  NaN
```
In [44]: df2[df2['E'].isin(['two','four'])]
Out[44]:
<p>| | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
<td>E</td>
<td></td>
</tr>
<tr>
<td>---</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td></td>
</tr>
</tbody>
</table>

### 6.3.5 Setting

Setting a new column automatically aligns the data by the indexes

In [45]: s1 = pd.Series([1,2,3,4,5,6], index=pd.date_range('20130102', periods=6))
In [46]: s1
Out[46]:
<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>2013-01-02</td>
<td>1</td>
</tr>
<tr>
<td>2013-01-03</td>
<td>2</td>
</tr>
<tr>
<td>2013-01-04</td>
<td>3</td>
</tr>
<tr>
<td>2013-01-05</td>
<td>4</td>
</tr>
<tr>
<td>2013-01-06</td>
<td>5</td>
</tr>
<tr>
<td>2013-01-07</td>
<td>6</td>
</tr>
</tbody>
</table>
Freq: D, dtype: int64

In [47]: df['F'] = s1

Setting values by label

In [48]: df.at[dates[0],'A'] = 0

Setting values by position

In [49]: df.iat[0,1] = 0

Setting by assigning with a numpy array

In [50]: df.loc[:,'D'] = np.array([5] * len(df))

The result of the prior setting operations

In [51]: df
Out[51]:
<p>| | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
<td>F</td>
<td></td>
</tr>
<tr>
<td>---</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td></td>
</tr>
<tr>
<td>2013-01-01</td>
<td>0.000000</td>
<td>0.000000</td>
<td>-1.509059</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>2013-01-02</td>
<td>1.212112</td>
<td>-0.173215</td>
<td>0.119209</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>2013-01-03</td>
<td>-0.861849</td>
<td>-2.104569</td>
<td>-0.494929</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>2013-01-04</td>
<td>0.721555</td>
<td>-0.706771</td>
<td>-1.039575</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>2013-01-05</td>
<td>-0.424972</td>
<td>0.567020</td>
<td>0.276232</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>2013-01-06</td>
<td>-0.673690</td>
<td>0.113648</td>
<td>-1.478427</td>
<td>5</td>
<td></td>
</tr>
</tbody>
</table>

A where operation with setting.

In [52]: df2 = df.copy()
In [53]: df2[df2 > 0] = -df2
In [54]: df2
Out[54]:
<p>| | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
<td>F</td>
<td></td>
</tr>
<tr>
<td>---</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td></td>
</tr>
<tr>
<td>2013-01-06</td>
<td>-0.673690</td>
<td>0.113648</td>
<td>-1.478427</td>
<td>5</td>
<td></td>
</tr>
</tbody>
</table>
2013-01-01  0.000000  0.000000 -1.509059 -5 NaN
2013-01-02  -1.212112 -0.173215 -0.119209 -5 -1
2013-01-03  -0.861849 -2.104569 -0.494929 -5 -2
2013-01-04  -0.721555 -0.706771 -1.039575 -5 -3
2013-01-05  -0.424972 -0.567020 -0.276232 -5 -4
2013-01-06  -0.673690 -0.113648 -1.478427 -5 -5

6.4 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  0.00 0.00 -1.50  5.0  NaN  1.0
2013-01-02  1.21 -0.17  0.11  5.0   1  1.0
2013-01-03  0.86 -2.10 -0.49  5.0  2.0  NaN
2013-01-04  0.72 -0.71 -1.04  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   E
2013-01-02  1.21 -0.17  0.11  5.0   1  1.0

Filling missing data

In [59]: df1.fillna(value=5)
Out[59]:
          A   B   C   D   F   E
2013-01-01  0.00 0.00 -1.50  5.0   5  1.0
2013-01-02  1.21 -0.17  0.11  5.0   1  1.0
2013-01-03  0.86 -2.10 -0.49  5.0   5  5.0
2013-01-04  0.72 -0.71 -1.04  5.0   5  5.0

To get the boolean mask where values are nan

In [60]: pd.isnull(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   True
2013-01-04 False False False False   False   True

6.5 Operations

See the Basic section on Binary Ops
6.5.1 Stats

Operations in general exclude missing data.

Performing a descriptive statistic

In [61]: df.mean()
Out[61]:
A  -0.004474
B  -0.383981
C  -0.687758
D   5.000000
F   3.000000
dtype: float64

Same operation on the other axis

In [62]: df.mean(1)
Out[62]:
2013-01-01  0.872735
2013-01-02  1.431621
2013-01-03  0.707731
2013-01-04  1.395042
2013-01-05  1.883656
2013-01-06  1.592306
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
2013-01-04   3
2013-01-05   5
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 -1.861849 -3.104569 -1.494929   4   1
2013-01-04 -2.278445 -3.706771 -4.039575  2   0
2013-01-05 -5.424972 -4.432980 -4.723768  0  -1
2013-01-06  NaN  NaN  NaN  NaN  NaN

6.5.2 Apply

Applying functions to the data

In [66]: df.apply(np.cumsum)
Out[66]:
<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013-01-01</td>
<td>0.000000</td>
<td>0.000000</td>
<td>-1.509059</td>
<td>5 NaN</td>
</tr>
<tr>
<td>2013-01-02</td>
<td>1.121212</td>
<td>-0.173215</td>
<td>-1.389850</td>
<td>10 1</td>
</tr>
<tr>
<td>2013-01-03</td>
<td>0.350263</td>
<td>-2.277784</td>
<td>-1.884779</td>
<td>15 3</td>
</tr>
<tr>
<td>2013-01-04</td>
<td>1.071818</td>
<td>-2.984555</td>
<td>-2.924354</td>
<td>20 6</td>
</tr>
<tr>
<td>2013-01-05</td>
<td>0.646846</td>
<td>-2.417535</td>
<td>-2.648122</td>
<td>25 10</td>
</tr>
<tr>
<td>2013-01-06</td>
<td>-0.026844</td>
<td>-2.303886</td>
<td>-4.126549</td>
<td>30 15</td>
</tr>
</tbody>
</table>

In [67]: df.apply(lambda x: x.max() - x.min())

Out[67]:
A    2.073961
B    2.671590
C    1.785291
D    0.000000
F    4.000000
dtype: float64

6.5.3 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    4  
1    2  
2    1  
3    2  
4    6  
5    4  
6    4  
7    6  
8    4  
9    4  
dtype: int32

In [70]: s.value_counts()

Out[70]:
4    5
6    2
2    2
1    1
dtype: int64

6.5.4 String Methods

Series is equipped with a set of string processing methods in the 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 str generally uses regular expressions by default (and in some cases always uses them). See more at Vectorized String Methods.


In [72]: s.str.lower()

Out[72]:
6.5. Operations 259
6.6 Merge

6.6.1 Concat

pandas provides various facilities for easily combining together Series, DataFrame, and Panel objects with various kinds of set logic for the indexes and relational algebra functionality in the case of join / merge-type operations.

See the Merging section

Concatenating pandas objects together with `concat()`:

```python
In [73]: df = pd.DataFrame(np.random.randn(10, 4))
In [74]: df
Out[74]:
     0       1       2       3
0 -0.548702  1.467327 -1.015962 -0.483075
1  1.637550 -1.217659 -0.291519 -1.745505
2 -0.263952  0.991460 -0.919069  0.266046
3 -0.709661  1.669052  1.037882 -1.705775
4 -0.919854 -0.042379  1.247642 -0.009920
5  0.290213  0.495767  0.362949  1.548106
6 -1.131345 -0.089329  0.337863 -0.945867
7 -0.932132  1.956030  0.017587 -0.016692
8 -0.575247  0.254161 -1.143704  0.215897
9  1.193555 -0.077118 -0.408530 -0.862495

# 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 -0.548702  1.467327 -1.015962 -0.483075
1  1.637550 -1.217659 -0.291519 -1.745505
2 -0.263952  0.991460 -0.919069  0.266046
3 -0.709661  1.669052  1.037882 -1.705775
4 -0.919854 -0.042379  1.247642 -0.009920
5  0.290213  0.495767  0.362949  1.548106
6 -1.131345 -0.089329  0.337863 -0.945867
7 -0.932132  1.956030  0.017587 -0.016692
8 -0.575247  0.254161 -1.143704  0.215897
9  1.193555 -0.077118 -0.408530 -0.862495
```
6.6.2 Join

SQL style merges. See the Database style joining

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

6.6.3 Append

Append rows to a dataframe. See the Appendix

In [82]: df = pd.DataFrame(np.random.randn(8, 4), columns=['A','B','C','D'])

In [83]: df
Out[83]:
   A            B            C            D
0  1.346061  1.511763  1.627081 -0.990582
1 -0.441652  1.211526  0.268520  0.024580
2 -1.577585  0.396823 -0.105381 -0.532532
3  1.453749  1.208843 -0.080952 -0.264610
4 -0.727965 -0.589346  0.339969 -0.693205
5 -0.339355  0.593616  0.884345  1.591431
6  0.141809  0.220390  0.435589  0.192451
7 -0.096701  0.803351  1.715071 -0.708758

In [84]: s = df.iloc[3]

In [85]: df.append(s, ignore_index=True)
Out[85]:
   A            B            C            D
0  1.346061  1.511763  1.627081 -0.990582
1 -0.441652  1.211526  0.268520  0.024580
2 -1.577585  0.396823 -0.105381 -0.532532
3  1.453749  1.208843 -0.080952 -0.264610
4 -0.727965 -0.589346  0.339969 -0.693205
5 -0.339355  0.593616  0.884345  1.591431
6  0.141809  0.220390  0.435589  0.192451
7 -0.096701  0.803351  1.715071 -0.708758
8  0.141809  0.220390  0.435589  0.192451
9 -0.096701  0.803351  1.715071 -0.708758

6.6. Merge

261
6.7 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*

```python
In [86]: 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 [87]: df
Out[87]:
   A    B    C             D
  0  foo  one  -1.202872  -0.055224
  1  bar  one   1.814470   2.395985
  2  foo  two   1.018601   1.552825
  3  bar  three  -0.595447   0.166599
  4  foo  two   1.395433   -0.047609
  5  bar  two   -0.392670  -0.136473
  6  foo  one    0.007207  -0.561757
  7  foo  three   1.928123  -1.623033

Grouping and then applying a function `sum` to the resulting groups.

```python
In [88]: df.groupby('A').sum()
Out[88]:
     C             D
   A
  bar -2.802588  2.42611
  foo  3.146492 -0.63958

Grouping by multiple columns forms a hierarchical index, which we then apply the function.

```python
In [89]: df.groupby(['A', 'B']).sum()
Out[89]:
   A    B    C             D
   A
  bar  one -1.814470  2.395985
  three -0.595447  0.166599
  two  -0.392670 -0.136473
  foo  one -1.195665 -0.616981
  three  1.928123 -1.623033
  two   2.414034  1.600434
```
6.8 Reshaping

See the sections on Hierarchical Indexing and Reshaping.

6.8.1 Stack

In [90]: tuples = list(zip(*[['bar', 'bar', 'baz', 'baz',
                           'foo', 'foo', 'qux', 'qux'],
                           ['one', 'two', 'one', 'two',
                            'one', 'two', 'one', 'two']]))

In [91]: index = pd.MultiIndex.from_tuples(tuples, names=['first', 'second'])

In [92]: df = pd.DataFrame(np.random.randn(8, 2), index=index, columns=['A', 'B'])

In [93]: df2 = df[:4]

In [94]: df2
Out[94]:
   A    B
first second
bar  one  0.029399 -0.542108
     two  0.282696 -0.087302
baz  one -1.575170  1.771208
     two  0.816482  1.100230

The stack() method “compresses” a level in the DataFrame’s columns.

In [95]: stacked = df2.stack()

In [96]: stacked
Out[96]:
   first second  A    B
bar  one      A  0.029399 -0.542108
     B        -0.087302
   two      A  0.282696 -0.087302
baz  one     B  1.771208
   two      A  0.816482
     B        1.100230
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 [97]: stacked.unstack()
Out[97]:
   first second  A    B
bar  one      A  0.029399 -0.542108
     B        -0.087302
   two      A  0.282696 -0.087302
baz  one     B  1.771208
   two      A  0.816482
     B        1.100230

In [98]: stacked.unstack(1)
Out[98]:
second   one   two
first
bar A  0.029399 0.282696
     B -0.542108 -0.087302
baz A -1.575170 0.816482
     B  1.771208 1.100230

In [99]: stacked.unstack(0)
Out[99]:
first  bar    baz
second
one A  0.029399 -1.575170
     B -0.542108  1.771208
    
two A  0.282696  0.816482
     B -0.087302  1.100230

6.8.2 Pivot Tables

See the section on *Pivot Tables*.

In [100]: 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 [101]: df
Out[101]:
   A     B     C     D     E
0  one  A   foo  1.418757 -0.179666
1  one  B  foo  -1.879024  1.291836
2  two  C   foo   0.536826 -0.009614
3  three A   bar   1.006160  0.392149
4    one B  bar  -0.029716  0.264599
5    one C  bar  -1.146178  0.314665
6    two A  foo   0.100900 -1.425638
7    three B  foo  -1.035018  1.024098
8    one C  foo   0.314665 -0.106062
9    one A  bar  -0.773723  1.824375
10   two B  bar  -1.170653  0.595974
11   three C  bar   0.648740  1.167115

We can produce pivot tables from this data very easily:

In [102]: pd.pivot_table(df, values='D', index=['A', 'B'], columns=['C'])
Out[102]:
   C    bar    foo
A  B
one  A  -0.773723  1.418757
     B  -0.029716 -1.879024
     C  -1.146178  0.314665
three A   1.006160  NaN
         B   NaN  -1.035018
         C   0.648740  NaN
two  A   NaN  0.100900
6.9 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 [103]: rng = pd.date_range('1/1/2012', periods=100, freq='S')

In [104]: ts = pd.Series(np.random.randint(0, 500, len(rng)), index=rng)

In [105]: ts.resample('5Min', how='sum')

Out[105]:
2012-01-01 25083
Freq: 5T, dtype: int32

Time zone representation

In [106]: rng = pd.date_range('3/6/2012 00:00', periods=5, freq='D')

In [107]: ts = pd.Series(np.random.randn(len(rng)), rng)

In [108]: ts

Out[108]:
2012-03-06 0.464000
2012-03-07 0.227371
2012-03-08 -0.496922
2012-03-09 0.306389
2012-03-10 -2.290613
Freq: D, dtype: float64

In [109]: ts_utc = ts.tz_localize('UTC')

In [110]: ts_utc

Out[110]:
2012-03-05 19:00:00+00:00 0.464000
2012-03-06 19:00:00+00:00 0.227371
2012-03-07 19:00:00+00:00 -0.496922
2012-03-08 19:00:00+00:00 0.306389
2012-03-09 19:00:00+00:00 -2.290613
Freq: D, dtype: float64

Convert to another time zone

In [111]: ts_utc.tz_convert('US/Eastern')

Out[111]:
2012-03-05 19:00:00-05:00 0.464000
2012-03-06 19:00:00-05:00 0.227371
2012-03-07 19:00:00-05:00 -0.496922
2012-03-08 19:00:00-05:00 0.306389
2012-03-09 19:00:00-05:00 -2.290613
Freq: D, dtype: float64

Converting between time span representations
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 [118]: prng = pd.period_range('1990Q1', '2000Q4', freq='Q-NOV')
In [119]: ts = pd.Series(np.random.randn(len(prng)), prng)
In [120]: ts.index = (prng.asfreq('M', 'e') + 1).asfreq('H', 's') + 9
In [121]: ts.head()
```

```
Out[121]:
1990-03-01 09:00 -0.902937
1990-06-01 09:00  0.068159
1990-09-01 09:00 -0.057873
1990-12-01 09:00 -0.368204
1991-03-01 09:00 -1.144073
Freq: H, dtype: float64
```

### 6.10 Categoricals

Since version 0.15, pandas can include categorical data in a DataFrame. For full docs, see the categorical introduction and the API documentation.
In [122]: df = pd.DataFrame({"id": [1, 2, 3, 4, 5, 6], "raw_grade": ['a', 'b', 'b', 'a', 'a', 'e']})

Convert the raw grades to a categorical data type.

In [123]: df["grade"] = df["raw_grade"].astype("category")

In [124]: df["grade"]
Out[124]:
0  a
1  b
2  b
3  a
4  a
5  e
Name: grade, dtype: category
Categories (3, object): [a, b, e]

Rename the categories to more meaningful names (assigning to Series.cat.categories is inplace!)

In [125]: df["grade"].cat.categories = ["very good", "good", "very bad"]

Reorder the categories and simultaneously add the missing categories (methods under Series.cat return a new Series per default).

In [126]: df["grade"] = df["grade"].cat.set_categories(["very bad", "bad", "medium", "good", "very good"])

In [127]: df["grade"]
Out[127]:
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 [128]: df.sort_values(by="grade")
Out[128]:
 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 shows also empty categories.

In [129]: df.groupby("grade").size()
Out[129]:
grade
very bad 1
bad 0
medium 0
good 2
very good 3
dtype: int64
6.11 Plotting

Plotting docs.

In [130]: ts = pd.Series(np.random.randn(1000), index=pd.date_range('1/1/2000', periods=1000))

In [131]: ts = ts.cumsum()

In [132]: ts.plot()
Out[132]: <matplotlib.axes._subplots.AxesSubplot at 0xaf4fd46c>

On DataFrame, plot() is a convenience to plot all of the columns with labels:

In [133]: df = pd.DataFrame(np.random.randn(1000, 4), index=ts.index, columns=['A', 'B', 'C', 'D'])

In [134]: df = df.cumsum()

In [135]: plt.figure(); df.plot(); plt.legend(loc='best')
Out[135]: <matplotlib.legend.Legend at 0xaf4256ac>
6.12 Getting Data In/Out

6.12.1 CSV

Writing to a csv file

In [136]: df.to_csv('foo.csv')

Reading from a csv file

In [137]: pd.read_csv('foo.csv')

Out [137]:

<table>
<thead>
<tr>
<th></th>
<th>Unnamed: 0</th>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>2000-01-01</td>
<td></td>
<td>0.266457</td>
<td>-0.399641</td>
<td>-0.219582</td>
<td>1.186860</td>
</tr>
<tr>
<td>1</td>
<td>2000-01-02</td>
<td></td>
<td>-1.170732</td>
<td>-0.345873</td>
<td>1.653061</td>
<td>-0.282953</td>
</tr>
<tr>
<td>2</td>
<td>2000-01-03</td>
<td></td>
<td>-1.734933</td>
<td>0.530468</td>
<td>2.060811</td>
<td>-0.515536</td>
</tr>
<tr>
<td>3</td>
<td>2000-01-04</td>
<td></td>
<td>-1.555121</td>
<td>1.452620</td>
<td>0.239859</td>
<td>-1.156896</td>
</tr>
<tr>
<td>4</td>
<td>2000-01-05</td>
<td></td>
<td>0.578117</td>
<td>0.511371</td>
<td>0.103552</td>
<td>-2.428202</td>
</tr>
<tr>
<td>5</td>
<td>2000-01-06</td>
<td></td>
<td>0.478344</td>
<td>0.449933</td>
<td>-0.741620</td>
<td>-1.962409</td>
</tr>
<tr>
<td>6</td>
<td>2000-01-07</td>
<td></td>
<td>1.235339</td>
<td>-0.091757</td>
<td>-1.543861</td>
<td>-1.084753</td>
</tr>
<tr>
<td>...</td>
<td></td>
<td></td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>
6.12.2 HDF5

Reading and writing to *HDFStores*

Writing to a HDF5 Store

```
In [138]: df.to_hdf('foo.h5','df')
```

Reading from a HDF5 Store

```
In [139]: pd.read_hdf('foo.h5','df')
```

<table>
<thead>
<tr>
<th>Date</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01</td>
<td>0.266457</td>
<td>-0.399641</td>
<td>-0.219582</td>
<td>1.186860</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>-1.170732</td>
<td>-0.345873</td>
<td>1.653061</td>
<td>-0.282953</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>-1.734933</td>
<td>0.530468</td>
<td>2.060811</td>
<td>-0.515536</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>-1.555121</td>
<td>1.452620</td>
<td>0.239859</td>
<td>-1.156896</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>0.578117</td>
<td>0.511371</td>
<td>0.103552</td>
<td>-2.428202</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>0.478344</td>
<td>0.449933</td>
<td>-0.741620</td>
<td>-1.962409</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>1.235339</td>
<td>-0.091757</td>
<td>-1.543861</td>
<td>-1.084753</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>2000-09-21</td>
<td>-10.390377</td>
<td>-8.727491</td>
<td>-6.399645</td>
<td>30.914107</td>
</tr>
<tr>
<td>2000-09-26</td>
<td>-11.856774</td>
<td>-10.671012</td>
<td>-3.216025</td>
<td>29.369368</td>
</tr>
</tbody>
</table>

[1000 rows x 4 columns]

6.12.3 Excel

Reading and writing to *MS Excel*

Writing to an excel file

```
In [140]: df.to_excel('foo.xlsx', sheet_name='Sheet1')
```

Reading from an excel file

```
In [141]: pd.read_excel('foo.xlsx', 'Sheet1', index_col=None, na_values=['NA'])
```

<table>
<thead>
<tr>
<th>Date</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01</td>
<td>0.266457</td>
<td>-0.399641</td>
<td>-0.219582</td>
<td>1.186860</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>-1.170732</td>
<td>-0.345873</td>
<td>1.653061</td>
<td>-0.282953</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>-1.734933</td>
<td>0.530468</td>
<td>2.060811</td>
<td>-0.515536</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>-1.555121</td>
<td>1.452620</td>
<td>0.239859</td>
<td>-1.156896</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>0.578117</td>
<td>0.511371</td>
<td>0.103552</td>
<td>-2.428202</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>0.478344</td>
<td>0.449933</td>
<td>-0.741620</td>
<td>-1.962409</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>1.235339</td>
<td>-0.091757</td>
<td>-1.543861</td>
<td>-1.084753</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>2000-09-21</td>
<td>-10.390377</td>
<td>-8.727491</td>
<td>-6.399645</td>
<td>30.914107</td>
</tr>
<tr>
<td>2000-09-26</td>
<td>-11.856774</td>
<td>-10.671012</td>
<td>-3.216025</td>
<td>29.369368</td>
</tr>
</tbody>
</table>

[1000 rows x 4 columns]
6.13 Gotchas

If you are trying an operation and you 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.
This is a guide to many pandas tutorials, geared mainly for new users.

### 7.1 Internal Guides

pandas own *10 Minutes to pandas*

More complex recipes are in the *Cookbook*

### 7.2 pandas Cookbook

The goal of this 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 that entails.

Here are links to the v0.1 release. For an up-to-date table of contents, see the pandas-cookbook GitHub repository. To run the examples in this tutorial, you’ll need to clone the GitHub repository and get IPython Notebook running. See How to use this cookbook.

- **A quick tour of the IPython Notebook**: Shows off IPython’s awesome tab completion and magic functions.
- **Chapter 1**: Reading your data into pandas is pretty much the easiest thing. Even when the encoding is wrong!
- **Chapter 2**: It’s not totally obvious how to select data from a pandas dataframe. Here we explain the basics (how to take slices and get columns)
- **Chapter 3**: Here we get into serious slicing and dicing and learn how to filter dataframes in complicated ways, really fast.
- **Chapter 4**: Groupby/aggregate is seriously my favorite thing about pandas and I use it all the time. You should probably read this.
- **Chapter 5**: Here you get to find out if it’s cold in Montreal in the winter (spoiler: yes). Web scraping with pandas is fun! Here we combine dataframes.
- **Chapter 6**: Strings with pandas are great. It has all these vectorized string operations and they’re the best. We will turn a bunch of strings containing “Snow” into vectors of numbers in a trice.
- **Chapter 7**: Cleaning up messy data is never a joy, but with pandas it’s easier.
- **Chapter 8**: Parsing Unix timestamps is confusing at first but it turns out to be really easy.
7.3 Lessons for New pandas Users

For more resources, please visit the main repository.

- **01 - Lesson:** Importing libraries - Creating data sets - Creating data frames - Reading from CSV - Exporting to CSV - Finding maximums - Plotting data
- **02 - Lesson:** Reading from TXT - Exporting to TXT - Selecting top/bottom records - Descriptive statistics - Grouping/sorting data
- **03 - Lesson:** Creating functions - Reading from EXCEL - Exporting to EXCEL - Outliers - Lambda functions - Slice and dice data
- **04 - Lesson:** Adding/deleting columns - Index operations
- **05 - Lesson:** Stack/Unstack/Transpose functions
- **06 - Lesson:** GroupBy function
- **07 - Lesson:** Ways to calculate outliers
- **08 - Lesson:** Read from Microsoft SQL databases
- **09 - Lesson:** Export to CSV/EXCEL/TXT
- **10 - Lesson:** Converting between different kinds of formats
- **11 - Lesson:** Combining data from various sources

7.4 Practical data analysis with Python

This guide is a comprehensive introduction to the data analysis process using the Python data ecosystem and an interesting open dataset. There are four sections covering selected topics as follows:

- Munging Data
- Aggregating Data
- Visualizing Data
- Time Series

7.5 Excel charts with pandas, vincent and xlsxwriter

- Using Pandas and XlsxWriter to create Excel charts

7.6 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 Tutorial, by Mikhail Semeniuk
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 3.4. Minor tweaks might be necessary for earlier python versions.

### 8.1 Idioms

These are some neat pandas idioms

if-then/if-then-else on one column, and assignment to another one or more columns:

```
In [1]: df = pd.DataFrame(
            ...:     {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40], 'CCC' : [100,50,-30,-50]}); df
            ...
Out[1]:
     AAA  BBB  CCC
0      4    10  100
1      5    20   50
2      6    30   -30
3      7    40   -50
```

#### 8.1.1 if-then...

An if-then on one column

```
In [2]: df.ix[df.AAA >= 5,'BBB'] = -1; df
Out[2]:
     AAA  BBB  CCC
0      4    10   100
1      5   -1    50
2      6   -1   -30
3      7   -1   -50
```

An if-then with assignment to 2 columns:
In [3]: df.ix[df.AAA >= 5,['BBB','CCC']] = 555; df
Out[3]:
   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

In [4]: df.ix[df.AAA < 5,['BBB','CCC']] = 2000; df
Out[4]:
   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


In [6]: df.where(df_mask,-1000)
Out[6]:
   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()

In [7]: df = pd.DataFrame({
   ...:     'AAA': [4,5,6,7], 'BBB': [10,20,30,40],'CCC': [100,50,-30,-50]}); df
   ...:}

Out[7]:
   AAA  BBB  CCC
0   4   10  100
1   5   20   50
2   6   30  -30
3   7   40  -50

In [8]: df['logic'] = np.where(df['AAA'] > 5,'high','low'); df
Out[8]:
   AAA  BBB  CCC  logic
0   4   10  100  low
1   5   20   50  low
2   6   30  -30  high
3   7   40  -50  high

8.1.2 Splitting

Split a frame with a boolean criterion

In [9]: df = pd.DataFrame({
   ...:     'AAA': [4,5,6,7], 'BBB': [10,20,30,40],'CCC': [100,50,-30,-50]}); df
   ...:}

Out[9]:
In [10]: dflow = df[df.AAA <= 5]

In [11]: dfhigh = df[df.AAA > 5]

In [12]: dflow, dfhigh

Out[12]:

<table>
<thead>
<tr>
<th>AAA</th>
<th>BBB</th>
<th>CCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>6</td>
<td>30</td>
</tr>
<tr>
<td>3</td>
<td>7</td>
<td>40</td>
</tr>
<tr>
<td>10</td>
<td>20</td>
<td>50</td>
</tr>
</tbody>
</table>

8.1.3 Building Criteria

Select with multi-column criteria

In [13]: df = pd.DataFrame({
    'AAA' : [4,5,6,7],
    'BBB' : [10,20,30,40],
    'CCC' : [100,50,-30,-50]
}); df

Out[13]:

<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>

...and (without assignment returns a Series)

In [14]: newseries = df.loc[(df['BBB'] < 25) & (df['CCC'] >= -40), 'AAA']; newseries

Out[14]:

<table>
<thead>
<tr>
<th>AAA</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
</tr>
<tr>
<td>1</td>
</tr>
</tbody>
</table>

Name: AAA, dtype: int64

...or (without assignment returns a Series)

In [15]: newseries = df.loc[(df['BBB'] > 25) | (df['CCC'] >= 75), 'AAA']; newseries

...or (with assignment modifies the DataFrame.)

In [16]: df.loc[(df['BBB'] > 25) & (df['CCC'] >= 75), 'AAA'] = 0.1; df

Out[16]:

<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 [17]: df = pd.DataFrame({
    'AAA' : [4,5,6,7],
    'BBB' : [10,20,30,40],
    'CCC' : [100,50,-30,-50]
}); df

Out[17]:

<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 [18]: aValue = 43.0

In [19]: df.ix[(df.CCC-aValue).abs().argsort()]
Out[19]:
AAA   BBB  CCC
0   4   10  100
1   5   20   50
2   6   30  -30
3   7   40  -50

Dynamically reduce a list of criteria using a binary operators

In [20]: df = pd.DataFrame(
        ....:   {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40], 'CCC' : [100,50,-30,-50]}); df
   ....:
Out[20]:
AAA   BBB  CCC
0   4   10  100
1   5   20   50
2   6   30  -30
3   7   40  -50

In [21]: Crit1 = df.AAA <= 5.5

In [22]: Crit2 = df.BBB == 10.0

In [23]: Crit3 = df.CCC > -40.0

One could hard code:

In [24]: AllCrit = Crit1 & Crit2 & Crit3

...Or it can be done with a list of dynamically built criteria

In [25]: CritList = [Crit1,Crit2,Crit3]

In [26]: AllCrit = functools.reduce(lambda x,y: x & y, CritList)

In [27]: df[AllCrit]
Out[27]:
AAA   BBB  CCC
0   4   10  100

8.2 Selection

8.2.1 DataFrames

The indexing docs.

Using both row labels and value conditionals
```python
In [28]: df = pd.DataFrame( .....:
            {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40],'CCC' : [100,50,-30,-50]}); df
        
Out[28]:
       AAA  BBB  CCC
      0   4    10   100
      1   5    20    50
      2   6    30   -30
      3   7    40   -50

In [29]: df[(df.AAA <= 6) & (df.index.isin([0,2,4]))]
        
Out[29]:
            AAA  BBB  CCC
           0    4    10   100
           2    6    30   -30

Use loc for label-oriented slicing and iloc positional slicing

In [30]: data = {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40],'CCC' : [100,50,-30,-50]}

In [31]: df = pd.DataFrame(data=data,index=['foo','bar','boo','kar']); df
        
Out[31]:
          AAA  BBB  CCC
        foo    4    10   100
        bar    5    20    50
        boo    6    30   -30
        kar    7    40   -50

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 [32]: df.loc['bar':'kar'] #Label
Out[32]:
           AAA  BBB  CCC
         bar    5    20    50
         boo    6    30   -30
         kar    7    40   -50

#Generic
In [33]: df.ix[0:3] #Same as .iloc[0:3]
Out[33]:
            AAA  BBB  CCC
           foo    4    10   100
           bar    5    20    50
           boo    6    30   -30

In [34]: df.ix['bar':'kar'] #Same as .loc['bar':'kar']
Out[34]:
           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.

8.2. Selection
In [35]: df2 = pd.DataFrame(data=data,index=[1,2,3,4]); #Note index starts at 1.

In [36]: df2.iloc[1:3] #Position-oriented
Out[36]:
   AAA  BBB  CCC
2  5   20   50
3  6   30  -30

In [37]: df2.loc[1:3] #Label-oriented
Out[37]:
   AAA  BBB  CCC
1  4    10  100
2  5    20   50
3  6    30  -30

In [38]: df2.ix[1:3] #General, will mimic loc (label-oriented)
Out[38]:
   AAA  BBB  CCC
1  4    10  100
2  5    20   50
3  6    30  -30

In [39]: df2.ix[0:3] #General, will mimic iloc (position-oriented), as loc[0:3] would raise a KeyError
Out[39]:
   AAA  BBB  CCC
1  4    10  100
2  5    20   50
3  6    30  -30

Using inverse operator (~) to take the complement of a mask

In [40]: df = pd.DataFrame(
   ....:   {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40], 'CCC' : [100,50,-30,-50]})
Out[40]:
   AAA  BBB  CCC
0  4    10  100
1  5    20   50
2  6   30  -30
3  7    40  -50

In [41]: df[~((df.AAA <= 6) & (df.index.isin([0,2,4])))]
Out[41]:
   AAA  BBB  CCC
1  5  20   50
3  7   40 -50

8.2.2 Panels

Extend a panel frame by transposing, adding a new dimension, and transposing back to the original dimensions

In [42]: rng = pd.date_range('1/1/2013',periods=100,freq='D')

In [43]: data = np.random.randn(100, 4)

In [44]: cols = ['A','B','C','D']
In [45]: df1, df2, df3 = pd.DataFrame(data, rng, cols), pd.DataFrame(data, rng, cols), pd.DataFrame(data, rng, cols)

In [46]: pf = pd.Panel({'df1':df1,'df2':df2,'df3':df3});pf
Out[46]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 100 (major_axis) x 4 (minor_axis)
Items axis: df1 to df3
Major_axis axis: 2013-01-01 00:00:00 to 2013-04-10 00:00:00
Minor_axis axis: A to D

#Assignment using Transpose  (pandas < 0.15)
In [47]: pf = pf.transpose(2,0,1)

In [48]: pf['E'] = pd.DataFrame(data, rng, cols)
In [49]: pf = pf.transpose(1,2,0);pf
Out[49]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 100 (major_axis) x 5 (minor_axis)
Items axis: df1 to df3
Major_axis axis: 2013-01-01 00:00:00 to 2013-04-10 00:00:00
Minor_axis axis: A to E

#Direct assignment  (pandas > 0.15)
In [50]: pf.loc[:,:,'F'] = pd.DataFrame(data, rng, cols);pf
Out[50]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 100 (major_axis) x 6 (minor_axis)
Items axis: df1 to df3
Major_axis axis: 2013-01-01 00:00:00 to 2013-04-10 00:00:00
Minor_axis axis: A to F

Mask a panel by using np.where and then reconstructing the panel with the new masked values

8.2.3 New Columns

Efficiently and dynamically creating new columns using applymap

In [51]: df = pd.DataFrame(
   ....:     {'AAA' : [1,2,1,3], 'BBB' : [1,1,2,2], 'CCC' : [2,1,3,1]}); df
   ....:
Out[51]:
   AAA  BBB  CCC
0   1    1    2
1   2    1    1
2   1    2    3
3   3    2    1

In [52]: source_cols = df.columns # or some subset would work too.
In [53]: new_cols = [str(x) + "_cat" for x in source_cols]
In [54]: categories = {1 : 'Alpha', 2 : 'Beta', 3 : 'Charlie'}
In [55]: df[new_cols] = df[source_cols].applymap(categories.get);df
Out[55]:
   AAA  BBB  CCC  AAA_cat  BBB_cat  CCC_cat
0   1    1    2      1       1      2
1   2    1    1      2       1      1
2   1    2    3      1       3      1
3   3    2    1      2       2      1
Keep other columns when using min() with groupby

**In [56]:** df = pd.DataFrame(
    ....:     {'AAA': [1,1,1,2,2,2,3,3], 'BBB': [2,1,3,4,5,1,2,3]});

**Out [56]:**

<table>
<thead>
<tr>
<th>AAA</th>
<th>BBB</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>6</td>
<td>3</td>
</tr>
<tr>
<td>7</td>
<td>3</td>
</tr>
</tbody>
</table>

Method 1: idxmin() to get the index of the mins

**In [57]:** df.loc[df.groupby("AAA")["BBB"].idxmin()]

**Out [57]:**

<table>
<thead>
<tr>
<th>AAA</th>
<th>BBB</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td>6</td>
<td>2</td>
</tr>
</tbody>
</table>

Method 2: sort then take first of each

**In [58]:** df.sort_values(by="BBB").groupby("AAA", as_index=False).first()

**Out [58]:**

<table>
<thead>
<tr>
<th>AAA</th>
<th>BBB</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
</tr>
</tbody>
</table>

Notice the same results, with the exception of the index.

### 8.3 MultIndexing

The `multindexing` docs.

Creating a multi-index from a labeled frame

**In [59]:** 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]});

**Out [59]:**

<table>
<thead>
<tr>
<th>One_X</th>
<th>One_Y</th>
<th>Two_X</th>
<th>Two_Y</th>
<th>row</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>1.2</td>
<td>1.11</td>
<td>1.22</td>
<td>0</td>
</tr>
<tr>
<td>1.1</td>
<td>1.2</td>
<td>1.11</td>
<td>1.22</td>
<td>1</td>
</tr>
<tr>
<td>1.1</td>
<td>1.2</td>
<td>1.11</td>
<td>1.22</td>
<td>2</td>
</tr>
</tbody>
</table>
# As Labelled Index

In [60]: df = df.set_index('row'); df
Out[60]:
<table>
<thead>
<tr>
<th>One_X</th>
<th>One_Y</th>
<th>Two_X</th>
<th>Two_Y</th>
</tr>
</thead>
<tbody>
<tr>
<td>row</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>1.1</td>
<td>1.2</td>
<td>1.11</td>
</tr>
<tr>
<td>1</td>
<td>1.1</td>
<td>1.2</td>
<td>1.11</td>
</tr>
<tr>
<td>2</td>
<td>1.1</td>
<td>1.2</td>
<td>1.11</td>
</tr>
</tbody>
</table>

# With Hierarchical Columns

In [61]: df.columns = pd.MultiIndex.from_tuples([tuple(c.split('_')) for c in df.columns]); df
Out[61]:
<table>
<thead>
<tr>
<th>One</th>
<th>Two</th>
</tr>
</thead>
<tbody>
<tr>
<td>X</td>
<td>Y</td>
</tr>
<tr>
<td>row</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>1.1</td>
</tr>
<tr>
<td>1</td>
<td>1.1</td>
</tr>
<tr>
<td>2</td>
<td>1.1</td>
</tr>
</tbody>
</table>

# Now stack & Reset

In [62]: df = df.stack(0).reset_index(1); df
Out[62]:
<table>
<thead>
<tr>
<th>level_1</th>
<th>X</th>
<th>Y</th>
</tr>
</thead>
<tbody>
<tr>
<td>row</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 One</td>
<td>1.10</td>
<td>1.20</td>
</tr>
<tr>
<td>0 Two</td>
<td>1.11</td>
<td>1.22</td>
</tr>
<tr>
<td>1 One</td>
<td>1.10</td>
<td>1.20</td>
</tr>
<tr>
<td>1 Two</td>
<td>1.11</td>
<td>1.22</td>
</tr>
<tr>
<td>2 One</td>
<td>1.10</td>
<td>1.20</td>
</tr>
<tr>
<td>2 Two</td>
<td>1.11</td>
<td>1.22</td>
</tr>
</tbody>
</table>

# And fix the labels (Notice the label 'level_1' got added automatically)

In [63]: df.columns = ['Sample','All_X','All_Y']; df
Out[63]:
<table>
<thead>
<tr>
<th>Sample</th>
<th>All_X</th>
<th>All_Y</th>
</tr>
</thead>
<tbody>
<tr>
<td>row</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 One</td>
<td>1.10</td>
<td>1.20</td>
</tr>
<tr>
<td>0 Two</td>
<td>1.11</td>
<td>1.22</td>
</tr>
<tr>
<td>1 One</td>
<td>1.10</td>
<td>1.20</td>
</tr>
<tr>
<td>1 Two</td>
<td>1.11</td>
<td>1.22</td>
</tr>
<tr>
<td>2 One</td>
<td>1.10</td>
<td>1.20</td>
</tr>
<tr>
<td>2 Two</td>
<td>1.11</td>
<td>1.22</td>
</tr>
</tbody>
</table>

### 8.3.1 Arithmetic

Performing arithmetic with a multi-index that needs broadcasting

In [64]: cols = pd.MultiIndex.from_tuples([(x,y) for x in ['A','B','C'] for y in ['O','I']])

In [65]: df = pd.DataFrame(np.random.randn(2,6),index=['n','m'],columns=cols); df
Out[65]:
<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>O</td>
<td>I</td>
<td>O</td>
</tr>
<tr>
<td>n</td>
<td>1.920906</td>
<td>-0.388231</td>
</tr>
<tr>
<td>m</td>
<td>-1.765956</td>
<td>0.850423</td>
</tr>
</tbody>
</table>
In [66]: df = df.div(df['C'], level=1); df
Out[66]:
     A    B    C
 0  4.77  1.0  5.75
 1 -2.37 -1.1  0.52

8.3.2 Slicing

Slicing a multi-index with `xs`

In [67]: coords = [('AA','one'), ('AA','six'), ('BB','one'), ('BB','two'), ('BB','six')]
In [68]: index = pd.MultiIndex.from_tuples(coords)
In [69]: df = pd.DataFrame([11,22,33,44,55], index, ['MyData']); df
Out[69]:
    MyData
AA one    11
  six    22
BB one    33
two   44
  six   55

To take the cross section of the 1st level and 1st axis the index:

In [70]: df.xs('BB', level=0, axis=0) #Note: level and axis are optional, and default to zero
Out[70]:
     MyData
one    33
two    44
six    55

...and now the 2nd level of the 1st axis.

In [71]: df.xs('six', level=1, axis=0)
Out[71]:
    MyData
AA  22
BB  55

Slicing a multi-index with `xs`, method #2

In [72]: index = list(itertools.product(['Ada', 'Quinn', 'Violet'],['Comp', 'Math', 'Sci']))
In [73]: headr = list(itertools.product(['Exams', 'Labs'], ['I', 'II']))
In [74]: indx = pd.MultiIndex.from_tuples(index, names=['Student', 'Course'])
In [75]: cols = pd.MultiIndex.from_tuples(headr) #Notice these are un-named
In [76]: data = [(70+x+y+(x*y)%3 for x in range(4)) for y in range(9)]
In [77]: df = pd.DataFrame(data, indx, cols); df
Out[77]:
Exams Labs
  I  II  I  II
Student Course
In [78]: All = slice(None)

In [79]: df.loc['Violet']
Out[79]:
<table>
<thead>
<tr>
<th>Exams</th>
<th>Labs</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>II</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Course</th>
</tr>
</thead>
<tbody>
<tr>
<td>Comp</td>
</tr>
<tr>
<td>Math</td>
</tr>
<tr>
<td>Sci</td>
</tr>
</tbody>
</table>

In [80]: df.loc[(All, 'Math'), All]
Out[80]:
<table>
<thead>
<tr>
<th>Exams</th>
<th>Labs</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>II</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Student</th>
<th>Course</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ada</td>
<td>Math</td>
</tr>
<tr>
<td>Quinn</td>
<td>Math</td>
</tr>
<tr>
<td>Violet</td>
<td>Math</td>
</tr>
</tbody>
</table>

In [81]: df.loc[(slice('Ada', 'Quinn'), 'Math'), All]
Out[81]:
<table>
<thead>
<tr>
<th>Exams</th>
<th>Labs</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>II</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Student</th>
<th>Course</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ada</td>
<td>Math</td>
</tr>
<tr>
<td>Quinn</td>
<td>Math</td>
</tr>
</tbody>
</table>

In [82]: df.loc[(All, 'Math'), ('Exams')]
Out[82]:
| I     | II   |

<table>
<thead>
<tr>
<th>Student</th>
<th>Course</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ada</td>
<td>Math</td>
</tr>
<tr>
<td>Quinn</td>
<td>Math</td>
</tr>
<tr>
<td>Violet</td>
<td>Math</td>
</tr>
</tbody>
</table>

In [83]: df.loc[(All, 'Math'), (All, 'II')]
Out[83]:
<table>
<thead>
<tr>
<th>Exams</th>
<th>Labs</th>
</tr>
</thead>
<tbody>
<tr>
<td>II</td>
<td>II</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Student</th>
<th>Course</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ada</td>
<td>Math</td>
</tr>
<tr>
<td>Quinn</td>
<td>Math</td>
</tr>
<tr>
<td>Violet</td>
<td>Math</td>
</tr>
</tbody>
</table>

Setting portions of a multi-index with xs

8.3. Multindexing
8.3.3 Sorting

Sort by specific column or an ordered list of columns, with a multi-index

In [84]: df.sort_values(by=('Labs', 'II'), ascending=False)
Out[84]:

<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>90</td>
</tr>
<tr>
<td></td>
<td>Comp</td>
<td>67</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>74</td>
</tr>
<tr>
<td></td>
<td>Comp</td>
<td>70</td>
<td>73</td>
</tr>
</tbody>
</table>

Partial Selection, the need for sortedness;

8.3.4 Levels

Prepending a level to a multiindex

Flatten Hierarchical columns

8.3.5 panelnd

The *panelnd* docs.

Construct a 5D panelnd

8.4 Missing Data

The *missing data* docs.

Fill forward a reversed timeseries

In [85]: df = pd.DataFrame(np.random.randn(6,1), index=pd.date_range('2013-08-01', periods=6, freq='B'), columns=list('A'))

In [86]: df.ix[3,'A'] = np.nan

In [87]: df.reindex(df.index[::-1]).ffill()
A
2013-08-08  0.104050
2013-08-07  1.906684
2013-08-06  1.906684
2013-08-05  0.639589
2013-08-02  -0.179642
2013-08-01  -1.054874
cumsum reset at NaN values

8.4.1 Replace

Using replace with backrefs

8.5 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

In [89]: 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}); df

Out[89]:

<table>
<thead>
<tr>
<th>adult</th>
<th>animal</th>
<th>size</th>
<th>weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>False</td>
<td>cat</td>
<td>S</td>
<td>8</td>
</tr>
<tr>
<td>False</td>
<td>dog</td>
<td>S</td>
<td>10</td>
</tr>
<tr>
<td>False</td>
<td>cat</td>
<td>M</td>
<td>11</td>
</tr>
<tr>
<td>False</td>
<td>fish</td>
<td>M</td>
<td>1</td>
</tr>
<tr>
<td>False</td>
<td>dog</td>
<td>M</td>
<td>20</td>
</tr>
<tr>
<td>True</td>
<td>cat</td>
<td>L</td>
<td>12</td>
</tr>
<tr>
<td>True</td>
<td>cat</td>
<td>L</td>
<td>12</td>
</tr>
</tbody>
</table>

#List the size of the animals with the highest weight.
In [90]: df.groupby('animal').apply(lambda subf: subf['size'][subf['weight'].idxmax()])
Out[90]:

animal
cat L
dog M
fish M
dtype: object

Using get_group

In [91]: gb = df.groupby(['animal'])

In [92]: gb.get_group('cat')
Out[92]:

<table>
<thead>
<tr>
<th>adult</th>
<th>animal</th>
<th>size</th>
<th>weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>False</td>
<td>cat</td>
<td>S</td>
<td>8</td>
</tr>
<tr>
<td>False</td>
<td>cat</td>
<td>M</td>
<td>11</td>
</tr>
</tbody>
</table>
Apply to different items in a group

```python
In [93]: 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 [94]: expected_df = gb.apply(GrowUp)
In [95]: expected_df
Out[95]:
   size  weight  adult
animal
   cat    L  12.4375   True
   dog    L  20.0000   True
   fish   L   1.2500   True
```

Expanding Apply

```python
In [96]: S = pd.Series([i / 100.0 for i in range(1,11)])
In [97]: def CumRet(x,y):
    ....:     return x * (1 + y)
    ....:
In [98]: def Red(x):
    ....:     return functools.reduce(CumRet,x,1.0)
    ....:
In [99]: pd.expanding_apply(S, Red)
Out[99]:
   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

```python
In [100]: df = pd.DataFrame({'A' : [1, 1, 2, 2], 'B' : [1, -1, 1, 2]})
In [101]: gb = df.groupby('A')
In [102]: def replace(g):
    ....:     mask = g < 0
    ....:     g.loc[mask] = g[~mask].mean()
    ....:     return g
In [103]: gb.transform(replace)
Out[103]:
   B
0  1
1  1
2  1
3  2

Sort groups by aggregated data

In [104]: 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 [105]: code_groups = df.groupby('code')
In [106]: agg_n_sort_order = code_groups[['data']].transform(sum).sort_values(by='data')
In [107]: sorted_df = df.ix[agg_n_sort_order.index]

In [108]: sorted_df
Out[108]:
   code  data  flag
0   foo  0.16  False
1   bar -0.21   True
2   bar -0.59     False
3   foo  0.16     False
4   foo  0.45   True
5   baz  0.33     False
6   baz  0.62   True

Create multiple aggregated columns

In [109]: rng = pd.date_range(start="2014-10-07", periods=10, freq='2min')
In [110]: ts = pd.Series(data = list(range(10)), index = rng)
In [111]: def MyCust(x):
   if len(x) > 2:
      return x[1] * 1.234
   return pd.NaT

In [112]: mhc = {'Mean' : np.mean, 'Max' : np.max, 'Custom' : MyCust}
In [113]: ts.resample("5min", how = mhc)
Out[113]:
      Max  Custom  Mean
2014-10-07 00:00:00   2 1.234   1.0
2014-10-07 00:05:00   4  NaN     3.5
2014-10-07 00:10:00   7 7.404   6.0
2014-10-07 00:15:00   9  NaN     8.5

In [114]: ts
Out[114]:
2014-10-07 00:00:00   0
2014-10-07 00:02:00   1
Create a value counts column and reassign back to the DataFrame

```
In [115]: df = pd.DataFrame({'Color': 'Red Red Red Blue'.split(),
                      'Value': [100, 150, 50, 50]}); df
```

```
Out[115]:
   Color  Value
0    Red   100
1    Red   150
2    Red    50
3    Blue    50
```

```
In [116]: df['Counts'] = df.groupby(['Color']).transform(len)
```

```
In [117]: df
```

```
Out[117]:
      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 [118]: df = pd.DataFrame({
                      'line_race': [10, 10, 8, 10, 10, 8],
                      'beyer': [99, 102, 103, 103, 88, 100],
                      'Paynter': [88, 100, 88, 100, 88, 100]},
                      index=['Last Gunfighter', 'Last Gunfighter', 'Last Gunfighter', 'Paynter', 'Paynter', 'Paynter']); df
```

```
Out[118]:
     beyer  line_race
0     99          10
1    102          10
2    103           8
3    103           8
4     88          10
5    100           8
```

```
In [119]: df['beyer_shifted'] = df.groupby(level=0)['beyer'].shift(1)
```

```
In [120]: df
```

```
Out[120]:
     beyer  line_race  beyer_shifted
0     99          10            NaN
1    102          10            99
2    103           8           102
3    103           8            NaN
4     88          10            NaN
5    100           8           103
Select row with maximum value from each group

```python
In [121]: 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'])
```

```python
In [122]: mask = df.groupby(level=0).agg('idxmax')
```

```python
In [123]: df_count = df.loc[mask['no']].reset_index()
```

```python
In [124]: df_count
Out [124]:
   host service  no
0  other    web  2
1  that     mail 1
2  this     mail 2
```

Grouping like Python’s `itertools.groupby`

```python
In [125]: df = pd.DataFrame([0, 1, 0, 1, 1, 1, 0, 1, 1], columns=['A'])
```

```python
In [126]: df.A.groupby((df.A != df.A.shift()).cumsum()).groups
Out [126]: {1: [0L], 2: [1L], 3: [2L], 4: [3L, 4L, 5L], 5: [6L], 6: [7L, 8L]}
```

```python
In [127]: df.A.groupby((df.A != df.A.shift()).cumsum()).cumsum()
Out [127]:
   0   0
   1   1
   2   0
   3   1
   4   2
   5   3
   6   0
   7   1
   8   2
dtype: int64
```

8.5.1 Expanding Data

Alignment and to-date

Rolling Computation window based on values instead of counts

Rolling Mean by Time Interval

8.5.2 Splitting

Splitting a frame

Create a list of dataframes, split using a delineation based on logic included in rows.

```python
In [128]: df = pd.DataFrame(data={'Case': ['A', 'A', 'A', 'B', 'A', 'A', 'B', 'A', 'A'],
                           'Data': np.random.randn(9)})
```

8.5. Grouping
In [129]: dfs = list(zip(*df.groupby(pd.rolling_median((1*(df['Case']=='B')).cumsum(),3,True))))[-1]

In [130]: dfs[0]
Out[130]:
   Case  Data
0    A   0.174068
1    A  -0.439461
2    A  -0.741343
3    B   0.079673

In [131]: dfs[1]
Out[131]:
   Case  Data
4    A  -0.922875
5    A   0.303638
6    B  -0.917368

In [132]: dfs[2]
Out[132]:
   Case  Data
7    A  -1.624062
8    A  -0.758514

8.5.3 Pivot

The Pivot docs.

Partial sums and subtotals

In [133]: df = pd.DataFrame(data={'Province': ['ON', 'QC', 'BC', 'AL', 'MN', 'ON'],
                           'City': ['Toronto', 'Montreal', 'Vancouver', 'Calgary', 'Edmonton', 'Winnipeg', 'Windsor'],
                           'Sales': [13, 6, 16, 8, 4, 3, 1]})

In [134]: table = pd.pivot_table(df, values=['Sales'], index=['Province'], columns=['City'], aggfunc=np.sum, margins=True)

In [135]: table.stack('City')
Out[135]:

<table>
<thead>
<tr>
<th>Province</th>
<th>City</th>
<th>Sales</th>
</tr>
</thead>
<tbody>
<tr>
<td>AL</td>
<td>All</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>Calgary</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>Edmonton</td>
<td>4</td>
</tr>
<tr>
<td>BC</td>
<td>All</td>
<td>16</td>
</tr>
<tr>
<td></td>
<td>Vancouver</td>
<td>16</td>
</tr>
<tr>
<td>MN</td>
<td>All</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>Winnipeg</td>
<td>3</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td></td>
<td>Calgary</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>Edmonton</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>Montreal</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>Toronto</td>
<td>13</td>
</tr>
<tr>
<td></td>
<td>Vancouver</td>
<td>16</td>
</tr>
<tr>
<td></td>
<td>Windsor</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Winnipeg</td>
<td>3</td>
</tr>
</tbody>
</table>

[20 rows x 1 columns]
Frequency table like `plyr` in R

In [136]: grades = [48,99,75,80,42,80,72,68,36,78]

In [137]: df = pd.DataFrame( {'ID': ['%d' % r for r in range(10)],
                           'Gender': ['F', 'M', 'F', 'M', 'F', 'M', 'M', 'F', 'M', 'M'],
                           'Class': ['algebra', 'stats', 'bio', 'algebra', 'algebra', 'stats', 'stats', 'algebra', 'stats', '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, False, False, False, True, True, False],
                           'Grade': grades})

In [138]: df.groupby('ExamYear').agg({'Participated': lambda x: x.value_counts()['yes'],
                           'Passed': lambda x: sum(x == 'yes'),
                           'Employed': lambda x: sum(x),
                           'Grade': lambda x: sum(x) / len(x)})

Out[138]:

<table>
<thead>
<tr>
<th>ExamYear</th>
<th>Grade</th>
<th>Employed</th>
<th>Participated</th>
<th>Passed</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>74</td>
<td>3</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>2008</td>
<td>68</td>
<td>0</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>2009</td>
<td>60</td>
<td>2</td>
<td>3</td>
<td>2</td>
</tr>
</tbody>
</table>

8.5.4 Apply

Rolling Apply to Organize - Turning embedded lists into a multi-index frame

In [139]: df = pd.DataFrame(data={'A' : [[2,4,8,16],[100,200],[10,20,30]], 'B' : [['a','b','c'],['jj','kk'],['ccc']]), index=['I','II','III'])

In [140]: def SeriesFromSubList(aList):
    .....:     return pd.Series(aList)
    .....:

In [141]: df_orgz = pd.concat(dict((ind,row.apply(SeriesFromSubList)) for ind,row in df.iterrows()))

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 [142]: df = pd.DataFrame(data=np.random.randn(2000,2)/10000,
                           index=pd.date_range('2001-01-01',periods=2000),
                           columns=['A','B']); df

Out[142]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>2001-01-01</td>
<td>-0.000056</td>
<td>-0.000059</td>
</tr>
<tr>
<td>2001-01-02</td>
<td>-0.000107</td>
<td>-0.000168</td>
</tr>
<tr>
<td>2001-01-03</td>
<td>0.000040</td>
<td>0.000061</td>
</tr>
<tr>
<td>2001-01-04</td>
<td>0.000039</td>
<td>0.000182</td>
</tr>
<tr>
<td>2001-01-05</td>
<td>0.000071</td>
<td>-0.000067</td>
</tr>
<tr>
<td>2001-01-06</td>
<td>0.000024</td>
<td>0.000031</td>
</tr>
<tr>
<td>2001-01-07</td>
<td>0.000012</td>
<td>-0.000021</td>
</tr>
</tbody>
</table>

8.5. Grouping
pandas: powerful Python data analysis toolkit, Release 0.17.0

2006-06-19 -0.000069 0.000283
2006-06-20 0.000089 0.000084
2006-06-21 0.000075 0.000041
2006-06-22 -0.000037 -0.000011
2006-06-23 -0.000070 -0.000048

[2000 rows x 2 columns]

In [143]: def gm(aDF,Const):
   ....:     v = (((aDF.A+aDF.B)+1).cumprod())-1)*Const
   ....:     return (aDF.index[0],v.iloc[-1])
   ....:

In [144]: S = pd.Series(dict([ gm(df.iloc[i:min(i+51,len(df)-1)],5) for i in range(len(df)-50) ])); S
Out[144]:
2001-01-01 -0.003108
2001-01-02 -0.001787
2001-01-03 0.000204
2001-01-04 -0.000166
2001-01-05 -0.002148
2001-01-06 -0.001831
2001-01-07 -0.001663
   ... ...
2006-04-28 -0.009152
2006-04-29 -0.006728
2006-04-30 -0.005840
2006-05-01 -0.003650
2006-05-02 -0.003801
2006-05-03 -0.004272
2006-05-04 -0.003839
dtype: float64

Rolling apply with a DataFrame returning a Scalar

Rolling Apply to multiple columns where function returns a Scalar (Volume Weighted Average Price)

In [145]: rng = pd.date_range(start = '2014-01-01', periods = 100)

In [146]: 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); df
Out[146]:
     Close  Open  Volume
2014-01-01  1.550590  0.458513  1371
2014-01-02 -0.818812 -0.508850  1433
2014-01-03  1.160619  0.257610   645
2014-01-04  0.081521 -1.773393   878
2014-01-05  1.083284 -1.773393  1143
2014-01-06  0.518721  0.284174  1722
2014-01-07  0.140661  1.146889  2968
   ... ... ... ...
2014-04-04  0.458193 -0.669474  1768
2014-04-05  0.108502 -1.616315   836
2014-04-06  1.418082 -1.294906   694
2014-04-07  0.486530  1.171647   796
2014-04-08  0.181885  0.501639  265
2014-04-09 -0.707238 -0.361868  1293
2014-04-10  1.211432  1.564429  1088
[100 rows x 3 columns]


In [148]: window = 5

In [149]: s = pd.concat([pd.Series(vwap(df.iloc[i:i+window]), index=[df.index[i+window]]) for i in range(len(df)-window)])

Out[149]:
2014-01-06  0.55
2014-01-07  0.06
2014-01-08  0.32
2014-01-09  0.03
2014-01-10  0.08
2014-01-11 -0.50
2014-01-12 -0.26
...          ...
2014-04-04  0.36
2014-04-05  0.48
2014-04-06  0.54
2014-04-07  0.46
2014-04-08  0.45
2014-04-09  0.53
2014-04-10  0.15
dtype: float64

8.6 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 [150]: dates = pd.date_range('2000-01-01', periods=5)

In [151]: dates.to_period(freq='M').to_timestamp()
Out[151]:
              '2000-01-01'],
             dtype='datetime64[ns]', freq=None)

8.6.1 Resampling

The Resample docs.
TimeGrouping of values grouped across time

8.6. Timeseries 297
TimeGrouping #2
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

8.7 Merge

The `Concat` docs. The `Join` docs.

Append two dataframes with overlapping index (emulate R `rbind`)

```
In [152]: rng = pd.date_range('2000-01-01', periods=6)

In [153]: df1 = pd.DataFrame(np.random.randn(6, 3), index=rng, columns=['A', 'B', 'C'])

In [154]: df2 = df1.copy()

In [155]: df = df1.append(df2, ignore_index=True); df
```

```
Out[155]:
     A       B       C
0 -0.1742  0.477257  0.239870
1 -0.6545  1.411456  1.778457
2  0.3516  0.307871 -0.286865
3  0.5654 -0.185821  0.937593
4  0.4467  0.566368  0.721476
5  1.7107 -0.667054 -0.651191
6 -0.1742  0.477257  0.239870
7 -0.6544 -1.411456 -1.778457
8  0.3516  0.307871 -0.286865
9  0.5654 -0.185821  0.937593
10 0.4464  0.566368  0.721476
11 1.7107  0.667054 -0.651191
```

Self Join of a DataFrame

```
In [156]: 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)}); df
```

```
Out[156]:
Area Bins    Data Test_0
0   A   110 -0.399974  0
1   A   110 -1.519206  1
2   A   160  1.678487  0
3   A   160  0.005345  1
4   A   160 -0.534461  2
5   C    40  0.255077  0
6   C    40  1.093310  1
```

```
In [157]: df['Test_1'] = df['Test_0'] - 1
```
In [158]: pd.merge(df, df, left_on=['Bins', 'Area', 'Test_0'], right_on=['Bins', 'Area', 'Test_1'], suffixes=('_L', '_R'))

Out[158]:

<table>
<thead>
<tr>
<th>Area</th>
<th>Bins</th>
<th>Data_L</th>
<th>Test_0_L</th>
<th>Test_1_L</th>
<th>Data_R</th>
<th>Test_0_R</th>
<th>Test_1_R</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>A</td>
<td>110</td>
<td>-0.399974</td>
<td>0</td>
<td>-1.519206</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>A</td>
<td>160</td>
<td>1.678487</td>
<td>0</td>
<td>-1</td>
<td>0.005345</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>A</td>
<td>160</td>
<td>0.005345</td>
<td>1</td>
<td>0</td>
<td>-0.534461</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>C</td>
<td>40</td>
<td>0.255077</td>
<td>0</td>
<td>-1</td>
<td>1.093310</td>
<td>1</td>
</tr>
</tbody>
</table>

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

8.8 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 [159]: df = pd.DataFrame(
      ....:     {u'stratifying_var': np.random.uniform(0, 100, 20),
      ....:      u'price': np.random.normal(100, 5, 20)})

In [160]: df[u'quartiles'] = pd.qcut(
      ....:     df[u'stratifying_var'],
      ....:     4,
      ....:     labels=[u'0-25%', u'25-50%', u'50-75%', u'75-100%'])

In [161]: df.boxplot(column=u'price', by=u'quartiles')
Out[161]: <matplotlib.axes._subplots.AxesSubplot at 0xa862ee0c>
8.9 Data In/Out

Performance comparison of SQL vs HDF5

8.9.1 CSV

The CSV docs

read_csv in action

appending to a csv

how to read in multiple files, appending to create a single dataframe

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

Parsing date components in multi-columns is faster with a format

```python
In [30]: i = pd.date_range('20000101', periods=10000)
In [31]: df = pd.DataFrame(dict(year=i.year, month=i.month, day=i.day))
In [32]: df.head()
Out[32]:
   day  month  year
0     1      1  2000
1     2      1  2000
2     3      1  2000
3     4      1  2000
4     5      1  2000
```

```python
In [33]: %timeit pd.to_datetime(df.year*10000+df.month*100+df.day, format='%Y%m%d')
100 loops, best of 3: 7.08 ms per loop
```

# simulate combining into a string, then parsing
```python
In [34]: ds = df.apply(lambda x: f"%04d%02d%02d" % (x['year'], x['month'], x['day']), axis=1)
In [35]: ds.head()
Out[35]:
0  20000101
1  20000102
2  20000103
3  20000104
4  20000105
```

```python
In [36]: %timeit pd.to_datetime(ds)
1 loops, best of 3: 488 ms per loop
```

**8.9.2 SQL**

The *SQL* docs

Reading from databases with SQL

**8.9.3 Excel**

The *Excel* docs

Reading from a filelike handle
Modifying formatting in XlsxWriter output

### 8.9.4 HTML

Reading HTML tables from a server that cannot handle the default request header

### 8.9.5 HDFStore

The [HDFStores](https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.HDFStore.html) 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](https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.HDFStore.html)

Creating a store chunk-by-chunk from a csv file

Appending to a store, while creating a unique index

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

```
In [162]: df = pd.DataFrame(np.random.randn(8,3))

In [163]: store = pd.HDFStore('test.h5')

In [164]: store.put('df',df)

# you can store an arbitrary python object via pickle
In [165]: store.get_storer('df').attrs.my_attribute = dict(A = 10)

In [166]: store.get_storer('df').attrs.my_attribute
Out[166]: {'A': 10}
```
8.9.6 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 msgpack, both of which are supported by pandas’ IO facilities.

8.10 Computation

Numerical integration (sample-based) of a time series
8.11 Timedeltas

The Timedeltas docs.

Using timedeltas

In [167]: s = pd.Series(pd.date_range('2012-1-1', periods=3, freq='D'))

In [168]: s - s.max()
Out[168]:
0   -2 days
1   -1 days
2    0 days
dtype: timedelta64[ns]

In [169]: s.max() - s
Out[169]:
0    2 days
1    1 days
2    0 days
dtype: timedelta64[ns]

In [170]: s - datetime.datetime(2011,1,1,3,5)
Out[170]:
0  364 days 20:55:00
1  365 days 20:55:00
2  366 days 20:55:00
dtype: timedelta64[ns]

In [171]: s + datetime.timedelta(minutes=5)
Out[171]:
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 [172]: datetime.datetime(2011,1,1,3,5) - s
Out[172]:
0  -365 days +03:05:00
1  -366 days +03:05:00
2  -367 days +03:05:00
dtype: timedelta64[ns]

In [173]: datetime.timedelta(minutes=5) + s
Out[173]:
0  2012-01-01 00:05:00
1  2012-01-02 00:05:00
2  2012-01-03 00:05:00
dtype: datetime64[ns]

Adding and subtracting deltas and dates

In [174]: deltas = pd.Series([datetime.timedelta(days=i) for i in range(3)])

In [175]: df = pd.DataFrame(dict(A = s, B = deltas)); df
Out[175]:
          A          B
0  2012-01-01 0 days
1  2012-01-02 1 days
2 2012-01-03 2 days

In [176]: df["New Dates"] = df["A"] + df["B"];

In [177]: df["Delta"] = df["A"] - df["New Dates"]; df
Out[177]:
         A    B  New Dates    Delta
0  2012-01-01 0 days 2012-01-01 0 days
1  2012-01-02 1 days 2012-01-03 -1 days
2  2012-01-03 2 days 2012-01-05 -2 days

In [178]: df.dtypes
Out[178]:
A  datetime64[ns]
B  timedelta64[ns]
New Dates  datetime64[ns]
Delta  timedelta64[ns]
dtype: object

Another example

Values can be set to NaT using np.nan, similar to datetime

In [179]: y = s - s.shift(); y
Out[179]:
0  NaT
1  1 days
2  1 days
dtype: timedelta64[ns]

In [180]: y[1] = np.nan; y
Out[180]:
0  NaT
1  NaT
2  1 days
dtype: timedelta64[ns]

8.12 Aliasing Axis Names

To globally provide aliases for axis names, one can define these 2 functions:

In [181]: def set_axis_alias(cls, axis, alias):
       ....:     if axis not in cls._AXIS_NUMBERS:
       ....:         raise Exception("invalid axis \[%s\] for alias \[%s\]" % (axis, alias))
       ....:     cls._AXIS_ALIASES[alias] = axis
       ....:

In [182]: def clear_axis_alias(cls, axis, alias):
       ....:     if axis not in cls._AXIS_NUMBERS:
       ....:         raise Exception("invalid axis \[%s\] for alias \[%s\]" % (axis, alias))
       ....:     cls._AXIS_ALIASES.pop(alias, None)
       ....:

In [183]: set_axis_alias(pd.DataFrame,'columns', 'myaxis2')

In [184]: df2 = pd.DataFrame(np.random.randn(3,2),columns=['c1','c2'],index=['i1','i2','i3'])

8.12. Aliasing Axis Names 305
8.13 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 [187]: def expand_grid(data_dict):
......:     rows = itertools.product(*data_dict.values())
......:     return pd.DataFrame.from_records(rows, columns=data_dict.keys())
......:
In [188]: df = expand_grid(
......:     {'height': [60, 70],
......:     'weight': [100, 140, 180],
......:     'sex': ['Male', 'Female']})
......:
In [189]: df
Out[189]:
   sex  weight  height
  0  Male     100     60
  1  Male     100     70
  2  Male     140     60
  3  Male     140     70
  4  Male     180     60
  5  Male     180     70
  6 Female    100     60
  7 Female    100     70
  8 Female    140     60
  9 Female    140     70
 10 Female   180     60
 11 Female   180     70
```
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:

```
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.

### 9.1 Series

**Warning:** In 0.13.0 Series has internally been refactored to no longer sub-class `ndarray` but instead subclass `NDFrame`, similarly to the rest of the pandas containers. This should be a transparent change with only very limited API implications (See the Internal Refactoring)

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**

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]`.

```
In [3]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])
In [4]: s
```
```python
Out[4]:
a -2.7828
b  0.4264
c -0.6505
d  1.1465
e -0.6631
dtype: float64

In [5]: s.index
Out[5]: Index([u'a', u'b', u'c', u'd', u'e'], dtype='object')

In [6]: pd.Series(np.random.randn(5))
Out[6]:
  0  0.2939
  1 -0.4049
  2  1.1665
  3  0.8420
  4  0.5398
dtype: float64

Note: Starting in v0.8.0, 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

If `data` is a dict, if `index` is passed the values in data corresponding to the labels in the index will be pulled out.
Otherwise, an index will be constructed from the sorted keys of the dict, if possible.

In [7]: d = {'a' : 0., 'b' : 1., 'c' : 2.}

In [8]: pd.Series(d)
Out[8]:
a 0
b 1
c 2
dtype: float64

In [9]: pd.Series(d, index=['b', 'c', 'd', 'a'])
Out[9]:
b 1
c 2
d NaN
a 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 [10]: pd.Series(5., index=['a', 'b', 'c', 'd', 'e'])
Out[10]:
a  5
b  5
c  5
d  5
```

Note: NaN (not a number) is the standard missing data marker used in pandas
9.1.1 Series is ndarray-like

Series acts very similarly to a ndarray, and is a valid argument to most NumPy functions. However, things like slicing also slice the index.

```
In [11]: s[0]
Out[11]: -2.7827595933769937

In [12]: s[:3]
Out[12]:
a  -2.7828
b   0.4264
c  -0.6505
dtype: float64

In [13]: s[s > s.median()]
Out[13]:
b   0.4264
d  1.1465
dtype: float64

In [14]: s[[4, 3, 1]]
Out[14]:
e  -0.6631
d  1.1465
b   0.4264
dtype: float64

In [15]: np.exp(s)
Out[15]:
a  0.0619
b  1.5318
c  0.5218
d  3.1472
e  0.5153
dtype: float64
```

We will address array-based indexing in a separate section.

9.1.2 Series is dict-like

A Series is like a fixed-size dict in that you can get and set values by index label:

```
In [16]: s['a']
Out[16]: -2.7827595933769937

In [17]: s['e'] = 12.

In [18]: s
Out[18]:
a  -2.7828
b   0.4264
c  -0.6505
dtype: float64
```
In [19]: 'e' in s
Out[19]: True

In [20]: 'f' in s
Out[20]: 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 [21]: s.get('f')
```

```python
In [22]: s.get('f', np.nan)
Out[22]: nan
```

See also the section on attribute access.

### 9.1.3 Vectorized operations and label alignment with Series

When doing data analysis, as with raw NumPy arrays looping through Series value-by-value is usually not necessary. Series can also be passed into most NumPy methods expecting an ndarray.

```python
In [23]: s + s
Out[23]:
     a   -5.5655
     b    0.8529
     c   -1.3010
     d    2.2930
     e    24.0000

dtype: float64
```

```python
In [24]: s * 2
Out[24]:
     a   -5.5655
     b    0.8529
     c   -1.3010
     d    2.2930
     e    24.0000

dtype: float64
```

```python
In [25]: np.exp(s)
Out[25]:
     a    0.0619
     b    1.5318
     c    0.5218
     d    3.1472
     e  162754.7914

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
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.

9.1.4 Name attribute

Series can also have a name attribute:

In [26]: s[1:] + s[:-1]
Out[26]:
a  NaN
b 0.8529
c -1.3010
d 2.2930
e  NaN
dtype: float64

9.2 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

The Series name will be assigned automatically in many cases, in particular when taking 1D slices of DataFrame as you will see below.
• 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.

9.2.1 From dict of Series or dicts

The result index will be the union of the indexes of the various Series. If there are any nested dicts, these will be first converted to Series. If no columns are passed, the columns will be the sorted list of dict keys.

```python
In [30]: d = {'one' : pd.Series([1., 2., 3.], index=['a', 'b', 'c']),
       ....:   'two' : pd.Series([1., 2., 3., 4.], index=['a', 'b', 'c', 'd'])
       ....:

In [31]: df = pd.DataFrame(d)
```

```python
In [32]: df
Out[32]:
   one  two
  a   1   1
  b   2   2
  c   3   3
  d  NaN   4

In [33]: pd.DataFrame(d, index=['d', 'b', 'a'])
Out[33]:
   one  two
  d  NaN   4
  b   2   2
  a   1   1

In [34]: pd.DataFrame(d, index=['d', 'b', 'a'], columns=['two', 'three'])
Out[34]:
   two  three
  d  NaN  
  b   2   NaN
  a   1   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.

```python
In [35]: df.index
Out[35]: Index([u'a', u'b', u'c', u'd'], dtype='object')

In [36]: df.columns
Out[36]: Index([u'one', u'two'], dtype='object')
```

9.2.2 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 [37]: d = {'one' : [1., 2., 3., 4.],
       ....:     'two' : [4., 3., 2., 1.]}   
       ....:

In [38]: pd.DataFrame(d)
Out[38]:
      one\n0  1
1  2
2  3
3  4

In [39]: pd.DataFrame(d, index=['a', 'b', 'c', 'd'])
Out[39]:
     one\n   a  1
   b  2
   c  3
   d  4

9.2.3 From structured or record array

This case is handled identically to a dict of arrays.

In [40]: data = np.zeros((2,), dtype=[('A', 'i4'),('B', 'f4'),('C', 'a10')])
In [41]: data[:] = [(1,2.,'Hello'), (2,3.,'World')]

In [42]: pd.DataFrame(data)
Out[42]:
      A  B    C
0  1  2   Hello
1  2  3   World

9.2.4 From a list of dicts

In [45]: data2 = [ {'a': 1, 'b': 2}, {'a': 5, 'b': 10, 'c': 20} ]

In [46]: pd.DataFrame(data2)
Out[46]:

Note:  DataFrame is not intended to work exactly like a 2-dimensional NumPy ndarray.
pandas: powerful Python data analysis toolkit, Release 0.17.0

```
a  b  c
0  1  2  NaN
1  5 10  20

In [47]: pd.DataFrame(data2, index=['first', 'second'])
Out[47]:
a  b  c
first 1  2  NaN
second 5 10  20

In [48]: pd.DataFrame(data2, columns=['a', 'b'])
Out[48]:
a  b
0  1  2
1  5 10
```

9.2.5 From a dict of tuples

You can automatically create a multi-indexed frame by passing a tuples dictionary.

```
In [49]: 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[49]:
a  b
A B  4  1  5  8 10
C  3  2  6  7  NaN
D  NaN NaN  NaN NaN  9
```

9.2.6 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).

Missing Data

Much more will be said on this topic in the Missing data section. To construct a DataFrame with missing data, use `np.nan` for those values which are missing. Alternatively, you may pass a `numpy.MaskedArray` as the data argument to the DataFrame constructor, and its masked entries will be considered missing.

9.2.7 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.  `DataFrame.from_records`

`DataFrame.from_records` takes a list of tuples or an ndarray with structured dtype. Works analogously to the normal `DataFrame` constructor, except that index maybe be a specific field of the structured dtype to use as the index. For example:
In [50]: data
Out[50]:
array([(1, 2.0, 'Hello'), (2, 3.0, 'World')],
dtype=[('A', '<i4'), ('B', '<f4'), ('C', 'S10')])

In [51]: pd.DataFrame.from_records(data, index='C')
Out[51]:
   A  B
C  Hello  1  2
  World  2  3

**DataFrame.from_items**

`DataFrame.from_items` works analogously to the form of the `dict` constructor that takes a sequence of (key, value) pairs, where the keys are column (or row, in the case of `orient='index'`) names, and the value are the column values (or row values). This can be useful for constructing a DataFrame with the columns in a particular order without having to pass an explicit list of columns:

In [52]: pd.DataFrame.from_items([('A', [1, 2, 3]), ('B', [4, 5, 6])])
Out[52]:
   A  B
0  1  4
1  2  5
2  3  6

If you pass `orient='index'`, the keys will be the row labels. But in this case you must also pass the desired column names:

In [53]: pd.DataFrame.from_items([('A', [1, 2, 3]), ('B', [4, 5, 6])],
                         orient='index', columns=['one', 'two', 'three'])
Out[53]:
   one  two  three
A  1  2  3
B  4  5  6

### 9.2.8 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:

In [54]: df['one']
Out[54]:
a  1
b  2
c  3
d  NaN
Name: one, dtype: float64

In [55]: df['three'] = df['one'] * df['two']

In [56]: df['flag'] = df['one'] > 2

In [57]: df
Out[57]:
   one  two  three  flag
0   1   1   1  False
Columns can be deleted or popped like with a dict:

```
In [58]: del df['two']
```

```
In [59]: three = df.pop('three')
```

```
In [60]: df
Out[60]:
    one  flag
   ---  ----
   a  1    False
   b  2    False
   c  3    True
   d  NaN  False
```

When inserting a scalar value, it will naturally be propagated to fill the column:

```
In [61]: df['foo'] = 'bar'
```

```
In [62]: df
Out[62]:
    one  flag  foo
   ---  ----  ---
   a  1    False  bar
   b  2    False  bar
   c  3    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 [63]: df['one_trunc'] = df['one'][:2]
```

```
In [64]: df
Out[64]:
    one  flag  foo  one_trunc
   ---  ----  ---  ------
   a  1    False  bar  1
   b  2    False  bar  2
   c  3    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:

```
In [65]: df.insert(1, 'bar', df['one'][:2])
```

```
In [66]: df
Out[66]:
     one  bar  flag  foo  one_trunc
    ---  ---  ----  ---  ------
   a  1  1    False  bar  1
   b  2  2    False  bar  2
   c  3  3    True  bar  NaN
   d  NaN NaN  False  bar  NaN
```
9.2.9 Assigning New Columns in Method Chains

New in version 0.16.0.

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 [67]: iris = pd.read_csv('data/iris.data')

In [68]: iris.head()
Out[68]:
<table>
<thead>
<tr>
<th>SepalLength</th>
<th>SepalWidth</th>
<th>PetalLength</th>
<th>PetalWidth</th>
<th>Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.1</td>
<td>3.5</td>
<td>1.4</td>
<td>0.2</td>
<td>Iris-setosa</td>
</tr>
<tr>
<td>4.9</td>
<td>3.0</td>
<td>1.4</td>
<td>0.2</td>
<td>Iris-setosa</td>
</tr>
<tr>
<td>4.7</td>
<td>3.2</td>
<td>1.3</td>
<td>0.2</td>
<td>Iris-setosa</td>
</tr>
<tr>
<td>4.6</td>
<td>3.1</td>
<td>1.5</td>
<td>0.2</td>
<td>Iris-setosa</td>
</tr>
<tr>
<td>5.0</td>
<td>3.6</td>
<td>1.4</td>
<td>0.2</td>
<td>Iris-setosa</td>
</tr>
</tbody>
</table>

In [69]: (iris.assign(sepal_ratio = iris['SepalWidth'] / iris['SepalLength']).head())

Out[69]:
<table>
<thead>
<tr>
<th>SepalLength</th>
<th>SepalWidth</th>
<th>PetalLength</th>
<th>PetalWidth</th>
<th>Name</th>
<th>sepal_ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.1</td>
<td>3.5</td>
<td>1.4</td>
<td>0.2</td>
<td>Iris-setosa</td>
<td>0.6863</td>
</tr>
<tr>
<td>4.9</td>
<td>3.0</td>
<td>1.4</td>
<td>0.2</td>
<td>Iris-setosa</td>
<td>0.6122</td>
</tr>
<tr>
<td>4.7</td>
<td>3.2</td>
<td>1.3</td>
<td>0.2</td>
<td>Iris-setosa</td>
<td>0.6809</td>
</tr>
<tr>
<td>4.6</td>
<td>3.1</td>
<td>1.5</td>
<td>0.2</td>
<td>Iris-setosa</td>
<td>0.6739</td>
</tr>
<tr>
<td>5.0</td>
<td>3.6</td>
<td>1.4</td>
<td>0.2</td>
<td>Iris-setosa</td>
<td>0.7200</td>
</tr>
</tbody>
</table>

Above was an example of inserting a precomputed value. We can also pass in a function of one argument to be evaluated on the DataFrame being assigned to.

In [70]: iris.assign(sepal_ratio = lambda x: (x['SepalWidth'] / x['SepalLength'])).head()

Out[70]:
<table>
<thead>
<tr>
<th>SepalLength</th>
<th>SepalWidth</th>
<th>PetalLength</th>
<th>PetalWidth</th>
<th>Name</th>
<th>sepal_ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.1</td>
<td>3.5</td>
<td>1.4</td>
<td>0.2</td>
<td>Iris-setosa</td>
<td>0.6863</td>
</tr>
<tr>
<td>4.9</td>
<td>3.0</td>
<td>1.4</td>
<td>0.2</td>
<td>Iris-setosa</td>
<td>0.6122</td>
</tr>
<tr>
<td>4.7</td>
<td>3.2</td>
<td>1.3</td>
<td>0.2</td>
<td>Iris-setosa</td>
<td>0.6809</td>
</tr>
<tr>
<td>4.6</td>
<td>3.1</td>
<td>1.5</td>
<td>0.2</td>
<td>Iris-setosa</td>
<td>0.6739</td>
</tr>
<tr>
<td>5.0</td>
<td>3.6</td>
<td>1.4</td>
<td>0.2</td>
<td>Iris-setosa</td>
<td>0.7200</td>
</tr>
</tbody>
</table>

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 chains 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:

In [71]: (iris.query('SepalLength > 5')
       ....:     .assign(SepalRatio = lambda x: x.SepalWidth / x.SepalLength,
       ....:                PetalRatio = lambda x: x.PetalWidth / x.PetalLength)
       ....:     .plot(kind='scatter', x='SepalRatio', y='PetalRatio'))

Out[71]: <matplotlib.axes._subplots.AxesSubplot at 0xa8682dec>
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.

**Warning:** Since the function signature of assign is **kwargs, a dictionary, the order of the new columns in the resulting DataFrame cannot be guaranteed to match the order you pass in. To make things predictable, items are inserted alphabetically (by key) at the end of the DataFrame.

All expressions are computed first, and then assigned. So you can’t refer to another column being assigned in the same call to assign. For example:

```python
In [72]: # Don't do this, bad reference to `C`
df.assign(C = lambda x: x['A'] + x['B'],
    D = lambda x: x['A'] + x['C'])
```

```python
In [2]: # Instead, break it into two assigns
(df.assign(C = lambda x: x['A'] + x['B']))
 .assign(D = lambda x: x['A'] + x['C']))
```
9.2.10 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>df[col]</td>
<td>Series</td>
</tr>
<tr>
<td>Select row by label</td>
<td>df.loc[label]</td>
<td>Series</td>
</tr>
<tr>
<td>Select row by integer location</td>
<td>df.iloc[loc]</td>
<td>Series</td>
</tr>
<tr>
<td>Slice rows</td>
<td>df[5:10]</td>
<td>DataFrame</td>
</tr>
<tr>
<td>Select rows by boolean vector</td>
<td>df[bool_vec]</td>
<td>DataFrame</td>
</tr>
</tbody>
</table>

Row selection, for example, returns a Series whose index is the columns of the DataFrame:

In [73]: df.loc['b']
Out[73]:
one    2
bar    2
flag   False
foo    bar
one_trunc    2
Name: b, dtype: object

In [74]: df.iloc[2]
Out[74]:
one    3
bar    3
flag   True
foo    bar
one_trunc  NaN
Name: c, dtype: object

For a more exhaustive treatment of more 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.

9.2.11 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 [75]: df = pd.DataFrame(np.random.randn(10, 4), columns=['A', 'B', 'C', 'D'])

In [76]: df2 = pd.DataFrame(np.random.randn(7, 3), columns=['A', 'B', 'C'])

In [77]: df + df2
Out[77]:
   A  B         C          D
0 -1.9160 -0.9862  -2.4213 NaN
1  0.9651  1.6767   0.3298 NaN
2 -1.6622  2.1966  -1.9169 NaN
3 -0.1887  0.7653  -0.0010 NaN
4 -1.0760  0.3969  -1.1774 NaN
5  2.8104 -0.1792  -0.5705 NaN
6 -1.2272  0.1963   0.5312 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:

```python
In [78]: df - df.iloc[0]
Out[78]:
   A    B    C    D
0  0.0000  0.0000  0.0000  0.0000
1  2.3859  1.3585  1.2234 -2.1065
2  2.1047  1.7004  1.3268 -0.6895
3  1.8741  2.7181  2.3819 -0.7597
4  2.1988  0.9662  0.8265  0.0932
5  4.9966  1.1967  1.3303 -0.2855
6  1.2632  0.5778  1.0712 -0.5254
7  3.4625  0.6322  1.0626 -0.4427
8  2.6802  3.1629  1.2977 -1.8177
9  1.3038  0.1957  3.5899 -0.8671
```

In the special case of working with time series data, and the DataFrame index also contains dates, the broadcasting will be column-wise:

```python
In [79]: index = pd.date_range('1/1/2000', periods=8)
In [80]: df = pd.DataFrame(np.random.randn(8, 3), index=index, columns=list('ABC'))
In [81]: df
Out[81]:
   A     B     C
2000-01-01 0.0627 -0.0284  0.4436
2000-01-02 -0.2688 -1.5776  1.8502
2000-01-03  0.6381  0.5566 -0.0712
2000-01-04  0.5114  0.1563 -1.0756
2000-01-05  1.6636 -0.4377 -0.0773
2000-01-06  0.0292  0.1790  1.7401
2000-01-07 -0.7290 -0.8980 -0.3142
2000-01-08 -0.0481 -0.8756  0.1691
```

```python
In [82]: type(df['A'])
Out[82]: pandas.core.series.Series
```

In the special case of working with time series data, and the DataFrame index also contains dates, the broadcasting will be column-wise:

```python
In [83]: df - df['A']
Out[83]:
   2000-01-01 00:00:00 2000-01-02 00:00:00 2000-01-03 00:00:00
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
2000-01-07  NaN     NaN     NaN
2000-01-08  NaN     NaN     NaN
2000-01-04 00:00:00 ... 2000-01-08 00:00:00  A    B    C
2000-01-01  NaN     ...       NaN  NaN  NaN  NaN  NaN
2000-01-02  NaN     ...       NaN  NaN  NaN  NaN  NaN
2000-01-03  NaN     ...       NaN  NaN  NaN  NaN  NaN
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
```

Chapter 9. Intro to Data Structures
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 [84]: df * 5 + 2
* Out[84]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01</td>
<td>2.3135</td>
<td>1.8579</td>
<td>4.2178</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>0.6561</td>
<td>-5.8882</td>
<td>11.2510</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>5.1903</td>
<td>-0.7830</td>
<td>1.6438</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>-0.5571</td>
<td>2.7814</td>
<td>-3.3781</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>10.3180</td>
<td>-0.1886</td>
<td>1.6135</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>2.1460</td>
<td>2.8950</td>
<td>10.7003</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>-1.6451</td>
<td>-2.4900</td>
<td>0.4289</td>
</tr>
<tr>
<td>2000-01-08</td>
<td>1.7596</td>
<td>-2.3780</td>
<td>2.8455</td>
</tr>
</tbody>
</table>

* In [85]: 1 / df
* Out[85]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01</td>
<td>15.9483</td>
<td>-35.1931</td>
<td>2.2545</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>-3.7205</td>
<td>-0.6339</td>
<td>0.5405</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>1.5672</td>
<td>-1.7966</td>
<td>-14.0388</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>-1.9553</td>
<td>6.3984</td>
<td>-0.9297</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>0.6011</td>
<td>-2.2845</td>
<td>-12.9363</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>34.2568</td>
<td>5.5863</td>
<td>0.5747</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>-1.3717</td>
<td>-1.1136</td>
<td>-3.1826</td>
</tr>
<tr>
<td>2000-01-08</td>
<td>-20.8019</td>
<td>-1.1421</td>
<td>5.9134</td>
</tr>
</tbody>
</table>

* In [86]: df ** 4
* Out[86]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01</td>
<td>1.5457e-05</td>
<td>6.5188e-07</td>
<td>3.8707e-02</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>5.2191e-03</td>
<td>6.1948e+00</td>
<td>1.1718e+01</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>1.6575e-01</td>
<td>9.5982e-02</td>
<td>2.5745e-05</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>6.8412e-02</td>
<td>5.9663e-04</td>
<td>1.3386e-06</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>7.6595e+00</td>
<td>3.6712e-02</td>
<td>3.5708e-05</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>7.2612e-07</td>
<td>1.0268e-03</td>
<td>9.1678e+00</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>2.8246e-01</td>
<td>6.5029e-01</td>
<td>9.7473e-03</td>
</tr>
<tr>
<td>2000-01-08</td>
<td>5.3406e-06</td>
<td>5.8781e-01</td>
<td>8.1783e-04</td>
</tr>
</tbody>
</table>

Boolean operators work as well:

* In [87]: df1 = pd.DataFrame({'a' : [1, 0, 1], 'b' : [0, 1, 1] }, dtype=bool)
* In [88]: df2 = pd.DataFrame({'a' : [0, 1, 1], 'b' : [1, 1, 0] }, dtype=bool)
In [89]: df1 & df2
Out[89]:
   a  b
0  0  0
1  1  1
2  1  0

In [90]: df1 | df2
Out[90]:
   a  b
0  1  1
1  1  1
2  1  1

In [91]: df1 ^ df2
Out[91]:
   a  b
0  1  1
1  1  0
2  0  1

In [92]: -df1
Out[92]:
   a  b
0  1  0
1  1  1
2  0  0

9.2.12 Transposing

To transpose, access the T attribute (also the transpose function), similar to an ndarray:

# only show the first 5 rows
In [93]: df[:5].T
Out[93]:
A  0.0627   -0.2688    0.6381  -0.5114     1.6636
B -0.0284  -1.5776   -0.5566   0.1563    -0.4377
C  0.4436   1.8502  -0.0712  -1.0756    -0.0773

9.2.13 DataFrame interoperability with NumPy functions

Elementwise NumPy ufuncs (log, exp, sqrt, ...) and various other NumPy functions can be used with no issues on DataFrame, assuming the data within are numeric:

In [94]: np.exp(df)
Out[94]:
       A         B         C
2000-01-01  1.0647  0.97200  1.5582
2000-01-02  0.7643  0.20650  6.3611
2000-01-03  1.8928  0.57320  0.9312
2000-01-04  0.5996  1.16920  0.3411
2000-01-05  5.2783  0.64550  0.9256
2000-01-06  1.0296  1.19600  5.6977
2000-01-07  0.4824  0.40740  0.7304
2000-01-08  0.9531  0.41660  1.1842
In [95]: np.asarray(df)
Out[95]:
array([[ 0.0627, -0.0284, 0.4436],
       [-0.2688, -1.5776, 1.8502],
       [ 0.6381, -0.5566, -0.0712],
       [-0.5114, 0.1563, -1.0756],
       [ 1.6636, -0.4377, -0.0773],
       [ 0.0292, 0.179 , 1.7401],
       [-0.729 , -0.898 , -0.3142],
       [-0.0481, -0.8756, 0.1691]])

The dot method on DataFrame implements matrix multiplication:

In [96]: df.T.dot(df)
Out[96]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>4.0471</td>
<td>-0.0390</td>
<td>0.1783</td>
</tr>
<tr>
<td>B</td>
<td>-0.0390</td>
<td>4.6207</td>
<td>-2.5806</td>
</tr>
<tr>
<td>C</td>
<td>0.1783</td>
<td>-2.5806</td>
<td>7.9431</td>
</tr>
</tbody>
</table>

Similarly, the dot method on Series implements dot product:

In [97]: s1 = pd.Series(np.arange(5,10))
In [98]: s1.dot(s1)
Out[98]: 255

DataFrame is not intended to be a drop-in replacement for ndarray as its indexing semantics are quite different in places from a matrix.

9.2.14 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 [99]: baseball = pd.read_csv('data/baseball.csv')
In [100]: print(baseball)

<table>
<thead>
<tr>
<th>id</th>
<th>player</th>
<th>year</th>
<th>stint</th>
<th>...</th>
<th>hbp</th>
<th>sh</th>
<th>sf</th>
<th>gidp</th>
</tr>
</thead>
<tbody>
<tr>
<td>88641</td>
<td>womacto01</td>
<td>2006</td>
<td>2</td>
<td>...</td>
<td>0</td>
<td>3</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>88643</td>
<td>schilcu01</td>
<td>2006</td>
<td>1</td>
<td>...</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>89533</td>
<td>aloumo01</td>
<td>2007</td>
<td>1</td>
<td>...</td>
<td>2</td>
<td>0</td>
<td>3</td>
<td>13</td>
</tr>
<tr>
<td>89534</td>
<td>alomasa02</td>
<td>2007</td>
<td>1</td>
<td>...</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

[100 rows x 23 columns]

In [101]: baseball.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 100 entries, 0 to 99
Data columns (total 23 columns):
   id                    100 non-null int64
   player                100 non-null object
   year                  100 non-null int64
   stint                 100 non-null int64
   team                  100 non-null object
   lg                     100 non-null object
   lgidweek              100 non-null object
   mgidweek              100 non-null object
   month                 100 non-null object
   teamid                100 non-null object
   teamid2               100 non-null object
   lgid                  100 non-null object
   nipa                                 | name key
   hack                                    | nipa
   hack_i                                   | hack
   id                                       | id
   year                                    | year
   team                                    | team
   lg                                       | lg
   lgid                                     | lgid
   lgidweek                                 | lgidweek
   mgidweek                                 | mgidweek
   month                                   | month
   teamid                                   | teamid
   teamid2                                  | teamid2
   lgidweek                                 | lgidweek

9.2. DataFrame
However, using `to_string` will return a string representation of the DataFrame in tabular form, though it won’t always fit the console width:

```
In [102]: print(baseball.iloc[-20:, :12].to_string())
```

```
id  player   year  stint  team  lg  g  ab  r  h  X2b  X3b
80   finlest01 2007  1   COL  NL  43  94  9  17  3   0
81   embrea101 2007  1   OAK  AL  4   0  0  0   0   0
82   edmonji01 2007  1   SLN  NL  117 365 39  92  15  2
83   easleda01 2007  1   NYN  NL  76  193 24  54  6   0
84   delgaca01 2007  1   NYN  NL  139 538 71 139 30  0
85   cormirh01 2007  1   CIN  NL  6   0  0  0   0   0
86   coninje01 2007  2   NYN  NL  21  41  2  8   2   0
87   coninje01 2007  2   CIN  NL  80  215 23  57  11  1
88   clemeno02 2007  1   NYA  AL  2   2  0  1   0   0
89   claytro01 2007  2   BOS  AL  8   6  1  0   0   0
90   claytro01 2007  1   TOR  AL  69  189 23  48  14  0
91   ciriije01 2007  2   ARI  NL  28  40  6  8   4   0
92   ciriije01 2007  1   MIN  AL  50  153 18  40  9   2
93   bondsba01 2007  1   SFN  NL  126 340 75  94  14  0
94   biggicr01 2007  1   HOU  NL  141 517 68 130 31  3
95   benitar01 2007  2   FLO  NL  34  0   0  0   0   0
96   benitar01 2007  1   SFN  NL  19  0   0  0   0   0
97   ausmubr01 2007  1   HOU  NL  117 349 38  82  16  3
98   alumono01 2007  1   NYN  NL  87  328 51 112 19  1
99   alomas02 2007  1   NYN  NL  8  22  1  3   1   0
```

New since 0.10.0, wide DataFrames will now be printed across multiple rows by default:

```
In [103]: pd.DataFrame(np.random.randn(3, 12))
```

```
   0     1     2     3     4     5     6     7     8     9    10    11
0  1.225021 -0.528620  0.448676  0.619107 -1.199110 -0.949097  2.169523
1 -1.753617  0.992384 -0.505601 -0.599848  0.133585  0.008836 -1.767710
2 -0.461585 -1.321106  1.745476  1.445100  0.991037 -0.860733 -0.870661
```

New since 0.10.0, wide DataFrames will now be printed across multiple rows by default:
You can change how much to print on a single row by setting the `display.width` option:

```python
In [104]: pd.set_option('display.width', 40) # default is 80
```

```python
In [105]: pd.DataFrame(np.random.randn(3, 12))
Out[105]:
   0     1     2
0 -1.280951 1.472585 -1.001914
1  0.130529 -1.603771 -0.128830
2 -1.084566 -0.515272  1.367586
   3     4     5
0  1.044770 -0.050668 -0.013289
1 -1.869301 -0.232977 -0.139801
2  0.963500  0.224105 -0.020051
   6     7     8
0 -0.291893  2.029038 -1.117195
1 -1.083341 -0.357234 -0.818199
2  0.524663  0.351081 -1.574209
  9    10    11
0  1.598577 -0.397325  0.151653
1 -0.886885  1.238885 -1.639274
2 -0.486856 -0.545888 -0.927076
```

You can also disable this feature via the `expand_frame_repr` option. This will print the table in one block.

### 9.2.15 DataFrame column attribute access and IPython completion

If a DataFrame column label is a valid Python variable name, the column can be accessed like attributes:

```python
In [106]: df = pd.DataFrame({'foo1' : np.random.randn(5),
                    'foo2' : np.random.randn(5)})
```

```python
In [107]: df
Out[107]:
   foo1  foo2
0  0.909160  1.360298
1 -0.667763 -1.603624
2 -0.101656 -1.648929
3  1.189682  0.145121
4 -0.090648 -2.536359
```

```python
In [108]: df.foo1
Out[108]:
   0  0.909160
   1 -0.667763
   2 -0.101656
   3  1.189682
   4 -0.090648
Name: foo1, dtype: float64
```

The columns are also connected to the IPython completion mechanism so they can be tab-completed:

```python
In [5]: df.fo<TAB>
```

```python
df.foo1  df.foo2
```
9.3 Panel

Panel is a somewhat less-used, but still important container for 3-dimensional data. The term panel data is derived from econometrics and is partially responsible for the name pandas: pan(el)-da(ta)-s. The names for the 3 axes are intended to give some semantic meaning to describing operations involving panel data and, in particular, econometric analysis of panel data. However, for the strict purposes of slicing and dicing a collection of DataFrame objects, you may find the axis names slightly arbitrary:

- **items**: axis 0, each item corresponds to a DataFrame contained inside
- **major_axis**: axis 1, it is the index (rows) of each of the DataFrames
- **minor_axis**: axis 2, it is the columns of each of the DataFrames

Construction of Panels works about like you would expect:

### 9.3.1 From 3D ndarray with optional axis labels

```python
In [109]: wp = pd.Panel(np.random.randn(2, 5, 4), items=['Item1', 'Item2'],
.....:     major_axis=pd.date_range('1/1/2000', periods=5),
.....:     minor_axis=['A', 'B', 'C', 'D'])

In [110]: wp
Out[110]:
<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
```

### 9.3.2 From dict of DataFrame objects

```python
In [111]: data = {'Item1': pd.DataFrame(np.random.randn(4, 3)),
.....:     'Item2': pd.DataFrame(np.random.randn(4, 2))}

In [112]: pd.Panel(data)
Out[112]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 4 (major_axis) x 3 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 0 to 3
Minor_axis axis: 0 to 2
```

Note that the values in the dict need only be convertible to DataFrame. Thus, they can be any of the other valid inputs to DataFrame as per above.

One helpful factory method is `Panel.from_dict`, which takes a dictionary of DataFrames as above, and the following named parameters:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Default</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>intersect</td>
<td>False</td>
<td>drops elements whose indices do not align</td>
</tr>
<tr>
<td>orient</td>
<td>items</td>
<td>use minor to use DataFrames' columns as panel items</td>
</tr>
</tbody>
</table>

For example, compare to the construction above:
In [113]: pd.Panel.from_dict(data, orient='minor')
Out[113]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 4 (major_axis) x 2 (minor_axis)
Items axis: 0 to 2
Major_axis axis: 0 to 3
Minor_axis axis: Item1 to Item2

Orient is especially useful for mixed-type DataFrames. If you pass a dict of DataFrame objects with mixed-type columns, all of the data will get upcasted to dtype=object unless you pass orient='minor':

In [114]: df = pd.DataFrame({'a': ['foo', 'bar', 'baz'],
                           'b': np.random.randn(3)},
                      index=['0', '1', '2'])

In [115]: data = {'item1': df, 'item2': df}

In [116]: panel = pd.Panel.from_dict(data, orient='minor')

In [117]: panel['a']
Out[117]:
    item1  item2
0    foo    foo
1    bar    bar
2    baz    baz

In [118]: panel['b']
Out[118]:
    item1  item2
0 -1.264356 -1.264356
1 -0.497629 -0.497629
2  1.789719  1.789719

In [119]: panel['b'].dtypes
Out[119]:
item1    float64
item2    float64
dtype: object

Note: Unfortunately Panel, being less commonly used than Series and DataFrame, has been slightly neglected feature-wise. A number of methods and options available in DataFrame are not available in Panel. This will get worked on, of course, in future releases. And faster if you join me in working on the codebase.

### 9.3.3 From DataFrame using to_panel method

This method was introduced in v0.7 to replace LongPanel.to_long, and converts a DataFrame with a two-level index to a Panel.
In [121]: midx = pd.MultiIndex(levels=[['one', 'two'], ['x', 'y']], labels=[[1,1,0,0],[1,0,1,0]])

In [122]: df = pd.DataFrame({'A' : [1, 2, 3, 4], 'B': [5, 6, 7, 8]}, index=midx)

In [123]: df.to_panel()
Out[123]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 2 (major_axis) x 2 (minor_axis)
Items axis: A to B
Major_axis axis: one to two
Minor_axis axis: x to y

### 9.3.4 Item selection / addition / deletion

Similar to DataFrame functioning as a dict of Series, Panel is like a dict of DataFrames:

In [124]: wp['Item1']
Out[124]:
         A   B   C   D
2000-01-01  0.835993 -0.621868 -0.173710 -0.174326
2000-01-02  -0.354356  2.090183 -0.736019 -1.250412
2000-01-03  -0.581326 -0.244477  0.917119  0.611695
2000-01-04  -1.576078 -0.528562 -0.704643 -0.481453
2000-01-05   1.085093 -1.229749  2.295679 -1.016910

In [125]: wp['Item3'] = wp['Item1'] / wp['Item2']

The API for insertion and deletion is the same as for DataFrame. And as with DataFrame, if the item is a valid python identifier, you can access it as an attribute and tab-complete it in IPython.

### 9.3.5 Transposing

A Panel can be rearranged using its `transpose` method (which does not make a copy by default unless the data are heterogeneous):

In [126]: wp.transpose(2, 0, 1)
Out[126]:
<class 'pandas.core.panel.Panel'>
Dimensions: 4 (items) x 3 (major_axis) x 5 (minor_axis)
Items axis: A to D
Major_axis axis: Item1 to Item3
Minor_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00

### 9.3.6 Indexing / Selection

```
<table>
<thead>
<tr>
<th>Operation</th>
<th>Syntax</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Select item</td>
<td>wp[item]</td>
<td>DataFrame</td>
</tr>
<tr>
<td>Get slice at major_axis label</td>
<td>wp.major_xs(val)</td>
<td>DataFrame</td>
</tr>
<tr>
<td>Get slice at minor_axis label</td>
<td>wp.minor_xs(val)</td>
<td>DataFrame</td>
</tr>
</tbody>
</table>
```

For example, using the earlier example data, we could do:
In [127]: wp['Item1']
Out[127]:

       A     B      C      D
2000-01-01  0.835993 -0.621868 -0.173710 -0.174326
2000-01-02  0.354356  2.090183  0.376019  1.250412
2000-01-03 -0.581326 -0.244477  0.917119  0.611695
2000-01-04 -1.576078 -0.528562 -0.704643 -0.481453
2000-01-05  1.085093  1.229749  2.295679 -1.016910

In [128]: wp.major_xs(wp.major_axis[2])
Out[128]:

       Item1   Item2   Item3
A     -0.581326 -1.271582  0.457167
B     -0.244477 -0.861256  0.283861
C      0.917119 -0.597879 -1.533955
D      0.611695 -0.118700 -5.153265

In [129]: wp.minor_axis
Out[129]: Index([u'A', u'B', u'C', u'D'], dtype='object')

In [130]: wp.minor_xs('C')
Out[130]:

       Item1   Item2   Item3
2000-01-01  0.173710  2.381645 -0.072937
2000-01-02 -0.736019  2.413161  0.305002
2000-01-03  0.917119 -0.597879 -1.533955
2000-01-04 -0.704643 -1.536019  0.458746
2000-01-05  2.295679  0.181524  12.646732

9.3.7 Squeezing

Another way to change the dimensionality of an object is to squeeze a 1-len object, similar to wp['Item1']

In [131]: wp.reindex(items=['Item1']).squeeze()
Out[131]:

       A     B      C      D
2000-01-01  0.835993 -0.621868 -0.173710 -0.174326
2000-01-02  0.354356  2.090183  0.376019  1.250412
2000-01-03 -0.581326 -0.244477  0.917119  0.611695
2000-01-04 -1.576078 -0.528562 -0.704643 -0.481453
2000-01-05  1.085093  1.229749  2.295679 -1.016910

In [132]: wp.reindex(items=['Item1'], minor=['B']).squeeze()
Out[132]:

Freq: D, Name: B, dtype: float64

9.3.8 Conversion to DataFrame

A Panel can be represented in 2D form as a hierarchically indexed DataFrame. See the section hierarchical indexing for more on this. To convert a Panel to a DataFrame, use the to_frame method:
In [133]: panel = pd.Panel(np.random.randn(3, 5, 4), items=['one', 'two', 'three'],
                           major_axis=pd.date_range('1/1/2000', periods=5),
                           minor_axis=['a', 'b', 'c', 'd'])

In [134]: panel.to_frame()
Out[134]:
<table>
<thead>
<tr>
<th></th>
<th>one</th>
<th>two</th>
<th>three</th>
</tr>
</thead>
<tbody>
<tr>
<td>major</td>
<td>minor</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2000-01-01 a</td>
<td>0.445900</td>
<td>-1.286198</td>
<td>-1.023189</td>
</tr>
<tr>
<td>b</td>
<td>-0.574496</td>
<td>-0.407154</td>
<td>0.591682</td>
</tr>
<tr>
<td>c</td>
<td>0.872979</td>
<td>0.068084</td>
<td>-0.008919</td>
</tr>
<tr>
<td>d</td>
<td>0.297255</td>
<td>-2.157051</td>
<td>-0.415572</td>
</tr>
<tr>
<td>2000-01-02 a</td>
<td>-1.022617</td>
<td>-0.443982</td>
<td>-0.772683</td>
</tr>
<tr>
<td>b</td>
<td>1.091870</td>
<td>-0.881639</td>
<td>-0.516197</td>
</tr>
<tr>
<td>c</td>
<td>1.831444</td>
<td>0.851834</td>
<td>0.626655</td>
</tr>
<tr>
<td>d</td>
<td>1.271808</td>
<td>-1.352515</td>
<td>0.269623</td>
</tr>
<tr>
<td>2000-01-03 a</td>
<td>-0.472876</td>
<td>0.228761</td>
<td>1.709250</td>
</tr>
<tr>
<td>b</td>
<td>-0.279340</td>
<td>0.416858</td>
<td>-0.830728</td>
</tr>
<tr>
<td>c</td>
<td>0.495966</td>
<td>0.301709</td>
<td>-0.290244</td>
</tr>
<tr>
<td>d</td>
<td>0.367858</td>
<td>0.569010</td>
<td>-1.588782</td>
</tr>
<tr>
<td>2000-01-04 a</td>
<td>-1.530917</td>
<td>-0.047619</td>
<td>0.639406</td>
</tr>
<tr>
<td>b</td>
<td>-0.285890</td>
<td>0.413370</td>
<td>1.055533</td>
</tr>
<tr>
<td>c</td>
<td>0.943062</td>
<td>0.573056</td>
<td>-0.260898</td>
</tr>
<tr>
<td>d</td>
<td>1.361752</td>
<td>-0.154419</td>
<td>-0.289725</td>
</tr>
<tr>
<td>2000-01-05 a</td>
<td>0.210373</td>
<td>0.987044</td>
<td>0.279621</td>
</tr>
<tr>
<td>b</td>
<td>-1.945608</td>
<td>0.063191</td>
<td>0.454423</td>
</tr>
<tr>
<td>c</td>
<td>2.532409</td>
<td>0.439086</td>
<td>-0.065750</td>
</tr>
<tr>
<td>d</td>
<td>0.373819</td>
<td>1.657475</td>
<td>1.465709</td>
</tr>
</tbody>
</table>

9.4 Panel4D (Experimental)

Panel4D is a 4-Dimensional named container very much like a Panel, but having 4 named dimensions. It is intended as a test bed for more N-Dimensional named containers.

- **labels**: axis 0, each item corresponds to a Panel contained inside
- **items**: axis 1, each item corresponds to a DataFrame contained inside
- **major_axis**: axis 2, it is the index (rows) of each of the DataFrames
- **minor_axis**: axis 3, it is the columns of each of the DataFrames

Panel4D is a sub-class of Panel, so most methods that work on Panels are applicable to Panel4D. The following methods are disabled:

- join, to_frame, to_excel, to_sparse, groupby

Construction of Panel4D works in a very similar manner to a Panel

9.4.1 From 4D ndarray with optional axis labels

In [135]: p4d = pd.Panel4D(np.random.randn(2, 2, 5, 4),
                          labels=['Label1', 'Label2'],
                          items=['Item1', 'Item2'],
                          major_axis=pd.date_range('1/1/2000', periods=5),
                          minor_axis=['A', 'B', 'C', 'D'])
......:

```
In [136]: p4d
Out[136]:
<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
```

9.4.2 From dict of Panel objects

```
In [137]: data = { 'Label1' : pd.Panel({ 'Item1' : pd.DataFrame(np.random.randn(4, 3)) }),
               'Label2' : pd.Panel({ 'Item2' : pd.DataFrame(np.random.randn(4, 2)) }) }

In [138]: pd.Panel4D(data)
Out[138]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 2 (labels) x 2 (items) x 4 (major_axis) x 3 (minor_axis)
Labels axis: Label1 to Label2
Items axis: Item1 to Item2
Major_axis axis: 0 to 3
Minor_axis axis: 0 to 2
```

Note that the values in the dict need only be convertible to Panels. Thus, they can be any of the other valid inputs to Panel as per above.

9.4.3 Slicing

Slicing works in a similar manner to a Panel. [] slices the first dimension. .ix allows you to slice arbitrarily and get back lower dimensional objects

```
In [139]: p4d['Label1']
Out[139]:
<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
```

4D -> Panel

```
In [140]: p4d.ix[:, :, :, 'A']
Out[140]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 2 (major_axis) x 5 (minor_axis)
Items axis: Label1 to Label2
Major_axis axis: Item1 to Item2
Minor_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
```

4D -> DataFrame

```
In [141]: p4d.ix[:, :, 0, 'A']
Out[141]:
```

9.4. Panel4D (Experimental)
**4D -> Series**

In [142]: p4d.ix[:,0,0,'A']

Out[142]:
Label1  1.127489
Label2  0.015494
Name: A, dtype: float64

**9.4.4 Transposing**

A Panel4D can be rearranged using its `transpose` method (which does not make a copy by default unless the data are heterogeneous):

In [143]: p4d.transpose(3, 2, 1, 0)

Out[143]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 4 (labels) x 5 (items) x 2 (major_axis) x 2 (minor_axis)
Labels axis: A to D
Items axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Major_axis axis: Item1 to Item2
Minor_axis axis: Label1 to Label2

**9.5 PanelND (Experimental)**

PanelND is a module with a set of factory functions to enable a user to construct N-dimensional named containers like Panel4D, with a custom set of axis labels. Thus a domain-specific container can easily be created.

The following creates a Panel5D. A new panel type object must be sliceable into a lower dimensional object. Here we slice to a Panel4D.

In [144]: from pandas.core import panelnd

In [145]: Panel5D = panelnd.create_nd_panel_factory(
        klass_name = 'Panel5D',
        orders = ['cool', 'labels', 'items', 'major_axis', 'minor_axis'],
        slices = {'labels': 'labels', 'items': 'items',
                  'major_axis': 'major_axis', 'minor_axis': 'minor_axis'},
        slicer = pd.Panel4D,
        aliases = {'major': 'major_axis', 'minor': 'minor_axis'},
        stat_axis = 2)

In [146]: p5d = Panel5D(dict(C1 = p4d))

In [147]: p5d

Out[147]:
<class 'pandas.core.panelnd.Panel5D'>
Dimensions: 1 (cool) x 2 (labels) x 2 (items) x 5 (major_axis) x 4 (minor_axis)
Cool axis: C1 to C1
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

# print a slice of our 5D
In [148]: p5d.ix['C1',:,:,0:3,:]
Out[148]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 2 (labels) x 2 (items) x 3 (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 2000-01-03 00:00:00
Minor_axis axis: A to D

# transpose it
In [149]: p5d.transpose(1,2,3,4,0)
Out[149]:
<class 'pandas.core.panelnd.Panel5D'>
Dimensions: 2 (cool) x 2 (labels) x 5 (items) x 4 (major_axis) x 1 (minor_axis)
Cool axis: Label1 to Label2
Labels axis: Item1 to Item2
Items axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Major_axis axis: A to D
Minor_axis axis: C1 to C1

# look at the shape & dim
In [150]: p5d.shape
Out[150]: (1, 2, 2, 5, 4)

In [151]: p5d.ndim
Out[151]: 5
ESSENTIAL BASIC FUNCTIONALITY

Here we discuss a lot of the essential functionality common to the pandas data structures. Here’s how to create some of the objects used in the examples from the previous section:

**In [1]:**

```python
index = pd.date_range('1/1/2000', periods=8)
```

**In [2]:**

```python
s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])
```

**In [3]:**

```python
df = pd.DataFrame(np.random.randn(8, 3), index=index,
                   columns=['A', 'B', 'C'])
```

**In [4]:**

```python
wp = pd.Panel(np.random.randn(2, 5, 4), items=['Item1', 'Item2'],
               major_axis=pd.date_range('1/1/2000', periods=5),
               minor_axis=['A', 'B', 'C', 'D'])
```

### 10.1 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.

**In [5]:**

```python
long_series = pd.Series(np.random.randn(1000))
```

**In [6]:**

```python
long_series.head()
```

```
Out[6]:
0   -0.305384
1   -0.479195
2    0.095031
3   -0.270099
4   -0.707140
dtype: float64
```

**In [7]:**

```python
long_series.tail(3)
```

```
Out[7]:
997    0.588446
998    0.026465
999   -1.728222
dtype: float64
```
10.2 Attributes and the raw ndarray(s)

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*
  - **Panel**: *items*, *major_axis*, and *minor_axis*

Note, these attributes can be safely assigned to!

In [8]: df[:2]
Out[8]:

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.187483</td>
<td>-1.933946</td>
<td>0.377312</td>
</tr>
<tr>
<td>0.734122</td>
<td>2.141616</td>
<td>-0.011225</td>
</tr>
</tbody>
</table>

In [9]: df.columns = [x.lower() for x in df.columns]

In [10]: df
Out[10]:

<table>
<thead>
<tr>
<th>a</th>
<th>b</th>
<th>c</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.187483</td>
<td>-1.933946</td>
<td>0.377312</td>
</tr>
<tr>
<td>0.734122</td>
<td>2.141616</td>
<td>-0.011225</td>
</tr>
<tr>
<td>0.048869</td>
<td>-1.360687</td>
<td>-0.479010</td>
</tr>
<tr>
<td>-0.859661</td>
<td>-0.231595</td>
<td>-0.527750</td>
</tr>
<tr>
<td>-1.296337</td>
<td>0.150680</td>
<td>0.123836</td>
</tr>
<tr>
<td>0.571764</td>
<td>1.555563</td>
<td>-0.823761</td>
</tr>
<tr>
<td>0.535420</td>
<td>-1.032853</td>
<td>1.469725</td>
</tr>
<tr>
<td>1.304124</td>
<td>1.449735</td>
<td>0.203109</td>
</tr>
</tbody>
</table>

To get the actual data inside a data structure, one need only access the **values** property:

In [11]: s.values
Out[11]: array([ 0.1122,  0.8717, -0.8161, -0.7849,  1.0307])

In [12]: df.values
Out[12]:

```
array([[ 0.1875, -1.9339,  0.3773],
       [ 0.7341,  2.1416, -0.0112],
       [ 0.0489, -1.3607, -0.4790],
       [-0.8597, -0.2316, -0.5278],
       [-1.2963,  0.1507,  0.1238],
       [ 0.5718,  1.5556, -0.8238],
       [ 0.5354, -1.0329,  1.4697],
       [ 1.3041,  1.4497,  0.2031]])
```

In [13]: wp.values
Out[13]:

```
array([[-1.032 ,  0.9698, -0.9627,  1.3821],
       [-0.9388,  0.6691, -0.4336, -0.2736],
       [ 0.6804, -0.3084, -0.2761, -1.8212],
       [-1.9936, -1.9274, -2.0279,  1.625 ],
       [ 0.5511,  3.0593,  0.4553, -0.0307],
       [ 0.9357,  1.0612, -2.1079,  0.1999]])
```
If a DataFrame or Panel 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.

### 10.3 Accelerated operations

pandas has support for accelerating certain types of binary numerical and boolean operations using the `numexpr` library (starting in 0.11.0) 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.

### 10.4 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.

#### 10.4.1 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 [14]: 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 [15]: df
Out[15]:
   one   three       two
a -0.626544     NaN  -0.351587
b -0.138894  -0.177289  1.136249
c  0.011617  0.462215  -0.448789
d     NaN  1.124472  -1.101558

In [16]: row = df.ix[1]

In [17]: column = df['two']

In [18]: df.sub(row, axis='columns')
Out[18]:
   one   three       two
a -0.487650     NaN  -1.487837
b     0.000000  0.000000    0.000000
c  0.150512  0.639504  -1.585038
d     NaN  1.301762  -2.237808

In [19]: df.sub(row, axis=1)
Out[19]:
   one   three       two
a -0.487650     NaN  -1.487837
b     0.000000  0.000000    0.000000
c  0.150512  0.639504  -1.585038
d     NaN  1.301762  -2.237808

In [20]: df.sub(column, axis='index')
Out[20]:
   one   three       two
a -0.274957     NaN     0.000000
b -1.275144 -1.313539    0.000000
c  0.460406  0.911003    0.000000
d     NaN  2.226031     0.000000

In [21]: df.sub(column, axis=0)
Out[21]:
   one   three       two
a -0.274957     NaN     0.000000
b -1.275144 -1.313539    0.000000
c  0.460406  0.911003    0.000000
d     NaN  2.226031     0.000000

Furthermore you can align a level of a multi-indexed DataFrame with a Series.

In [22]: dfmi = df.copy()

In [23]: dfmi.index = pd.MultiIndex.from_tuples([(1,'a'),(1,'b'),(1,'c'),(2,'a')],
                                            names=['first','second'])

In [24]: dfmi.sub(column, axis=0, level='second')
Out[24]:
   one   three       two
first second
l a  -0.274957     NaN  0.000000
   b -1.275144 -1.313539  0.000000
c  0.460406  0.911003  0.000000

Chapter 10. Essential Basic Functionality
With Panel, describing the matching behavior is a bit more difficult, so the arithmetic methods instead (and perhaps confusingly?) give you the option to specify the broadcast axis. For example, suppose we wished to demean the data over a particular axis. This can be accomplished by taking the mean over an axis and broadcasting over the same axis:

```
In [25]: major_mean = wp.mean(axis='major')

In [26]: major_mean
Out[26]:
       Item1       Item2
A  -0.546569  -0.260774
B   0.492478   0.147993
C  -0.649010  -0.532794
D   0.176307   0.623812
```

```
In [27]: wp.sub(major_mean, axis='major')
Out[27]:
<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
```

And similarly for axis="items" and axis="minor".

**Note:** I could be convinced to make the axis argument in the DataFrame methods match the broadcasting behavior of Panel. Though it would require a transition period so users can change their code...

### 10.4.2 Missing data / operations with fill values

In Series and DataFrame (though not yet in Panel), 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 [28]: df
Out[28]:
     one three two
a -0.626544 NaN -0.351587
b -0.138894 -0.177289 1.136249
c  0.011617  0.462215 -0.448789
d  NaN      1.124472 -1.101558
```

```
In [29]: df2
Out[29]:
     one three two
a -0.626544  1.000000 -0.351587
b -0.138894 -0.177289 1.136249
c  0.011617  0.462215 -0.448789
d  NaN      1.124472 -1.101558
```

```
In [30]: df + df2
Out[30]:
     one three two
a -1.253088 NaN -0.703174
```

### 10.4. Flexible binary operations
In [31]: df.add(df2, fill_value=0)
Out[31]:
    one  three  two
a -1.253088  1.000000 -0.703174
b -0.277789 -0.354579  2.272499
c  0.023235  0.924429 -0.897577
d   NaN    2.248945 -2.203116

10.4.3 Flexible Comparisons

Starting in v0.8, pandas introduced binary comparison methods eq, ne, lt, gt, le, and ge to Series and DataFrame whose behavior is analogous to the binary arithmetic operations described above:

In [32]: df.gt(df2)
Out[32]:
    one  three  two
a   False  False  False
b   False  False  False
c   False  False  False
d   False  False  False

In [33]: df2.ne(df)
Out[33]:
    one  three  two
a   False   True  False
b   False  False   False
c   False  False  False
d    True  False  False

These operations produce a pandas object the same type as the left-hand-side input that if of dtype bool. These boolean objects can be used in indexing operations, see here

10.4.4 Boolean Reductions

You can apply the reductions: empty, any(), all(), and bool() to provide a way to summarize a boolean result.

In [34]: (df > 0).all()
Out[34]:
    one  three  two
    False   False  False
dtype: bool

In [35]: (df > 0).any()
Out[35]:
    one  three  two
    True    True    True
dtype: bool

You can reduce to a final boolean value.
In [36]: (df > 0).any().any()
Out[36]: True

You can test if a pandas object is empty, via the `empty` property.

In [37]: df.empty
Out[37]: False

In [38]: pd.DataFrame(columns=list('ABC')).empty
Out[38]: True

To evaluate single-element pandas objects in a boolean context, use the method `bool()`:

In [39]: pd.Series([True]).bool()
Out[39]: True

In [40]: pd.Series([False]).bool()
Out[40]: False

In [41]: pd.DataFrame([[True]]).bool()
Out[41]: True

In [42]: pd.DataFrame([[False]]).bool()
Out[42]: False

**Warning:** You might be tempted to do the following:

```python
>>> df:
...

Or

```python
>>> df and df2
```

These both will raise as you are trying to compare multiple values.

`ValueError: The truth value of an array is ambiguous. Use a.empty, a.any() or a.all().` 

See `gotchas` for a more detailed discussion.

### 10.4.5 Comparing if objects are equivalent

Often you may find there is more than one way to compute the same result. As a simple example, consider `df+df` and `df*2`. To test that these two computations produce the same result, given the tools shown above, you might imagine using `(df+df == df*2).all()`. But in fact, this expression is False:

In [43]: df+df == df*2
Out[43]:
        one  three  two
    a   True   False   True
    b   True  True   True
    c   True  True   True
    d  False  True   True

In [44]: (df+df == df*2).all()
Out[44]:
    one   False
three    False
two      True
dtype:   bool

Notice that the boolean DataFrame $df+df == df*2$ contains some False values! That is because NaNs do not compare as equals:

In [45]: np.nan == np.nan
Out[45]: False

So, as of v0.13.1, NDFrames (such as Series, DataFrames, and Panels) have an `equals()` method for testing equality, with NaNs in corresponding locations treated as equal.

In [46]: (df+df).equals(df*2)
Out[46]: True

Note that the Series or DataFrame index needs to be in the same order for equality to be True:

In [47]: df1 = pd.DataFrame({'col': ['foo', 0, np.nan]})
In [48]: df2 = pd.DataFrame({'col': [np.nan, 0, 'foo']}, index=[2,1,0])
In [49]: df1.equals(df2)
Out[49]: False
In [50]: df1.equals(df2.sort_index())
Out[50]: True

### 10.4.6 Comparing array-like objects

You can conveniently do element-wise comparisons when comparing a pandas data structure with a scalar value:

In [51]: pd.Series(['foo', 'bar', 'baz']) == 'foo'
Out[51]:
0   True
1  False
2  False
dtype: bool

In [52]: pd.Index(['foo', 'bar', 'baz']) == 'foo'
Out[52]: array([ True, False, False], dtype=bool)

Pandas also handles element-wise comparisons between different array-like objects of the same length:

In [53]: pd.Series(['foo', 'bar', 'baz']) == pd.Index(['foo', 'bar', 'qux'])
Out[53]:
0   True
1   True
2  False
dtype: bool

In [54]: pd.Series(['foo', 'bar', 'baz']) == np.array(['foo', 'bar', 'qux'])
Out[54]:
0   True
1   True
2  False
dtype: bool
Trying to compare Index or Series objects of different lengths will raise a ValueError:

In [55]: pd.Series(['foo', 'bar', 'baz']) == pd.Series(['foo', 'bar'])
ValueError: Series lengths must match to compare

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:

In [55]: np.array([1, 2, 3]) == np.array([2])
Out[55]: array([False, True, False], dtype=bool)

or it can return False if broadcasting can not be done:

In [56]: np.array([1, 2, 3]) == np.array([1, 2])
Out[56]: False

### 10.4.7 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 [57]: df1 = pd.DataFrame({'A': [1., np.nan, 3., 5., np.nan],
                      'B': [np.nan, 2., 3., np.nan, 6.]})

In [58]: df2 = pd.DataFrame({'A': [5., 2., 4., np.nan, 3., 7.],
                      'B': [np.nan, np.nan, 3., 4., 6., 8.]})

In [59]: df1
Out[59]:
   A   B
0  1  NaN
1  NaN  2
2  3  3
3  5  NaN
4  NaN  6

In [60]: df2
Out[60]:
   A   B
0  5  NaN
1  2  NaN
2  4  3
3  NaN  4
4  3  6
5  7  8

In [61]: df1.combine_first(df2)
Out[61]:
   A   B
0  1 NaN
10.4.8 General DataFrame Combine

The `combine_first()` method above calls the more general DataFrame method `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 [62]: combiner = lambda x, y: np.where(pd.isnull(x), y, x)

In [63]: df1.combine(df2, combiner)
```

```
Out[63]:
   A  B
0  1  NaN
1  2  2
2  3  3
3  5  4
4  3  6
5  7  8
```

10.5 Descriptive statistics

A large number of methods for computing descriptive statistics and other related operations on `Series`, `DataFrame`, and `Panel`. 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)
- **Panel**: “items” (axis=0), “major” (axis=1, default), “minor” (axis=2)

For example:

```
In [64]: df
Out[64]:
   one three two
   a  -0.626544 NaN  -0.351587
   b  -0.138894 -0.177289  1.136249
   c   0.011617  0.462215  -0.448789
   d   NaN  1.124472  -1.101558

In [65]: df.mean(0)
Out[65]:
   one     -0.251274
   three   0.469799
   two    -0.191421
dtype: float64
```
In [66]: df.mean(1)
Out[66]:
   a  -0.489066
   b   0.273355
   c  0.008348
   d  0.011457
dtype: float64

All such methods have a skipna option signaling whether to exclude missing data (True by default):

In [67]: df.sum(0, skipna=False)
Out[67]:
   one    NaN
   three   NaN
   two -0.765684
dtype: float64

In [68]: df.sum(axis=1, skipna=True)
Out[68]:
   a  -0.978131
   b   0.820066
   c   0.025044
   d   0.022914
dtype: float64

Combined with the broadcasting / arithmetic behavior, one can describe various statistical procedures, like standardization (rendering data zero mean and standard deviation 1), very concisely:

In [69]: ts_stand = (df - df.mean()) / df.std()
   
In [70]: ts_stand.std()
Out[70]:
   one  1
   three 1
   two  1
dtype: float64

In [71]: xs_stand = df.sub(df.mean(1), axis=0).div(df.std(1), axis=0)
   
In [72]: xs_stand.std(1)
Out[72]:
   a  1
   b  1
   c  1
   d  1
dtype: float64

Note that methods like cumsum() and cumprod() preserve the location of NA values:

In [73]: df.cumsum()
Out[73]:
   a  -0.626544    NaN -0.351587
   b  -0.765438 -0.177289   0.784662
   c  -0.753821  0.284925  0.335874
   d     NaN   1.409398  -0.765684

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.

10.5. Descriptive statistics
<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>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>Unbiased standard deviation</td>
</tr>
<tr>
<td>var</td>
<td>Unbiased variance</td>
</tr>
<tr>
<td>sem</td>
<td>Unbiased standard error of the mean</td>
</tr>
<tr>
<td>skew</td>
<td>Unbiased skewness (3rd moment)</td>
</tr>
<tr>
<td>kurt</td>
<td>Unbiased 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:

```
In [74]: np.mean(df['one'])
Out[74]: -0.25127365175839511

In [75]: np.mean(df['one'].values)
Out[75]: nan
```

Series also has a method `nunique()` which will return the number of unique non-null values:

```
In [76]: series = pd.Series(np.random.randn(500))
In [77]: series[20:500] = np.nan
In [78]: series[10:20] = 5
In [79]: series.nunique()
Out[79]: 11
```

### 10.5.1 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):

```
In [80]: series = pd.Series(np.random.randn(1000))
In [81]: series[::2] = np.nan
In [82]: series.describe()
Out[82]:
   count     500.000000
   mean    -0.039663
   std      1.069371
   min     -3.463789
```
In [83]: frame = pd.DataFrame(np.random.randn(1000, 5), columns=['a', 'b', 'c', 'd', 'e'])
In [84]: frame.ix[:2] = np.nan
In [85]: frame.describe()
Out[85]:

<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>count</td>
<td>500.000000</td>
<td>500.000000</td>
<td>500.000000</td>
<td>500.000000</td>
<td>500.000000</td>
</tr>
<tr>
<td>mean</td>
<td>0.000954</td>
<td>-0.044014</td>
<td>0.075936</td>
<td>-0.003679</td>
<td>0.020751</td>
</tr>
<tr>
<td>std</td>
<td>1.005133</td>
<td>0.974882</td>
<td>0.967432</td>
<td>1.004732</td>
<td>0.963812</td>
</tr>
<tr>
<td>min</td>
<td>-3.010899</td>
<td>-2.782760</td>
<td>-3.401252</td>
<td>-2.944925</td>
<td>-3.794127</td>
</tr>
<tr>
<td>25%</td>
<td>-0.682900</td>
<td>-0.681161</td>
<td>-0.528190</td>
<td>-0.663503</td>
<td>-0.615717</td>
</tr>
<tr>
<td>50%</td>
<td>-0.001651</td>
<td>-0.006279</td>
<td>0.040098</td>
<td>-0.003378</td>
<td>0.006282</td>
</tr>
<tr>
<td>75%</td>
<td>0.656439</td>
<td>0.632852</td>
<td>0.717919</td>
<td>0.687214</td>
<td>0.653423</td>
</tr>
<tr>
<td>max</td>
<td>3.007143</td>
<td>2.627688</td>
<td>2.702490</td>
<td>2.850852</td>
<td>3.072117</td>
</tr>
</tbody>
</table>

dtype: float64

You can select specific percentiles to include in the output:

In [86]: series.describe(percentiles=[.05, .25, .75, .95])
Out[86]:

<table>
<thead>
<tr>
<th></th>
<th>count</th>
<th>mean</th>
<th>std</th>
<th>min</th>
<th>5%</th>
<th>25%</th>
<th>75%</th>
<th>95%</th>
</tr>
</thead>
<tbody>
<tr>
<td>count</td>
<td>500.000000</td>
<td>-0.039663</td>
<td>1.069371</td>
<td>-3.463789</td>
<td>-1.741334</td>
<td>-0.731101</td>
<td>0.672758</td>
<td>1.854383</td>
</tr>
<tr>
<td>mean</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>std</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>min</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>25%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>75%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>95%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>max</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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 [87]: s = pd.Series(['a', 'a', 'b', 'b', 'a', 'a', np.nan, 'c', 'd', 'a'])
In [88]: s.describe()
Out[88]:

<table>
<thead>
<tr>
<th>count</th>
<th>unique</th>
<th>top</th>
<th>freq</th>
</tr>
</thead>
<tbody>
<tr>
<td>9</td>
<td>4</td>
<td>a</td>
<td>5</td>
</tr>
</tbody>
</table>
dtype: object

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:

In [89]: frame = pd.DataFrame({'a': ['Yes', 'Yes', 'No', 'No'], 'b': range(4)})
In [90]: frame.describe()
This behaviour can be controlled by providing a list of types as include/exclude arguments. The special value all can also be used:

In [91]: frame.describe(include=['object'])
Out[91]:
    a
   count 4
   unique 2
   top  No
   freq  2

In [92]: frame.describe(include=['number'])
Out[92]:
   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

In [93]: frame.describe(include='all')
Out[93]:
   a       b
  count  4.000000  NaN
   unique 2   NaN
   top   No    NaN
   freq  2   NaN
   mean  NaN   1.500000
   std   NaN   1.290994
   min   NaN   0.000000
   25%   NaN   0.750000
   50%   NaN   1.500000
   75%   NaN   2.250000
   max   NaN   3.000000

That feature relies on select_dtypes. Refer to there for details about accepted inputs.

10.5.2 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 [94]: s1 = pd.Series(np.random.randn(5))

In [95]: s1
Out[95]:
0   -0.872725
1    1.522411
2    0.080594
3   -1.676067
4    0.435804
dtype: float64

In [96]: s1.idxmin(), s1.idxmax()
Out[96]: (3, 1)

In [97]: df1 = pd.DataFrame(np.random.randn(5,3), columns=['A','B','C'])

In [98]: df1
Out[98]:
   A        B         C
0  0.445734 -1.649461  0.169660
1  1.246181  0.131682 -2.001988
2 -1.273023  0.870502  0.214583
3  0.088452 -0.173364  1.207466
4  0.546121  0.409515 -0.310515

In [99]: df1.idxmin(axis=0)
Out[99]:
A    2
B    0
C    1
dtype: int64

In [100]: df1.idxmax(axis=1)
Out[100]:
0    A
1    A
2    B
3    C
4    A
dtype: object

When there are multiple rows (or columns) matching the minimum or maximum value, \texttt{idxmin()} and \texttt{idxmax()} return the first matching index:

In [101]: df3 = pd.DataFrame([2, 1, 1, 3, np.nan], columns=['A'], index=list('edcba'))

In [102]: df3
Out[102]:
   A
a  NaN
d  1
c  1
b  3
e  2

In [103]: df3['A'].idxmin()
Out[103]: 'd'
pandas: powerful Python data analysis toolkit, Release 0.17.0

Note: idxmin and idxmax are called argmin and argmax in NumPy.

10.5.3 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:
In [104]: data = np.random.randint(0, 7, size=50)
In [105]:
Out[105]:
array([5,
3,
0,

data
3, 2, 2, 1, 4, 0, 4, 0, 2, 0, 6, 4, 1, 6, 3, 3, 0, 2, 1, 0, 5, 5,
6, 1, 5, 6, 2, 0, 0, 6, 3, 3, 5, 0, 4, 3, 3, 3, 0, 6, 1, 3, 5, 5,
4, 0, 6])

In [106]: s = pd.Series(data)
In [107]: s.value_counts()
Out[107]:
0
11
3
10
6
7
5
7
4
5
2
5
1
5
dtype: int64
In [108]: pd.value_counts(data)
Out[108]:
0
11
3
10
6
7
5
7
4
5
2
5
1
5
dtype: int64

Similarly, you can get the most frequently occurring value(s) (the mode) of the values in a Series or DataFrame:
In [109]: s5 = pd.Series([1, 1, 3, 3, 3, 5, 5, 7, 7, 7])
In [110]: s5.mode()
Out[110]:
0
3
1
7
dtype: int64
In [111]: df5 = pd.DataFrame({"A": np.random.randint(0, 7, size=50),
.....:
"B": np.random.randint(-10, 15, size=50)})
.....:
In [112]: df5.mode()
Out[112]:
A B
0 1 -5

350

Chapter 10. Essential Basic Functionality


10.5.4 Discretization and quantiling

Continuous values can be discretized using the `cut()` (bins based on values) and `qcut()` (bins based on sample quantiles) functions:

```python
In [113]: arr = np.random.randn(20)
In [114]: factor = pd.cut(arr, 4)

In [115]: factor
Out[115]:
[(-0.645, 0.336], (-2.61, -1.626], (-1.626, -0.645], (-1.626, -0.645], ...
(0.336, 1.316], (0.336, 1.316], (0.336, 1.316], (0.336, 1.316], (-2.61, -1.626]]
Length: 20
Categories (4, object): [(-2.61, -1.626] < (-1.626, -0.645] < (-0.645, 0.336] < (0.336, 1.316)]

In [116]: factor = pd.cut(arr, [-5, -1, 0, 1, 5])

In [117]: factor
Out[117]:
[(-1, 0], (-5, -1], (-1, 0], (-5, -1], (-1, 0], ..., (0, 1], (1, 5], (0, 1], (0, 1], (-5, -1]]
Length: 20
Categories (4, object): [(-5, -1] < (-1, 0] < (0, 1] < (1, 5)]

qcut() computes sample quantiles. For example, we could slice up some normally distributed data into equal-size quartiles like so:

```python
In [118]: arr = np.random.randn(30)
In [119]: factor = pd.qcut(arr, [0, .25, .5, .75, 1])

In [120]: factor
Out[120]:
[(-0.139, 1.00736], (1.00736, 1.976], (1.00736, 1.976], [-1.0705, -0.439], [-1.0705, -0.439], ...
(1.00736, 1.976], [-1.0705, -0.439], (-0.439, -0.139], (-0.439, -0.139], (-0.439, -0.139]]
Length: 30
Categories (4, object): [(-1.0705, -0.439] < (-0.439, -0.139] < (-0.139, 1.00736] < (1.00736, 1.976)]

In [121]: pd.value_counts(factor)
Out[121]:
(1.00736, 1.976]    8
[-1.0705, -0.439]    8
(-0.439, 1.00736]   7
(-0.439, -0.139]    7
dtype: int64
```

We can also pass infinite values to define the bins:

```python
In [122]: arr = np.random.randn(20)
In [123]: factor = pd.cut(arr, [-np.inf, 0, np.inf])

In [124]: factor
Out[124]:
[(-inf, 0], (0, inf], (0, inf], (0, inf], (0, inf], (0, inf], ...
(-inf, 0], (0, inf], (0, inf], (0, inf], (0, inf], (0, inf],
Length: 20
Categories (2, object): [(-inf, 0] < {0, inf}]
```
10.6 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. Elementwise function application: applymap()

10.6.1 Tablewise Function Application

New in version 0.16.2.

DataFrames and Series can of course just be passed into functions. However, if the function needs to be called in a chain, consider using the pipe() method. Compare the following

```python
>>> f(g(h(df), arg1=1), arg2=2, arg3=3)
```

with the equivalent

```python
>>> (df.pipe(h)
     .pipe(g, arg1=1)
     .pipe(f, arg2=2, arg3=3)
)
```

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 f, g, and h each expected the 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.poisson, 'data') to pipe:

```python
In [125]: import statsmodels.formula.api as sm
In [126]: bb = pd.read_csv('data/baseball.csv', index_col='id')
In [127]: (bb.query('h > 0')
     ....:     .assign(ln_h = lambda df: np.log(df.h))
     ....:     .pipe((sm.poisson, 'data'), 'hr ~ ln_h + year + g + C(lg)')
     ....:     .fit()
     ....:     .summary())
```

Optimization terminated successfully.
Current function value: 2.116284
Iterations 24

Out[127]:
<class 'statsmodels.iolib.summary.Summary'>

```
```
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 (pd.DataFrame.pipe?? in IPython).

### 10.6.2 Row or Column-wise Function Application

Arbitrary functions can be applied along the axes of a DataFrame or Panel using the `apply()` method, which, like the descriptive statistics methods, take an optional `axis` argument:

```python
In [128]: df.apply(np.mean)
Out[128]:
one  -0.251274
three  0.469799
two  -0.191421
dtype: float64
```

```python
In [129]: df.apply(np.mean, axis=1)
Out[129]:
a  -0.489066
b   0.273355
c  0.008348
d  0.011457
dtype: float64
```

```python
In [130]: df.apply(lambda x: x.max() - x.min())
Out[130]:
one  0.638161
three  1.301762
two  2.237808
dtype: float64
```

```python
In [131]: df.apply(np.cumsum)
Out[131]:
     one  three  two
a  -0.626544  NaN  -0.351587
b  -0.765438 -0.177289  0.784662
c  -0.753821  0.284925  0.335874
d   NaN  1.409398 -0.765684
```

```python
In [132]: df.apply(np.exp)
```
Depending on the return type of the function passed to `apply()`, the result will either be of lower dimension or the same dimension.

`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 [133]: tsdf = pd.DataFrame(np.random.randn(1000, 3), columns=['A', 'B', 'C'],
                       index=pd.date_range('1/1/2000', periods=1000))
```

```python
In [134]: tsdf.apply(lambda x: x.idxmax())
Out[134]:
A 2001-04-27
B 2002-06-02
C 2000-04-02
```

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 [135]: tsdf
Out[135]:
   A       B       C
2000-01-01 1.796883 -0.930690 3.542846
2000-01-02 -1.242888 -0.695279 -1.000884
2000-01-03 -0.720299 0.546303 -0.082042
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 -0.527402 0.933507 0.129646
2000-01-09 -0.338903 -1.265452 -1.969004
2000-01-10 0.532566 0.341548 0.150493
```

```python
In [136]: tsdf.apply(pd.Series.interpolate)
Out[136]:
   A       B       C
2000-01-01 1.796883 -0.930690 3.542846
2000-01-02 -1.242888 -0.695279 -1.000884
2000-01-03 -0.720299 0.546303 -0.082042
2000-01-04 -0.681720 0.623743 -0.039704
2000-01-05 -0.643140 0.701184 0.002633
2000-01-06 -0.604561 0.778625 0.044971
2000-01-07 -0.565982 0.856066 0.087309
```
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.

See also:
The section on `GroupBy` demonstrates related, flexible functionality for grouping by some criterion, applying, and combining the results into a Series, DataFrame, etc.

### 10.6.3 Applying elementwise Python 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:

```python
In [137]: df4
Out[137]:
     one  three  two
  a -0.626544  NaN  -0.351587
  b -0.138894 -0.177289  1.136249
  c  0.011617  0.462215 -0.448789
  d  NaN       1.124472 -1.101558

In [138]: f = lambda x: len(str(x))

In [139]: df4['one'].map(f)
Out[139]:
  a  14
  b  15
  c  15
  d  3
Name: one, dtype: int64

In [140]: df4.applymap(f)
Out[140]:
     one  three  two
  a   14     3   15
  b   15     15   11
  c   15    14   15
  d    3    13   14

Series.map() has an additional feature which is that it can be used to easily “link” or “map” values defined by a secondary series. This is closely related to merging/joining functionality:

```python
In [141]: s = pd.Series({'six': 6., 'seven': 7.})

In [142]: t = pd.Series({'six': 6., 'seven': 7.})

In [143]: s
Out[143]:
  a  six
  b  seven
```
10.6.4 Applying with a Panel

Applying with a Panel will pass a Series to the applied function. If the applied function returns a Series, the result of the application will be a Panel. If the applied function reduces to a scalar, the result of the application will be a DataFrame.

Note: Prior to 0.13.1 apply on a Panel would only work on ufuncs (e.g. np.sum/np.max).

In [145]: import pandas.util.testing as tm

In [146]: panel = tm.makePanel(5)

In [147]: panel['ItemA']

In [148]: result = panel.apply(lambda x: x*2, axis='items')

In [149]: result['ItemA']
A reduction operation.

In [152]: panel.apply(lambda x: x.dtype, axis='items')

Out[152]:
                  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

A similar reduction type operation

In [153]: panel.apply(lambda x: x.sum(), axis='major_axis')

Out[153]:

<table>
<thead>
<tr>
<th></th>
<th>ItemA</th>
<th>ItemB</th>
<th>ItemC</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>3.427831</td>
<td>-2.581431</td>
<td>0.840809</td>
</tr>
<tr>
<td>B</td>
<td>3.241522</td>
<td>-1.409935</td>
<td>-1.114512</td>
</tr>
<tr>
<td>C</td>
<td>5.783237</td>
<td>0.319672</td>
<td>-0.431906</td>
</tr>
<tr>
<td>D</td>
<td>-1.325260</td>
<td>-2.914834</td>
<td>0.857043</td>
</tr>
</tbody>
</table>

This last reduction is equivalent to

In [154]: panel.sum('major_axis')

Out[154]:

<table>
<thead>
<tr>
<th></th>
<th>ItemA</th>
<th>ItemB</th>
<th>ItemC</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>3.427831</td>
<td>-2.581431</td>
<td>0.840809</td>
</tr>
<tr>
<td>B</td>
<td>3.241522</td>
<td>-1.409935</td>
<td>-1.114512</td>
</tr>
<tr>
<td>C</td>
<td>5.783237</td>
<td>0.319672</td>
<td>-0.431906</td>
</tr>
<tr>
<td>D</td>
<td>-1.325260</td>
<td>-2.914834</td>
<td>0.857043</td>
</tr>
</tbody>
</table>

A transformation operation that returns a Panel, but is computing the z-score across the major_axis.

In [155]: result = panel.apply(lambda x: (x-x.mean())/x.std(), axis='major_axis')

In [156]: result

Out[156]:
<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 [157]: result['ItemA']

Out[157]:
                  A  B    C    D
2000-01-03 -0.469761 1.156225 -0.441347 1.341731
2000-01-04 1.422763 -0.444015 -0.882647 0.398661
2000-01-05 -0.156654 -1.453694 0.367936 -0.619210
Apply can also accept multiple axes in the axis argument. This will pass a DataFrame of the cross-section to the applied function.

In [158]: f = lambda x: ((x.T-x.mean(axis=1))/x.std(axis=1)).T

In [159]: result = panel.apply(f, axis=['items','major_axis'])

In [160]: result
Out[160]:
<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 [161]: result.loc[:,:,'ItemA']
Out[161]:
<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>0.864236</td>
<td>1.132969</td>
<td>0.557316</td>
<td>0.575106</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>0.795745</td>
<td>0.652527</td>
<td>0.534808</td>
<td>-0.070674</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>-0.310864</td>
<td>0.558627</td>
<td>1.086688</td>
<td>-1.051477</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>-0.001065</td>
<td>0.832460</td>
<td>0.846006</td>
<td>0.043602</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>1.128946</td>
<td>1.152469</td>
<td>-0.218186</td>
<td>-0.891680</td>
</tr>
</tbody>
</table>

This is equivalent to the following

In [162]: result = pd.Panel(dict([(ax, f(panel.loc[:,:ax]))
     | .....: for ax in panel.minor_axis ]))
     | .....:

In [163]: result
Out[163]:
<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 [164]: result.loc[:,:,'ItemA']
Out[164]:
<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>0.864236</td>
<td>1.132969</td>
<td>0.557316</td>
<td>0.575106</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>0.795745</td>
<td>0.652527</td>
<td>0.534808</td>
<td>-0.070674</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>-0.310864</td>
<td>0.558627</td>
<td>1.086688</td>
<td>-1.051477</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>-0.001065</td>
<td>0.832460</td>
<td>0.846006</td>
<td>0.043602</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>1.128946</td>
<td>1.152469</td>
<td>-0.218186</td>
<td>-0.891680</td>
</tr>
</tbody>
</table>

10.7 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 [165]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [166]: s
Out[166]:
a -1.010924
b -0.672504
c -1.139222
d  0.354653
e  0.563622
dtype: float64

In [167]: s.reindex(['e', 'b', 'f', 'd'])
Out[167]:
e  0.563622
b -0.672504
f   NaN
d  0.354653
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 [168]: df
Out[168]:
   one  three  two
a -0.626544  NaN -0.351587
b -0.138894 -0.177289  1.136249
c  0.011617  0.462215 -0.448789
d   NaN   1.124472 -1.101558

In [169]: df.reindex(index=['c', 'f', 'b'], columns=['three', 'two', 'one'])
Out[169]:
   three  two   one
  c  0.462215 -0.448789  0.011617
  f   NaN    NaN     NaN
  b -0.177289  1.136249 -0.138894
```

For convenience, you may utilize the `reindex_axis()` method, which takes the labels and a keyword axis parameter.

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:

```python
In [170]: rs = s.reindex(df.index)

In [171]: rs
Out[171]:
a -1.010924
b -0.672504
c -1.139222
d  0.354653
dtype: float64
```
In [172]: rs.index is df.index
Out[172]: True

This means that the reindexed Series’s index is the same Python object as the DataFrame’s index.

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.

### 10.7.1 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 [173]: df2
Out[173]:

<table>
<thead>
<tr>
<th></th>
<th>one</th>
<th>two</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>-0.626544</td>
<td>-0.351587</td>
</tr>
<tr>
<td>b</td>
<td>-0.138894</td>
<td>1.136249</td>
</tr>
<tr>
<td>c</td>
<td>0.011617</td>
<td>-0.448789</td>
</tr>
</tbody>
</table>

In [174]: df3
Out[174]:

<table>
<thead>
<tr>
<th></th>
<th>one</th>
<th>two</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>-0.375270</td>
<td>-0.463545</td>
</tr>
<tr>
<td>b</td>
<td>0.112379</td>
<td>1.024292</td>
</tr>
<tr>
<td>c</td>
<td>0.262891</td>
<td>-0.560746</td>
</tr>
</tbody>
</table>

In [175]: df.reindex_like(df2)
Out[175]:

<table>
<thead>
<tr>
<th></th>
<th>one</th>
<th>two</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>-0.626544</td>
<td>-0.351587</td>
</tr>
<tr>
<td>b</td>
<td>-0.138894</td>
<td>1.136249</td>
</tr>
<tr>
<td>c</td>
<td>0.011617</td>
<td>-0.448789</td>
</tr>
</tbody>
</table>

### 10.7.2 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 [176]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [177]: s1 = s[:4]

In [178]: s2 = s[1:]

In [179]: s1.align(s2)
Out[179]:
   a    NaN
   b  1.092702
   c -1.481449
   d  1.781190
   e    NaN

dtype: float64, a    NaN
   b  1.092702
   c -1.481449
   d  1.781190
   e -0.031543

dtype: float64)

In [180]: s1.align(s2, join='inner')
Out[180]:
   b  1.092702
   c -1.481449
   d  1.781190

dtype: float64, b  1.092702
   c -1.481449
   d  1.781190

dtype: float64)

In [181]: s1.align(s2, join='left')
Out[181]:
   a -0.365106
   b  1.092702
   c -1.481449
   d  1.781190

dtype: float64, a    NaN
   b  1.092702
   c -1.481449
   d  1.781190

dtype: float64)

For DataFrames, the join method will be applied to both the index and the columns by default:

In [182]: df.align(df2, join='inner')
Out[182]:
   one  two
   a -0.626544 -0.351587
   b -0.138894  1.136249
   c  0.011617 -0.448789

dtype: float64, one  two
   a -0.626544 -0.351587
   b -0.138894  1.136249
   c  0.011617 -0.448789

You can also pass an axis option to only align on the specified axis:

In [183]: df.align(df2, join='inner', axis=0)
Out[183]:
   one  three  two
   a -0.626544 -0.351587
   b -0.138894  1.136249
   c  0.011617 -0.448789

10.7. Reindexing and altering labels
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:

```
In [184]: df.align(df2.ix[0], axis=1)
Out[184]:
   one  three  two
a -0.626544 NaN -0.351587
b -0.138894 -0.177289 1.136249
c 0.011617 0.462215 -0.448789
```

10.7.3 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 [185]: rng = pd.date_range('1/3/2000', periods=8)
In [186]: ts = pd.Series(np.random.randn(8), index=rng)
In [187]: ts2 = ts[[0, 3, 6]]
```

```
In [188]: ts
Out[188]:
2000-01-03  0.480993
2000-01-04  0.604244
2000-01-05 -0.487265
2000-01-06  1.990533
2000-01-07  0.327007
2000-01-08  1.053639
2000-01-09 -2.927808
2000-01-10  0.082065
Freq: D, dtype: float64
```

```
In [189]: ts2
Out[189]:
2000-01-03  0.480993
2000-01-06  1.990533
2000-01-09 -2.927808
dtype: float64
```

```
In [190]: ts2.reindex(ts.index)
```
Out[190]:
2000-01-03  0.480993
2000-01-04   NaN
2000-01-05   NaN
2000-01-06  1.990533
2000-01-07   NaN
2000-01-08   NaN
2000-01-09 -2.927808
2000-01-10   NaN
Freq: D, dtype: float64

In [191]: ts2.reindex(ts.index, method='ffill')
Out[191]:
2000-01-03  0.480993
2000-01-04  0.480993
2000-01-05  0.480993
2000-01-06  1.990533
2000-01-07  1.990533
2000-01-08  1.990533
2000-01-09 -2.927808
2000-01-10 -2.927808
Freq: D, dtype: float64

In [192]: ts2.reindex(ts.index, method='bfill')
Out[192]:
2000-01-03  0.480993
2000-01-04  1.990533
2000-01-05  1.990533
2000-01-06  1.990533
2000-01-07 -2.927808
2000-01-08 -2.927808
2000-01-09 -2.927808
2000-01-10   NaN
Freq: D, dtype: float64

In [193]: ts2.reindex(ts.index, method='nearest')
Out[193]:
2000-01-03  0.480993
2000-01-04  0.480993
2000-01-05  1.990533
2000-01-06  1.990533
2000-01-07  1.990533
2000-01-08 -2.927808
2000-01-09 -2.927808
2000-01-10 -2.927808
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`:

In [194]: ts2.reindex(ts.index).fillna(method='ffill')
Out[194]:
2000-01-03  0.480993
2000-01-04  0.480993
2000-01-05  1.990533
2000-01-06  1.990533
2000-01-07  1.990533
2000-01-08 -2.927808
2000-01-09 -2.927808
2000-01-10 -2.927808

10.7. Reindexing and altering labels 363
reindex() will raise a ValueError if the index is not monotonic increasing or descreasing. fillna() and interpolate() will not make any checks on the order of the index.

### 10.7.4 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:

```python
In [195]: ts2.reindex(ts.index, method='ffill', limit=1)
Out[195]:
2000-01-03  0.480993
2000-01-04  0.480993
2000-01-05  NaN
2000-01-06  1.990533
2000-01-07  1.990533
2000-01-08  NaN
2000-01-09 -2.927808
2000-01-10 -2.927808
Freq: D, dtype: float64
```

In contrast, tolerance specifies the maximum distance between the index and indexer values:

```python
In [196]: ts2.reindex(ts.index, method='ffill', tolerance='1 day')
Out[196]:
2000-01-03  0.480993
2000-01-04  0.480993
2000-01-05  NaN
2000-01-06  1.990533
2000-01-07  1.990533
2000-01-08  NaN
2000-01-09 -2.927808
2000-01-10 -2.927808
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.

### 10.7.5 Dropping labels from an axis

A method closely related to reindex is the drop() function. It removes a set of labels from an axis:

```python
In [197]: df
Out[197]:
     one  three  two
a -0.626544  NaN -0.351587
b -0.138894 -0.177289  1.136249
c  0.011617  0.462215 -0.448789
d  NaN       1.124472 -1.101558

In [198]: df.drop(['a', 'd'], axis=0)
Out[198]:
     one  three  two
     a -0.626544  NaN -0.351587
     b -0.138894 -0.177289  1.136249
     c  0.011617  0.462215 -0.448789
```
b -0.138894 -0.177289 1.136249
c 0.011617 0.462215 -0.448789

In [199]: df.drop(['one'], axis=1)
Out[199]:
            three    two
a      NaN -0.351587
b -0.177289  1.136249
c  0.462215 -0.448789
d  1.124472 -1.101558

Note that the following also works, but is a bit less obvious / clean:

In [200]: df.reindex(df.index.difference(['a', 'd']))
Out[200]:
            one    three    two
b -0.138894 -0.177289  1.136249
c  0.011617  0.462215 -0.448789

10.7.6 Renaming / mapping labels

The rename() method allows you to relabel an axis based on some mapping (a dict or Series) or an arbitrary function.

In [201]: s
Out[201]:
a  -0.365106
b   1.092702
c  -1.481449
d   1.781190
e  -0.031543
dtype: float64

In [202]: s.rename(str.upper)
Out[202]:
A   -0.365106
B    1.092702
C   -1.481449
D    1.781190
E   -0.031543
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). But if you pass a dict or Series, it need only contain a subset of the labels as keys:

In [203]: df.rename(columns={'one': 'foo', 'two': 'bar'},
                 index={'a': 'apple', 'b': 'banana', 'd': 'durian'})
Out[203]:
               foo    three    bar
apple -0.626544     NaN -0.351587
banana -0.138894 -0.177289  1.136249
c    0.011617  0.462215 -0.448789
durian     NaN  1.124472 -1.101558

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. The Panel class has a related rename_axis() class which can rename any of its three axes.

10.7. Reindexing and altering labels
10.8 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. Other data structures, like DataFrame and Panel, 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
- **Panel**: item labels

Thus, for example, iterating over a DataFrame gives you the column names:

```python
In [204]: df = pd.DataFrame({"col1" : np.random.randn(3), "col2" : np.random.randn(3)},
                    index=["a", "b", "c"])

In [205]: for col in df:
       ....:     print(col)
       ....:
       col1
       col2
```

Pandas objects also have the dict-like `iteritems()` 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 tuples of the values. This is a lot faster as `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 using e.g. 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:

```
In [206]: df = pd.DataFrame({'a': [1, 2, 3], 'b': ['a', 'b', 'c']})

In [207]: for index, row in df.iterrows():
   ...:     row['a'] = 10
   ...:

In [208]: df
Out[208]:
   a  b
0  1  a
1  2  b
2  3  c
```

### 10.8.1 iteritems

Consistent with the dict-like interface, `iteritems()` iterates through key-value pairs:

- **Series**: (index, scalar value) pairs
- **DataFrame**: (column, Series) pairs
- **Panel**: (item, DataFrame) pairs

For example:

```
In [209]: for item, frame in wp.iteritems():
   ...:     print(item)
   ...:     print(frame)
   ...:
Item1
   0   2000-01-01 -1.032011  0.969818 -0.962723  1.382083
   1   2000-01-02 -0.938794  0.669142 -0.433567 -0.273610
   2   2000-01-03  0.680433 -0.308450 -0.276099 -1.821168
   3   2000-01-04 -1.993606 -1.927385 -2.027924  1.624972
   4   2000-01-05  0.551135  3.059267  0.455264 -0.030740
Item2
   0   2000-01-01  0.935716  1.061192 -2.107852  0.199905
   1   2000-01-02  0.323586 -0.641630 -0.587514  0.053897
   2   2000-01-03  0.194889 -0.381994  0.318587  2.089075
   3   2000-01-04 -0.728293 -0.090255 -0.748199  1.318931
   4   2000-01-05 -2.029766  0.792652  0.461007 -0.542749
```

### 10.8.2 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:

```
In [210]: for row_index, row in df.iterrows():
   ...:     print('$s\n%s' % (row_index, row))
   ...:
```

10.8. Iteration
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 [211]: df_orig = pd.DataFrame([[1, 1.5]], columns=['int', 'float'])
```

```python
In [212]: df_orig.dtypes
Out[212]:
int  int64
float float64
dtype: object
```

```python
In [213]: row = next(df_orig.iterrows())[1]
```

```python
In [214]: row
Out[214]:
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 [215]: row['int'].dtype
Out[215]: dtype('float64')
```

```python
In [216]: df_orig['int'].dtype
Out[216]: dtype('int64')
```

To preserve dtypes while iterating over the rows, it is better to use `itertuples()` which returns tuples of the values and which is generally much faster as `iterrows`.

For instance, a contrived way to transpose the DataFrame would be:

```python
In [217]: df2 = pd.DataFrame({'x': [1, 2, 3], 'y': [4, 5, 6]})
```

```python
In [218]: print(df2)
x y
0 1 4
1 2 5
2 3 6
```

```python
In [219]: print(df2.T)
x 1 2 3
y 4 5 6
```
In [220]: df2_t = pd.DataFrame(dict((idx, values) for idx, values in df2.iterrows()))

In [221]: print(df2_t)
   0   1   2
x  1  2  3
y  4  5  6

10.8.3 `itertuples`

The `itertuples()` method will return an iterator yielding a tuple 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 [222]: for row in df.itertuples():
   ....:     print(row)
   ....:         (0, 1, 'a')
   ....:         (1, 2, 'b')
   ....:         (2, 3, 'c')

This method does not convert the row to a Series object but just returns the values inside a tuple. Therefore, `itertuples()` preserves the data type of the values and is generally faster as `iterrows()`.

10.9 `.dt accessor`

Series has an accessor to succinctly return datetime like properties for the `values` of the Series, if it is a date-time/period like Series. This will return a Series, indexed like the existing Series.

```
# datetime
In [223]: s = pd.Series(pd.date_range('20130101 09:10:12', periods=4))

In [224]: s
Out[224]:
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 [225]: s.dt.hour
Out[225]:
0    9
1    9
2    9
3    9
dtype: int64

In [226]: s.dt.second
Out[226]:
0    12
1    12
2    12
3    12
dtype: int64
```
```
In [227]: s.dt.day
Out[227]:
0   1  
1   2  
2   3  
3   4  
dtype: int64
```

This enables nice expressions like this:

```
In [228]: s[s.dt.day==2]
Out[228]:
1   2013-01-02 09:10:12  
dtype: datetime64[ns]
```

You can easily produces tz aware transformations:

```
In [229]: stz = s.dt.tz_localize('US/Eastern')
In [230]: stz
Out[230]:
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 [231]: stz.dt.tz
Out[231]: <DstTzInfo 'US/Eastern' LMT-1 day, 19:04:00 STD>
```

You can also chain these types of operations:

```
In [232]: s.dt.tz_localize('UTC').dt.tz_convert('US/Eastern')
Out[232]:
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.dt.strftime()` which supports the same format as the standard `strftime()`.

```
# DatetimeIndex
In [233]: s = pd.Series(pd.date_range('20130101', periods=4))

In [234]: s
Out[234]:
0   2013-01-01  
1   2013-01-02  
2   2013-01-03  
3   2013-01-04  
dtype: datetime64[ns]

In [235]: s.dt.strftime('%Y/%m/%d')
Out[235]:
0   2013/01/01  
1   2013/01/02  
2   2013/01/03  
```
# PeriodIndex

In [236]: s = pd.Series(pd.period_range('20130101', periods=4))

In [237]: s
Out[237]:
0  2013-01-01
1  2013-01-02
2  2013-01-03
3  2013-01-04
dtype: object

In [238]: s.dt.strftime('%Y/%m/%d')
Out[238]:
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.

# period

In [239]: s = pd.Series(pd.period_range('20130101', periods=4, freq='D'))

In [240]: s
Out[240]:
0  2013-01-01
1  2013-01-02
2  2013-01-03
3  2013-01-04
dtype: object

In [241]: s.dt.year
Out[241]:
0  2013
1  2013
2  2013
3  2013
dtype: int64

In [242]: s.dt.day
Out[242]:
0  1
1  2
2  3
3  4
dtype: int64

# timedelta

In [243]: s = pd.Series(pd.timedelta_range('1 day 00:00:05', periods=4, freq='s'))

In [244]: s
Out[244]:
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 [245]: s.dt.days
Out[245]:
0   1
1   1
2   1
3   1
dtype: int64

In [246]: s.dt.seconds
Out[246]:
0    5
1    6
2    7
3    8
dtype: int64

In [247]: s.dt.components
Out[247]:
   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

Note: Series.dt will raise a TypeError if you access with a non-datetimelike values

10.10 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:

In [248]: s = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog', 'cat'])

In [249]: s.str.lower()
Out[249]:
0   a
1   b
2   c
3  aaba
4  baca
5    NaN
6  caba
7    dog
8    cat
dtype: object

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).

Please see Vectorized String Methods for a complete description.
10.11 Sorting

**Warning:** The sorting API is substantially changed in 0.17.0, see [here](#) for these changes. In particular, all sorting methods now return a new object by default, and *DO NOT* operate in-place (except by passing `inplace=True`).

There are two obvious kinds of sorting that you may be interested in: sorting by label and sorting by actual values.

10.11.1 By Index

The primary method for sorting axis labels (indexes) are the `Series.sort_index()` and the `DataFrame.sort_index()` methods.

```python
In [250]: unsorted_df = df.reindex(index=['a', 'd', 'c', 'b'],
                          columns=['three', 'two', 'one'])

# DataFrame
In [251]: unsorted_df.sort_index()
Out[251]:
    three two one
   a     NaN  NaN  NaN
   b     NaN  NaN  NaN
   c     NaN  NaN  NaN
   d     NaN  NaN  NaN

In [252]: unsorted_df.sort_index(ascending=False)
Out[252]:
    three two one
   d     NaN  NaN  NaN
   c     NaN  NaN  NaN
   b     NaN  NaN  NaN
   a     NaN  NaN  NaN

In [253]: unsorted_df.sort_index(axis=1)
Out[253]:
   one  three  two
   a     NaN   NaN
   d     NaN   NaN
   c     NaN   NaN
   b     NaN   NaN
   a     NaN   NaN

# Series
In [254]: unsorted_df['three'].sort_index()
Out[254]:
   a     NaN
   b     NaN
   c     NaN
   d     NaN
Name: three, dtype: float64
```

10.11.2 By Values

The `Series.sort_values()` and `DataFrame.sort_values()` are the entry points for value sorting (that is the values in a column or row). `DataFrame.sort_values()` can accept an optional `by` argument for `axis=0`
which will use an arbitrary vector or a column name of the DataFrame to determine the sort order:

```python
In [255]: df1 = pd.DataFrame({'one':[2,1,1,1], 'two':[1,3,2,4], 'three':[5,4,3,2]})
In [256]: df1.sort_values(by='two')
Out[256]:
    one three two
0   2     5   1
2   1     3   2
1   1     4   3
3   1     2   4
```

The `by` argument can take a list of column names, e.g.:

```python
In [257]: df[['one', 'two', 'three']].sort_values(by=['one','two'])
Out[257]:
    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:

```python
In [258]: s[2] = np.nan
In [259]: s.sort_values()
Out[259]:
     0   A
     3  Aaba
     1   B
     4   Baca
     6   CABA
     8   cat
     7   dog
     2  NaN
     5  NaN
dtype: object
In [260]: s.sort_values(na_position='first')
Out[260]:
     2  NaN
     5  NaN
     0   A
     3  Aaba
     1   B
     4   Baca
     6   CABA
     8   cat
     7   dog
dtype: object
```

### 10.11.3 `searchsorted`

Series has the `searchsorted()` method, which works similar to `numpy.ndarray.searchsorted()`.

```python
In [261]: ser = pd.Series([1, 2, 3])
```
In [262]: ser.searchsorted([0, 3])
Out[262]: array([0, 2])

In [263]: ser.searchsorted([0, 4])
Out[263]: array([0, 3])

In [264]: ser.searchsorted([1, 3], side='right')
Out[264]: array([1, 3])

In [265]: ser.searchsorted([1, 3], side='left')
Out[265]: array([0, 2])

In [266]: ser = pd.Series([3, 1, 2])

In [267]: ser.searchsorted([0, 3], sorter=np.argsort(ser))
Out[267]: array([0, 2])

10.11.4 smallest / largest values

New in version 0.14.0.

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 [268]: s = pd.Series(np.random.permutation(10))

In [269]: s
Out[269]:
0  9
1  8
2  5
3  3
4  6
5  7
6  0
7  2
8  4
9  1
dtype: int32

In [270]: s.sort_values()
Out[270]:
6  0
9  1
7  2
3  3
8  4
2  5
4  6
5  7
1  8
0  9
dtype: int32

In [271]: s.nsmallest(3)
Out[271]:
6  0
In [272]: s.nlargest(3)
Out[272]:
0 9
1 8
5 7
dtype: int32

New in version 0.17.0.

DataFrame also has the nlargest and nsmallest methods.

In [273]: 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 [274]: df.nlargest(3, 'a')
Out[274]:
   a  b  c
5  11 f 3.0
3  10 c 3.2
4  8  e NaN

In [275]: df.nlargest(5, ['a', 'c'])
Out[275]:
   a  b  c
5  11 f 3.0
3  10 c 3.2
4  8  e NaN
2  1 d 4.0
1 -1 b 2.0

In [276]: df.nsmallest(3, 'a')
Out[276]:
   a  b  c
0 -2 a 1
1 -1 b 2
6 -1 f 4

In [277]: df.nsmallest(5, ['a', 'c'])
Out[277]:
   a  b  c
0 -2 a 1
1 -1 b 2
6 -1 f 4
2  1 d 4
4  8  e NaN

10.11.5 Sorting by a multi-index column

You must be explicit about sorting when the column is a multi-index, and fully specify all levels to by.
10.12 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 methods have the side effect of modifying your data; almost all methods return new objects, leaving the original object untouched. If data is modified, it is because you did so explicitly.

10.13 dtypes

The main types stored in pandas objects are `float`, `int`, `bool`, `datetime64[ns]` and `datetime64[ns, tz]` (in >= 0.17.0), `timedelta[ns]`, `category` (in >= 0.15.0), and `object`. In addition these dtypes have item sizes, e.g. `int64` and `int32`. See Series with TZ for more detail on `datetime64[ns, tz]` dtypes.

A convenient `dtypes` attribute for DataFrames returns a Series with the data type of each column.
On a Series use the `dtype` attribute.

```python
In [283]: dft['A'].dtype
Out[283]: dtype('float64')
```

If a pandas object contains data 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).

```python
# these ints are coerced to floats
In [284]: pd.Series([1, 2, 3, 4, 5, 6.])
Out[284]:
0  1  
1  2  
2  3  
3  4  
4  5  
5  6  
dtype: float64

# string data forces an `object` dtype
In [285]: pd.Series([1, 2, 3, 6., 'foo'])
Out[285]:
0  1    
1  2    
2  3    
3  6    
4  foo  
dtype: object
```

The method `get_dtype_counts()` will return the number of columns of each type in a DataFrame:

```python
In [286]: dft.get_dtype_counts()
Out[286]:
bool          1
datetime64[ns] 1
float32       1
float64       1
int64         1
int8          1
object        1
dtype: int64
```

Numeric dtypes will propagate and can coexist in DataFrames (starting in v0.11.0). 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 [287]: df1 = pd.DataFrame(np.random.randn(8, 1), columns=['A'], dtype='float32')

In [288]: df1
Out[288]:
A
0  0.647650
1  0.822993
```
In [289]: df1.dtypes
Out[289]:
A  float32
dtype: object

In [290]: df2 = pd.DataFrame(dict(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 [291]: df2
Out[291]:
   A     B     C
0  0.027588  0.296947  0.0
1 -1.150391  0.007045  255
2  0.246460  0.707877   1
3 -0.455078  0.950661  0.0
4 -1.507812  0.087527  0.0
5 -0.502441 -0.339212  0.0
6  0.528809 -0.278698  0.0
7  0.590332  1.775379  0.0

In [292]: df2.dtypes
Out[292]:
A  float16
B  float64
C   uint8
dtype: object

10.13.1 defaults

By default integer types are int64 and float types are float64, REGARDLESS of platform (32-bit or 64-bit). The following will all result in int64 dtypes.

In [293]: pd.DataFrame([1, 2], columns=['a']).dtypes
Out[293]:
a  int64
dtype: object

In [294]: pd.DataFrame({'a': [1, 2]}).dtypes
Out[294]:
a  int64
dtype: object

In [295]: pd.DataFrame({'a': list(range(2))}, index=list(range(2))).dtypes
Out[295]:
a  int64
dtype: object

Numpy, however will choose platform-dependent types when creating arrays. The following WILL result in int32
on 32-bit platform.

In [296]: frame = pd.DataFrame(np.array([[1, 2]]))

### 10.13.2 upcasting

Types can potentially be *upcasted* when combined with other types, meaning they are promoted from the current type (say `int` to `float`)

In [297]: df3 = df1.reindex_like(df2).fillna(value=0.0) + df2

In [298]: df3
Out[298]:
<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
</table>
| 0 | 0.675238 | 0.296947 | 0 
| 1 | -0.327398 | 0.007045 | 255 
| 2 | 2.025163 | 0.707877 | 1 
| 3 | -1.998126 | 0.950661 | 0 
| 4 | -1.631068 | 0.087527 | 0 
| 5 | 1.737299 | -0.339212 | 0 
| 6 | 0.385030 | -0.278698 | 0 
| 7 | -2.294758 | 1.775379 | 0 

In [299]: df3.dtypes
Out[299]:
|   |  
|---|---|
| A | float32 
| B | float64 
| C | float64 

dtype: object

The `values` attribute on a DataFrame return the *lower-common-denominator* of the dtypes, meaning the dtype that can accommodate **ALL** of the types in the resulting homogeneous dtype numpy array. This can force some *upcasting.*

In [300]: df3.values.dtype
Out[300]: dtype('float64')

### 10.13.3 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.

In [301]: df3
Out[301]:
<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
</table>
| 0 | 0.675238 | 0.296947 | 0 
| 1 | -0.327398 | 0.007045 | 255 
| 2 | 2.025163 | 0.707877 | 1 
| 3 | -1.998126 | 0.950661 | 0 
| 4 | -1.631068 | 0.087527 | 0 
| 5 | 1.737299 | -0.339212 | 0 
| 6 | 0.385030 | -0.278698 | 0 
| 7 | -2.294758 | 1.775379 | 0 

380 Chapter 10. Essential Basic Functionality
In [302]: df3.dtypes
Out[302]:
A  float32
B  float64
C  float64
dtype: object

# conversion of dtypes
In [303]: df3.astype('float32').dtypes
Out[303]:
A  float32
B  float32
C  float32
dtype: object

10.13.4 object conversion

`convert_objects()` is a method to try to force conversion of types from the `object` dtype to other types. To force conversion of specific types that are `number like`, e.g. could be a string that represents a number, pass `convert_numeric=True`. This will force strings and numbers alike to be numbers if possible, otherwise they will be set to `np.nan`.

In [304]: df3['D'] = '1.'

In [305]: df3['E'] = '1'

In [306]: df3.convert_objects(convert_numeric=True).dtypes
Out[306]:
A  float32
B  float64
C  float64
D  float64
E  int64
dtype: object

# same, but specific dtype conversion
In [307]: df3['D'] = df3['D'].astype('float16')

In [308]: df3['E'] = df3['E'].astype('int32')

In [309]: df3.dtypes
Out[309]:
A  float32
B  float64
C  float64
D  float16
E  int32
dtype: object

To force conversion to `datetime64[ns]`, pass `convert_dates='coerce'`. This will convert any datetime-like object to dates, forcing other values to `NaT`. This might be useful if you are reading in data which is mostly dates, but occasionally has non-dates intermixed and you want to represent as missing.

In [310]: import datetime

In [311]: s = pd.Series([datetime.datetime(2001,1,1,0,0),
In [312]: s
Out[312]:
0 2001-01-01 00:00:00
1 foo
2 1
3 1
4 2001-01-04 00:00:00
5 20010105

dtype: object

In [313]: s.convert_objects(convert_dates='coerce')
Out[313]:
0 2001-01-01
1 NaT
2 NaT
3 NaT
4 2001-01-04
5 2001-01-05
dtype: datetime64[ns]

In addition, convert_objects() will attempt the soft conversion of any object dtypes, meaning that if all the objects in a Series are of the same type, the Series will have that dtype.

10.13.5 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 (starting in 0.11.0) See also integer na gotchas

In [314]: dfi = df3.astype('int32')

In [315]: dfi['E'] = 1

In [316]: dfi
Out[316]:
A  B  C  D  E
0 0  0  0  1  1
1 0  255 1  1
2 2  1  1  1
3 -1  0  0  1  1
4 -1  0  0  1  1
5 1  0  0  1  1
6 0  0  0  1  1
7 -2  1  0  1  1

In [317]: dfi.dtypes
Out[317]:
A  int32
B  int32
C  int32
D  int32
E  int64
dtype: object
In [318]: casted = dfi[dfi>0]

In [319]: casted
Out[319]:
   A  B  C  D  E
0  NaN  NaN  NaN  1  1
1  NaN  NaN  255  1  1
2  2  NaN  1  1  1
3  NaN  NaN  NaN  1  1
4  NaN  NaN  NaN  1  1
5  1  NaN  NaN  1  1
6  NaN  NaN  NaN  1  1
7  NaN  1  NaN  1  1

In [320]: casted.dtypes
Out[320]:
A float64
B float64
C float64
D int32
E int64
dtype: object

While float dtypes are unchanged.

In [321]: dfa = df3.copy()

In [322]: dfa['A'] = dfa['A'].astype('float32')

In [323]: dfa.dtypes
Out[323]:
A float32
B float64
C float64
D float16
E int32
dtype: object

In [324]: casted = dfa[df2>0]

In [325]: casted
Out[325]:
   A       B       C       D       E
0 0.675238 0.296947  NaN      NaN      NaN
1  NaN 0.007045  255      NaN      NaN
2 2.025163 0.707877  1      NaN      NaN
3  NaN 0.950661  NaN      NaN      NaN
4  NaN 0.087527  NaN      NaN      NaN
5  NaN  NaN      NaN      NaN      NaN
6 0.385030  NaN      NaN      NaN      NaN
7-2.294758 1.775379  NaN      NaN      NaN

In [326]: casted.dtypes
Out[326]:
A float32
B float64
C float64
D float16

10.13. dtypes
10.14 Selecting columns based on `dtype`

New in version 0.14.1.

The `select_dtypes()` method implements subsetting of columns based on their `dtype`.

First, let’s create a `DataFrame` with a slew of different dtypes:

```python
In [327]: 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).values,
                      'category': pd.Series(list("ABC")).astype('category'))
```

```python
In [328]: df['tdeltas'] = df.dates.diff()
In [329]: df['uint64'] = np.arange(3, 6).astype('u8')
In [330]: df['other_dates'] = pd.date_range('20130101', periods=3).values
In [331]: df['tz_aware_dates'] = pd.date_range('20130101', periods=3, tz='US/Eastern')
```

```python
In [332]: df
Out[332]:
   bool1 bool2 category       dates       float64       int64   string    
0   True  False       A 2015-10-09 20:16:59.250117    4     1     a
1  False   True       B 2015-10-10 20:16:59.250117    5     2     b
2  True   False       C 2015-10-11 20:16:59.250117    6     3     c
```

```
   uint8  tdeltas  uint64  other_dates  tz_aware_dates
0    3      NaT     3 2013-01-01 2013-01-01 00:00:00-05:00
1    4  1 days     4 2013-01-02 2013-01-02 00:00:00-05:00
2    5  1 days     5 2013-01-03 2013-01-03 00:00:00-05:00
```

And the dtypes:

```python
In [333]: df.dtypes
Out[333]:
bool1    bool
bool2    bool
category category
dates    datetime64[ns]
float64  float64
int64    int64
string  object
uint8    uint8
tdeltas  timedelta64[ns]
uint64  uint64
other_dates    datetime64[ns]
```

E float64
dtype: object
tz_aware_dates
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 [334]: df.select_dtypes(include=[bool])
Out[334]:
   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 [335]: df.select_dtypes(include=['bool'])
Out[335]:
   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 [336]: df.select_dtypes(include=['number', 'bool'], exclude=['unsignedinteger'])
Out[336]:
   bool1  bool2  float64  int64  tdeltas
0   True  False     4      1   NaT
1  False   True      5      2  1 days
2   True  False      6      3  1 days
```

To select string columns you must use the `object` dtype:

```
In [337]: df.select_dtypes(include=['object'])
Out[337]:
   string
0    a
1    b
2    c
```

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:

```
In [338]: def subtypes(dtype):
      ...:
      ...:     subs = dtype.__subclasses__()
      ...:
      ...:     if not subs:
      ...:         return dtype
      ...:
      ...:     return [dtype, [subtypes(dt) for dt in subs]]
      ...
```

All numpy dtypes are subclasses of `numpy.generic`:

```
In [339]: subtypes(np.generic)
Out[339]:
[numpy.generic,
 [numpy.number,
  [numpy.integer,
  ...:  [numpy.object,
  [numpy.bool,
  [numpy.float,
  [numpy.int,
  [numpy.timedelta,
```
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.

Note: The include and exclude parameters must be non-string sequences.
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:

```

In [2]: s.str.lower()
Out[2]:
0    a
1    b
2    c
3   aaba
4    baca
5     NaN
6    caba
7    dog
8    cat
dtype: object

In [3]: s.str.upper()
Out[3]:
0    A
1    B
2    C
3   AABA
4   BACA
5     NaN
6    CABA
7    DOG
8    CAT
dtype: object

In [4]: s.str.len()
Out[4]:
0    1
1    1
2    1
3    4
4    4
5     NaN
6    4
7    3
8    3
dtype: float64
```
In [5]: idx = pd.Index([' jack', 'jill ', ' jesse ', 'frank'])

In [6]: idx.str.strip()
Out[6]: Index([u'jack', u'jill', u'jesse', u'frank'], dtype='object')

In [7]: idx.str.lstrip()
Out[7]: Index([u'jack', u'jill ', u'jesse ', u'frank'], dtype='object')

In [8]: idx.str.rstrip()
Out[8]: Index([u' jack', u'jill', u' jesse', u'frank'], dtype='object')

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:

In [9]: df = pd.DataFrame(randn(3, 2), columns=[' Column A ', ' Column B '],
...: index=range(3))

In [10]: df
Out[10]:
   Column A      Column B
0  0.017428    0.039049
1 -2.240248    0.847859
2 -1.342107    0.368828

Since df.columns is an Index object, we can use the .str accessor

In [11]: df.columns.str.strip()
Out[11]: Index([u'Column A', u'Column B'], dtype='object')

In [12]: df.columns.str.lower()
Out[12]: Index([u' column a ', u' 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, lowercasing all names, and replacing any remaining whitespaces with underscores:

In [13]: df.columns = df.columns.str.strip().str.lower().str.replace(' ', '_')

In [14]: df
Out[14]:
   column_a      column_b
0  0.017428    0.039049
1 -2.240248    0.847859
2 -1.342107    0.368828

11.1 Splitting and Replacing Strings

Methods like split return a Series of lists:

In [15]: s2 = pd.Series(['a_b_c', 'c_d_e', np.nan, 'f_g_h'])

In [16]: s2.str.split(' _')
Out[16]:
0    [a, b, c]
1    [c, d, e]
2      NaN
Elements in the split lists can be accessed using `get` or `[]` notation:

```python
In[17]: s2.str.split('_').str.get(1)
Out[17]:
0 b
1 d
2 NaN
3 g
dtype: object

In[18]: s2.str.split('_').str[1]
Out[18]:
0 b
1 d
2 NaN
3 g
dtype: object
```

Easy to expand this to return a DataFrame using `expand`.

```python
In[19]: s2.str.split('_', expand=True)
Out[19]:
   0  1  2
0  a  b  c
1  c  d  e
2  NaN None None
3  f  g  h
```

It is also possible to limit the number of splits:

```python
In[20]: s2.str.split('_', expand=True, n=1)
Out[20]:
   0  1
0  a  b_c
1  c  d_e
2  NaN None
3  f  g_h
```

`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:

```python
In[21]: s2.str.rsplit('_', expand=True, n=1)
Out[21]:
   0  1
0  a_b  c
1  c_d  e
2  NaN None
3  f_g  h
```

Methods like `replace` and `findall` take regular expressions, too:

```python
In[22]: s3 = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', '', np.nan, 'CABA', 'dog', 'cat'])

In[23]: s3
Out[23]:
```

11.1. Splitting and Replacing Strings
In [24]: s3.str.replace('^a|dog', 'XX-XX ', case=False)
Out[24]:
0   A
1   B
2   C
3   XX-XX ba
4   XX-XX ca
5
6   NaN
7   XX-XX BA
8   XX-XX
9   XX-XX t
dtype: object

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 $:

# Consider the following badly formatted financial data
In [25]: dollars = pd.Series(['12', '-$10', '$10,000'])

# This does what you'd naively expect:
In [26]: dollars.str.replace('$', '')
Out[26]:
0   12
1  -10
2 10,000
dtype: object

# But this doesn't:
In [27]: dollars.str.replace('-$', '-')
Out[27]:
0   12
1  -$10
2 $10,000
dtype: object

# We need to escape the special character (for >1 len patterns)
In [28]: dollars.str.replace(r'-$', '-')
11.2 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.

```python
In [29]: s = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog', 'cat'])

In [30]: s.str[0]
Out[30]:
0    A
1    B
2    C
3    A
4    B
5    NaN
6    C
7    d
8    c
dtype: object
```

```python
In [31]: s.str[1]
Out[31]:
0    NaN
1    NaN
2    NaN
3    a
4    a
5    NaN
6    A
7    o
8    a
dtype: object
```

11.3 Extracting Substrings

The method `extract` (introduced in version 0.13) accepts regular expressions with match groups. Extracting a regular expression with one group returns a Series of strings.

```python
In [32]: pd.Series(['a1', 'b2', 'c3']).str.extract('[ab](\d)')
Out[32]:
0    a
1    b
2    NaN
dtype: object
```

Elements that do not match return NaN. Extracting a regular expression with more than one group returns a DataFrame with one column per group.

```python
In [33]: pd.Series(['a1', 'b2', 'c3']).str.extract('([ab])(\d)')
Out[33]:
       0
0   a    1
1   b    2
2  NaN  NaN
```
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 results dtype always is object, even if no match is found and the result only contains NaN.

Named groups like

```
In [34]: pd.Series(['a1', 'b2', 'c3']).str.extract('(?P<letter>[ab])(?P<digit>\d)')
Out[34]:
   letter digit
0   a       1
1   b       2
2  NaN      NaN
```

and optional groups like

```
In [35]: pd.Series(['a1', 'b2', '3']).str.extract('(?P<letter>[ab])?(?P<digit>\d)')
Out[35]:
   letter digit
0   a       1
1   b       2
2  NaN      3
```

can also be used.

### 11.3.1 Testing for Strings that Match or Contain a Pattern

You can check whether elements contain a pattern:

```
In [36]: pattern = r'[a-z][0-9]'
```

```
In [37]: pd.Series(['1', '2', '3a', '3b', '03c']).str.contains(pattern)
Out[37]:
0  False
1  False
2  False
3  False
4  False
dtype: bool
```

or match a pattern:

```
In [38]: pd.Series(['1', '2', '3a', '3b', '03c']).str.match(pattern, as_indexer=True)
Out[38]:
0  False
1  False
2  False
3  False
4  False
dtype: bool
```

The distinction between match and contains is strictness: match relies on strict re.match, while contains relies on re.search.
Warning: In previous versions, `match` was for extracting groups, returning a not-so-convenient Series of tuples. The new method `extract` (described in the previous section) is now preferred. This old, deprecated behavior of `match` is still the default. As demonstrated above, use the new behavior by setting `as_indexer=True`. In this mode, `match` is analogous to `contains`, returning a boolean Series. The new behavior will become the default behavior in a future release.

Methods like `match`, `contains`, `startswith`, and `endswith` take an extra `na` argument so missing values can be considered True or False:

```python
In [39]: s4 = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog', 'cat'])

In [40]: s4.str.contains('A', na=False)
Out[40]:
    0   True
    1   False
    2   False
    3   True
    4   False
    5   False
    6   True
    7   False
    8   False
dtype: bool
```

### 11.3.2 Creating Indicator Variables

You can extract dummy variables from string columns. For example if they are separated by a ‘|’:

```python
In [41]: s = pd.Series(['a', 'a|b', np.nan, 'a|c'])

In [42]: s.str.get_dummies(sep='|')
Out[42]:
    a  b  c
  0  1  0  0
  1  1  1  0
  2  0  0  0
  3  1  0  1
```

See also `get_dummies()`.

### 11.4 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>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 with some other string</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>
</tbody>
</table>

Continued on next page
Table 11.1 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>center()</td>
<td>Equivalent to str.center</td>
</tr>
<tr>
<td>ljust()</td>
<td>Equivalent to str.ljust</td>
</tr>
<tr>
<td>rjust()</td>
<td>Equivalent to str.rjust</td>
</tr>
<tr>
<td>zfill()</td>
<td>Equivalent to str.zfill</td>
</tr>
<tr>
<td>wrap()</td>
<td>Split long strings into lines with length less than a given width</td>
</tr>
<tr>
<td>slice()</td>
<td>Slice each string in the Series</td>
</tr>
<tr>
<td>slice_replace()</td>
<td>Replace slice in each string with passed value</td>
</tr>
<tr>
<td>count()</td>
<td>Count occurrences of pattern</td>
</tr>
<tr>
<td>startswith()</td>
<td>Equivalent to str.startswith(pat) for each element</td>
</tr>
<tr>
<td>endswith()</td>
<td>Equivalent to str.endswith(pat) for each element</td>
</tr>
<tr>
<td>findall()</td>
<td>Compute list of all occurrences of pattern/regex for each string</td>
</tr>
<tr>
<td>match()</td>
<td>Call re.match on each element, returning matched groups as list</td>
</tr>
<tr>
<td>extract()</td>
<td>Call re.match on each element, as match does, but return matched groups as strings for convenience.</td>
</tr>
<tr>
<td>len()</td>
<td>Compute string lengths</td>
</tr>
<tr>
<td>strip()</td>
<td>Equivalent to str.strip</td>
</tr>
<tr>
<td>rstrip()</td>
<td>Equivalent to str.rstrip</td>
</tr>
<tr>
<td>lstrip()</td>
<td>Equivalent to str.lstrip</td>
</tr>
<tr>
<td>partition()</td>
<td>Equivalent to str.partition</td>
</tr>
<tr>
<td>rpartition()</td>
<td>Equivalent to str.rpartition</td>
</tr>
<tr>
<td>lower()</td>
<td>Equivalent to str.lower</td>
</tr>
<tr>
<td>upper()</td>
<td>Equivalent to str.upper</td>
</tr>
<tr>
<td>find()</td>
<td>Equivalent to str.find</td>
</tr>
<tr>
<td>rfind()</td>
<td>Equivalent to str.rfind</td>
</tr>
<tr>
<td>index()</td>
<td>Equivalent to str.index</td>
</tr>
<tr>
<td>rindex()</td>
<td>Equivalent to str.rindex</td>
</tr>
<tr>
<td>capitalize()</td>
<td>Equivalent to str.capitalize</td>
</tr>
<tr>
<td>swapcase()</td>
<td>Equivalent to str.swapcase</td>
</tr>
<tr>
<td>normalize()</td>
<td>Return Unicode normal form. Equivalent to unicodedata.normalize</td>
</tr>
<tr>
<td>translate()</td>
<td>Equivalent to str.translate</td>
</tr>
<tr>
<td>isalnum()</td>
<td>Equivalent to str.isalnum</td>
</tr>
<tr>
<td>isalpha()</td>
<td>Equivalent to str.isalpha</td>
</tr>
<tr>
<td>isdigit()</td>
<td>Equivalent to str.isdigit</td>
</tr>
<tr>
<td>isspace()</td>
<td>Equivalent to str.isspace</td>
</tr>
<tr>
<td>islower()</td>
<td>Equivalent to str.islower</td>
</tr>
<tr>
<td>isupper()</td>
<td>Equivalent to str.isupper</td>
</tr>
<tr>
<td>istitle()</td>
<td>Equivalent to str.istitle</td>
</tr>
<tr>
<td>isnumeric()</td>
<td>Equivalent to str.isnumeric</td>
</tr>
<tr>
<td>isdecimal()</td>
<td>Equivalent to str.isdecimal</td>
</tr>
</tbody>
</table>
12.1 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
```

There is also an API 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 info.

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")
Out[7]: 101

In [8]: pd.set_option("max_r", 102)

In [9]: pd.get_option("display.max_rows")
Out[9]: 102
```
The following will not work because it matches multiple option names, e.g. display.max_colwidth, display.max_rows, display.max_columns:

```
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 describe_option. When called with no argument describe_option will print out the descriptions for all available options.

### 12.2 Getting and Setting Options

As described above, get_option() and set_option() are available from the pandas namespace. To change an option, call set_option(‘option regex’, new_value)

```
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: that the option ‘mode.sim_interactive’ is mostly used for debugging purposes.

All options also have a default value, and you can use reset_option to do just that:

```
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):

```
In [19]: pd.reset_option("\^display")
height has been deprecated.

line_width has been deprecated, use display.width instead (currently both are identical)

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:
```
12.3 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)
```

12.4 Frequently Used Options

The following is a walkthrough 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 [23]: df = pd.DataFrame(np.random.randn(7,2))

In [24]: pd.set_option('max_rows', 7)

In [25]: df
Out[25]:
   0   1
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 -0.494929  1.071804
6  0.721555 -0.706771

In [26]: pd.set_option('max_rows', 5)

In [27]: df
Out[27]:

display.expand_frame_repr allows for the representation of dataframes to stretch across pages, wrapped over the full column vs row-wise.

In [29]: df = pd.DataFrame(np.random.randn(5,10))

In [30]: pd.set_option('expand_frame_repr', True)

In [31]: df
Out[31]:
   0   1   2   3   4   5   6  
0 -1.039575 0.271860 -0.424972 0.567020 0.276232 -1.087401 -0.673690
1  0.404705 0.577046 -1.715002 -1.039268 -0.370647 -1.157892 -1.344312
2  1.643563 -1.469388  0.357021 -0.674600 -1.776904 -0.968914 -1.294524
3 -0.013960 -0.362543 -0.006154 -0.923061  0.895717  0.805244 -1.206412
4 -1.170299 -0.226169  0.410835  0.813850  0.132003 -0.827317 -0.076467

In [32]: pd.set_option('expand_frame_repr', False)

In [33]: df
Out[33]:
   0    1    2    3    4    5    6  
0 -1.039575 0.271860 -0.424972 0.567020 0.276232 -1.087401 -0.673690
1  0.404705 0.577046 -1.715002 -1.039268 -0.370647 -1.157892 -1.344312
2  1.643563 -1.469388  0.357021 -0.674600 -1.776904 -0.968914 -1.294524
3 -0.013960 -0.362543 -0.006154 -0.923061  0.895717  0.805244 -1.206412
4 -1.170299 -0.226169  0.410835  0.813850  0.132003 -0.827317 -0.076467

In [34]: 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.

In [35]: df = pd.DataFrame(np.random.randn(10,10))

In [36]: pd.set_option('max_rows', 5)

In [37]: pd.set_option('large_repr', 'truncate')

In [38]: df
Out[38]:
   0    1    2    3    4    5    6  
0 -1.039575 0.271860 -0.424972 0.567020 0.276232 -1.087401 -0.673690
1  0.404705 0.577046 -1.715002 -1.039268 -0.370647 -1.157892 -1.344312
2  1.643563 -1.469388  0.357021 -0.674600 -1.776904 -0.968914 -1.294524
3 -0.013960 -0.362543 -0.006154 -0.923061  0.895717  0.805244 -1.206412
4 -1.170299 -0.226169  0.410835  0.813850  0.132003 -0.827317 -0.076467
5 -1.895997 -0.718187 -0.854867  0.068688 -0.086458  0.841538  0.503708
6  0.422724 -0.894330 -0.226237 -1.537330  0.857889 -1.090525  1.351199
7 -0.213677 -1.655269 -0.189146 -1.184503  0.437637  0.781720  0.785450
8  0.178007  0.849589 -0.794281  0.422610  0.295417  0.048730 -0.774380
9 -0.058681  0.037836  0.254181  0.901468 -0.211842  0.784232 -0.389162
```python
0 -1.413681 1.607920 1.024180 0.569605 0.875906 -2.211372 0.974466
1 0.545952 -1.219217 -1.226825 0.769804 -1.281247 -0.727707 -0.121306
8 -2.484478 -0.281461 0.030711 0.109121 1.126203 -0.977349 1.474071
9 -1.071357 0.441153 2.353925 0.583787 0.221471 -0.744471 0.758527
```

```
In [39]: pd.set_option('large_repr', 'info')
```

```
In [40]: df
Out[40]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10 entries, 0 to 9
Data columns (total 10 columns):
  0       10 non-null float64
  1       10 non-null float64
  2       10 non-null float64
  3       10 non-null float64
  4       10 non-null float64
  5       10 non-null float64
  6       10 non-null float64
  7       10 non-null float64
  8       10 non-null float64
  9       10 non-null float64
dtypes: float64(10)
memory usage: 880.0 bytes
```

```
In [41]: pd.reset_option('large_repr')
```

```
In [42]: pd.reset_option('max_rows')
```

display.max_colwidth sets the maximum width of columns. Cells of this length or longer will be truncated with an ellipsis.

```
In [43]: df = pd.DataFrame(np.array([['foo', 'bar', 'bim', 'uncomfortably long string'],
                       ['horse', 'cow', 'banana', 'apple']]))
```

```
In [44]: pd.set_option('max_colwidth',40)
```

```
In [45]: df
Out[45]:
0 1 2 3
foo bar bim uncomfortably long string
horse cow banana apple
```

```
In [46]: pd.set_option('max_colwidth', 6)
```

```
In [47]: df
Out[47]:
```

12.4. Frequently Used Options
In [48]: pd.reset_option('max_colwidth')

display.max_info_columns sets a threshold for when by-column info will be given.

In [49]: df = pd.DataFrame(np.random.randn(10,10))

In [50]: pd.set_option('max_info_columns', 11)

In [51]: df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10 entries, 0 to 9
Data columns (total 10 columns):
0 10 non-null float64
1 10 non-null float64
2 10 non-null float64
3 10 non-null float64
4 10 non-null float64
5 10 non-null float64
6 10 non-null float64
7 10 non-null float64
8 10 non-null float64
9 10 non-null float64
dtypes: float64(10)
memory usage: 880.0 bytes

In [52]: pd.set_option('max_info_columns', 5)

In [53]: df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10 entries, 0 to 9
Columns: 10 entries, 0 to 9
dtypes: float64(10)
memory usage: 880.0 bytes

In [54]: 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 [55]: df = pd.DataFrame(np.random.choice([0,1,np.nan], size=(10,10)))

In [56]: df
Out[56]:
   0  1  2  3  4  5  6  7  8  9
0  0  1  1  0  1  0  NaN  1  NaN
1  NaN  0  0  1  1  NaN  1  0  1
2  NaN  NaN  1  1  0  NaN  0  1  NaN
3  0  1  1  NaN  0  NaN  1  NaN  NaN
4  0  1  0  0  1  0  0  NaN  0  0
5  NaN  1  NaN  NaN  NaN  NaN  0  1  NaN
6  0  1  0  0  NaN  1  NaN  NaN  0  NaN
7  NaN  1  1  NaN  1  1  1  NaN  NaN
8  0  0  NaN  0  NaN  1  0  0  NaN  NaN
In [57]: pd.set_option('max_info_rows', 11)

In [58]: df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10 entries, 0 to 9
Data columns (total 10 columns):
0 8 non-null float64
1 5 non-null float64
2 8 non-null float64
3 7 non-null float64
4 5 non-null float64
5 7 non-null float64
6 6 non-null float64
7 6 non-null float64
8 8 non-null float64
9 3 non-null float64
dtypes: float64(10)
memory usage: 880.0 bytes

In [59]: pd.set_option('max_info_rows', 5)

In [60]: df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10 entries, 0 to 9
Data columns (total 10 columns):
0 float64
1 float64
2 float64
3 float64
4 float64
5 float64
6 float64
7 float64
8 float64
9 float64
dtypes: float64(10)
memory usage: 880.0 bytes

In [61]: pd.reset_option('max_info_rows')

display.precision sets the output display precision in terms of decimal places. This is only a suggestion.

In [62]: df = pd.DataFrame(np.random.randn(5,5))

In [63]: pd.set_option('precision', 7)

In [64]: df
Out[64]:
  0   1   2   3   4
0 -2.049028  2.846612  -1.208049  -0.450392  2.423905
1  0.121108  0.266916  0.843826  -0.222540  2.021981
2 -0.716789 -2.224485  -1.061137  -0.232825  0.430793
3 -0.665478  1.829808  -1.406509  1.078248  0.322774
4  0.200324  0.890024  0.194813  0.351633  0.448881

In [65]: pd.set_option('precision', 4)
display.chop_threshold sets at what level pandas rounds to zero when it displays a Series of DataFrame. Note, this does not effect the precision at which the number is stored.

In [67]: df = pd.DataFrame(np.random.randn(6,6))
In [68]: pd.set_option('chop_threshold', 0)
In [69]: df
Out[69]:
<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>-0.1979</td>
<td>0.9657</td>
<td>-1.5229</td>
<td>-0.1166</td>
<td>0.2956</td>
</tr>
<tr>
<td>1</td>
<td>1.6406</td>
<td>1.9058</td>
<td>2.7721</td>
<td>0.0888</td>
<td>-1.1442</td>
</tr>
<tr>
<td>2</td>
<td>0.9254</td>
<td>-0.0064</td>
<td>-0.8204</td>
<td>-0.6009</td>
<td>-1.0393</td>
</tr>
<tr>
<td>3</td>
<td>-0.8241</td>
<td>-0.3377</td>
<td>-0.9278</td>
<td>-0.8401</td>
<td>0.2485</td>
</tr>
<tr>
<td>4</td>
<td>0.4320</td>
<td>-0.4607</td>
<td>0.3365</td>
<td>-3.2076</td>
<td>-1.5359</td>
</tr>
<tr>
<td>5</td>
<td>-0.6731</td>
<td>-0.7411</td>
<td>-0.1109</td>
<td>-2.6729</td>
<td>0.8645</td>
</tr>
</tbody>
</table>

In [70]: pd.set_option('chop_threshold', .5)
In [71]: df
Out[71]:
<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>0.0000</td>
<td>0.9657</td>
<td>-1.5229</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>1</td>
<td>1.6406</td>
<td>1.9058</td>
<td>2.7721</td>
<td>0.0000</td>
<td>-1.1442</td>
</tr>
<tr>
<td>2</td>
<td>0.9254</td>
<td>0.0000</td>
<td>-0.8204</td>
<td>-0.6009</td>
<td>-1.0393</td>
</tr>
<tr>
<td>3</td>
<td>-0.8241</td>
<td>0.0000</td>
<td>-0.9278</td>
<td>-0.8401</td>
<td>0.0000</td>
</tr>
<tr>
<td>4</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>-3.2076</td>
<td>-1.5359</td>
</tr>
<tr>
<td>5</td>
<td>-0.6731</td>
<td>-0.7411</td>
<td>0.0000</td>
<td>-2.6729</td>
<td>0.8645</td>
</tr>
</tbody>
</table>

In [72]: pd.reset_option('chop_threshold')

display.colheader_justify controls the justification of the headers. Options are ‘right’, and ‘left’.

In [73]: 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')

In [74]: pd.set_option('colheader_justify', 'right')
In [75]: df
Out[75]:
<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.9331</td>
<td>0.3</td>
</tr>
<tr>
<td>1</td>
<td>0.2888</td>
<td>0.2</td>
</tr>
<tr>
<td>2</td>
<td>1.3250</td>
<td>0.2</td>
</tr>
<tr>
<td>3</td>
<td>0.5892</td>
<td>0.7</td>
</tr>
<tr>
<td>4</td>
<td>0.5314</td>
<td>0.1</td>
</tr>
<tr>
<td>5</td>
<td>-1.1987</td>
<td>0.7</td>
</tr>
</tbody>
</table>
```
In [76]: pd.set_option('colheader_justify', 'left')
```
```
In [77]: df
Out[77]:
   A    B    C
0  0.9331  0.3  0
1  0.2888  0.2  0
2  1.3250  0.2  0
3  0.5892  0.7  0
4  0.5314  0.1  0
5 -1.1987  0.7  0
```
```
In [78]: pd.reset_option('colheader_justify')
```

### 12.5 List of Options

<table>
<thead>
<tr>
<th>Option</th>
<th>Default</th>
<th>Function</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>display.chop_threshold</code></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><code>display.colheader_justify</code></td>
<td>right</td>
<td>Controls the justification of column headers. Used by <code>DataFrameFormatter</code>.</td>
</tr>
<tr>
<td><code>display.column_space</code></td>
<td>12</td>
<td>No description available.</td>
</tr>
<tr>
<td><code>display.date_dayfirst</code></td>
<td>False</td>
<td>When True, prints and parses dates with the day first, e.g., 20/01/2005.</td>
</tr>
<tr>
<td><code>display.date_yearfirst</code></td>
<td>False</td>
<td>When True, prints and parses dates with the year first, e.g., 2005/01/20.</td>
</tr>
<tr>
<td><code>display.encoding</code></td>
<td>UTF-8</td>
<td>Defaults to the detected encoding of the console.</td>
</tr>
<tr>
<td><code>display.expand_frame_repr</code></td>
<td>True</td>
<td>The callable should accept a floating point number and return a string with the desired format.</td>
</tr>
<tr>
<td><code>display.float_format</code></td>
<td>None</td>
<td>The default format writing format, if None, then put default to ‘fixed’ and append will default to ‘table’.</td>
</tr>
<tr>
<td><code>display.height</code></td>
<td>60</td>
<td>For DataFrames exceeding <code>max_rows</code>/<code>max_cols</code>, the repr (and HTML repr) can show a truncated view.</td>
</tr>
<tr>
<td><code>display.large_repr</code></td>
<td>truncate</td>
<td>Deprecated. Use <code>display.max_rows</code> instead.</td>
</tr>
<tr>
<td><code>display.line_width</code></td>
<td>80</td>
<td>The maximum width in characters of a column in the repr of a pandas data structure.</td>
</tr>
<tr>
<td><code>display.max_columns</code></td>
<td>20</td>
<td>This sets the maximum number of rows pandas should output when printing out various output.</td>
</tr>
<tr>
<td><code>display.max_colwidth</code></td>
<td>50</td>
<td>When pretty-printing a long sequence, no more than <code>max_seq_items</code> will be printed. If items are omitted, they will be denoted by the addition of “…” to the resulting string.</td>
</tr>
<tr>
<td><code>display.max_info_columns</code></td>
<td>100</td>
<td>max_info_columns is used in <code>DataFrame.info</code> method to decide if per column information will be printed.</td>
</tr>
<tr>
<td><code>display.max_info_rows</code></td>
<td>1690785</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><code>display.max_pages</code></td>
<td>True</td>
<td>Displays the number of nested levels to process when pretty-printing.</td>
</tr>
<tr>
<td><code>display.max_rows</code></td>
<td>60</td>
<td>When True, IPython notebook will use html representation for pandas objects (if it is available).</td>
</tr>
<tr>
<td><code>display.max_seq_items</code></td>
<td>100</td>
<td>Controls the number of nested levels to process when pretty-printing</td>
</tr>
<tr>
<td><code>display.memory_usage</code></td>
<td>True</td>
<td>When True, IPython notebook will use html representation for pandas objects (if it is available).</td>
</tr>
<tr>
<td><code>display.mpl_style</code></td>
<td>None</td>
<td>Floating point output precision in terms of number of places after the decimal, for regular float printing.</td>
</tr>
<tr>
<td><code>display.mult_sparse</code></td>
<td>True</td>
<td>Whether to print out dimensions at the end of DataFrame repr.</td>
</tr>
<tr>
<td><code>display.notebook_repr_html</code></td>
<td>True</td>
<td>If ‘truncating’ is specified, only the first <code>display.width</code> characters will be printed.</td>
</tr>
<tr>
<td><code>display.pprint_nest_depth</code></td>
<td>3</td>
<td>‘Sparsify’ MultiIndex display (don’t display repeated elements in outer levels within group).</td>
</tr>
<tr>
<td><code>display.precision</code></td>
<td>6</td>
<td>Settings this to ‘default’ will modify the <code>DataFrame</code> method to decide if per column information will be printed.</td>
</tr>
<tr>
<td><code>display.show_dimensions</code></td>
<td>True</td>
<td>When True, IPython notebook will use html representation for pandas objects (if it is available).</td>
</tr>
<tr>
<td><code>display.width</code></td>
<td>80</td>
<td>Controls the number of nested levels to process when pretty-printing</td>
</tr>
<tr>
<td><code>io.excel.xls.writer</code></td>
<td>xlwt</td>
<td>The default Excel writer engine for ‘xls’ files.</td>
</tr>
<tr>
<td><code>io.excel.xlsm.writer</code></td>
<td>openpyxl</td>
<td>The default Excel writer engine for ‘xlsm’ files.</td>
</tr>
<tr>
<td><code>io.excel.xlsx.writer</code></td>
<td>openpyxl</td>
<td>Available options: ‘openpyxl’ (the default) and ‘xlwgp4’ (a drop-in replacement for xlwt).</td>
</tr>
<tr>
<td><code>io.hdf.default_format</code></td>
<td>None</td>
<td>The default Excel writer engine for ‘xls’ files.</td>
</tr>
<tr>
<td><code>io.hdf.dropna_table</code></td>
<td>True</td>
<td>drop ALL nan rows when appending to a table</td>
</tr>
<tr>
<td><code>mode.chained_assignment</code></td>
<td>warn</td>
<td>Raise an exception, warn, or no action if trying to use chained assignment, The default is warn.</td>
</tr>
<tr>
<td><code>mode.sim_interactive</code></td>
<td>False</td>
<td>Whether to simulate interactive mode for purposes of testing</td>
</tr>
<tr>
<td><code>mode.use_inf_as_null</code></td>
<td>False</td>
<td>True means treat None, NaN, -INF, INF as null (old way), False means None and NaN are non-null.</td>
</tr>
</tbody>
</table>

403
12.6 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:

```
In [79]: import numpy as np
In [80]: pd.set_eng_float_format(accuracy=3, use_eng_prefix=True)
In [81]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])
In [82]: s/1.e3
Out[82]:
a   -236.866u
b    846.974u
c  -685.597u
d   609.099u
e  -303.961u
dtype: float64
In [83]: s/1.e6
Out[83]:
a   -236.866n
b    846.974n
c  -685.597n
d   609.099n
e  -303.961n
dtype: float64
```

To round floats on a case-by-case basis, you can also use `round()`.

12.7 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 its width is corresponding to 2 alphabets. If DataFrame or Series contains these characters, default output cannot be aligned properly.

**Note:** Screen captures are attached for each outputs to show the actual results.

```
In [84]: df = pd.DataFrame({'\u005c': ['UK', '\u005c'], '\u005c': ['Alice', '\u005c']})
In [85]: df;
```
Enable `display.unicode.east_asian_width` allows pandas to check each character’s “East Asian Width” property. These characters can be aligned properly by checking this property, but it takes longer time than standard `len` function.

In [86]: pd.set_option('display.unicode.east_asian_width', True)

In [87]: df;

In addition, Unicode contains characters which width is “Ambiguous”. These character’s width should be either 1 or 2 depending on terminal setting or encoding. Because this cannot be distinguished from Python, `display.unicode.ambiguous_as_wide` option is added to handle this.

By default, “Ambiguous” character’s width, “¡” (inverted exclamation) in below example, is regarded as 1.

In [88]: df = pd.DataFrame({'a': ['xxx', u'¡¡'], 'b': ['yyy', u'¡¡']})

In [89]: df;

Enabling `display.unicode.ambiguous_as_wide` lets pandas to figure these character’s width as 2. Note that this option will be effective only when `display.unicode.east_asian_width` is enabled. Confirm starting position has been changed, but is not aligned properly because the setting is mismatched with this environment.

In [90]: pd.set_option('display.unicode.ambiguous_as_wide', True)

In [91]: df;

12.7. Unicode Formatting
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. Expect more work to be invested in higher-dimensional data structures (including Panel) in the future, especially in label-based advanced indexing.

**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

**Warning:** In 0.15.0 Index has internally been refactored to no longer subclass ndarray but instead subclass PandasObject, similarly to the rest of the pandas objects. This should be a transparent change with only very limited API implications (See the Internal Refactoring)

See the MultiIndex / Advanced Indexing for MultiIndex and more advanced indexing documentation.

See the cookbook for some advanced strategies

### 13.1 Different Choices for Indexing

New in version 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 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!)
- A boolean array

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

See more at Selection by Position

- .ix supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type. .ix is the most general and will support any of the inputs in .loc and .iloc. ix also supports floating point label schemes. ix is exceptionally useful when dealing with mixed positional and label based hierarchical indexes.

However, when an axis is integer based, ONLY label based access and not positional access is supported. Thus, in such cases, it’s usually better to be explicit and use .iloc or .loc.

See more at Advanced Indexing and Advanced Hierarchical.

Getting values from an object with multi-axes selection uses the following notation (using .loc as an example, but applies to .iloc and .ix 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 equiv to p.loc['a', :, :])

<table>
<thead>
<tr>
<th>Object Type</th>
<th>Indexers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series</td>
<td>s.loc[indexer]</td>
</tr>
<tr>
<td>DataFrame</td>
<td>df.loc[row_indexer, column_indexer]</td>
</tr>
<tr>
<td>Panel</td>
<td>p.loc[item_indexer, major_indexer, minor_indexer]</td>
</tr>
</tbody>
</table>

### 13.2 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. Thus,

<table>
<thead>
<tr>
<th>Object Type</th>
<th>Selection</th>
<th>Return Value Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series</td>
<td>series[label]</td>
<td>scalar value</td>
</tr>
<tr>
<td>DataFrame</td>
<td>frame[colname]</td>
<td>Series corresponding to colname</td>
</tr>
<tr>
<td>Panel</td>
<td>panel[itemname]</td>
<td>DataFrame corresponding to the itemname</td>
</tr>
</tbody>
</table>

Here we construct a simple time series data set to use for illustrating the indexing functionality:

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

In [4]: panel = pd.Panel({'one': df, 'two': df - df.mean()})

In [5]: panel
Out[5]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 8 (major_axis) x 4 (minor_axis)
Items axis: one to two
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-08 00:00:00
Minor_axis axis: A to D

Note: None of the indexing functionality is time series specific unless specifically stated.

Thus, as per above, we have the most basic indexing using []:

In [6]: s = df['A']

In [7]: s[dates[5]]
Out[7]: -0.67368970808837025

In [8]: panel['two']
Out[8]:
   A      B      C      D
2000-01-01  0.409571  0.113086 -0.610826 -0.936507
2000-01-02  1.152571  0.222735  1.017442 -0.845111
2000-01-03 -0.921390 -1.708620  0.403304  1.270929
2000-01-04  0.662014 -0.310822 -0.141342  0.470985
2000-01-05 -0.484513  0.962970  1.174465 -0.888276
2000-01-06 -0.733231  0.509598 -0.580194  0.724113
2000-01-07  0.345164  0.972995 -0.816769 -0.840143
2000-01-08 -0.430188 -0.761943 -0.446079  1.044010

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:

In [9]: df
Out[9]:
   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

13.2. Basics
In [10]: df[\['B', 'A'\]] = df[\['A', 'B'\]]

In [11]: df
Out[11]:
   A    B    C    D
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 0.407046  0.577046 -1.715002 -1.039268
7 -0.370647  0.1157892  1.344312  0.844885

You may find this useful for applying a transform (in-place) to a subset of the columns.

### 13.3 Attribute Access

You may access an index on a `Series`, column on a `DataFrame`, and an item on a `Panel` directly as an attribute:

In [12]: sa = pd.Series([1,2,3],index=list('abc'))

In [13]: dfa = df.copy()

In [14]: sa.b
Out[14]: 2

In [15]: dfa.A
Out[15]:
   A    B    C    D
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 0.407046  0.577046 -1.715002 -1.039268
7 -0.370647  0.1157892  1.344312  0.844885

Freq: D, Name: A, dtype: float64

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 fails silently, creating a new attribute rather than a new column.

In [17]: sa.a = 5

In [18]: sa
Out[18]:
   a  5
   b  2
c  3
dtype: int64

In [19]: dfa.A = list(range(len(dfa.index)))  # ok if A already exists

In [20]: dfa
Out[20]:
     A         B        C        D
2000-01-01  0 -1.509059 -1.135632
2000-01-02  1  0.119209  1.044236
2000-01-03  2 -0.494929  1.071804
2000-01-04  3 -1.039575  0.271860
2000-01-05  4  0.276232 -1.087401
2000-01-06  5 -1.478427  0.524988
2000-01-07  6 -1.715002 -1.039268
2000-01-08  7 -1.344312  0.844885

In [21]: dfa['A'] = list(range(len(dfa.index)))  # use this form to create a new column

In [22]: dfa
Out[22]:
     A         B        C        D
2000-01-01  0 -1.509059 -1.135632
2000-01-02  1  0.119209  1.044236
2000-01-03  2 -0.494929  1.071804
2000-01-04  3 -1.039575  0.271860
2000-01-05  4  0.276232 -1.087401
2000-01-06  5 -1.478427  0.524988
2000-01-07  6 -1.715002 -1.039268
2000-01-08  7 -1.344312  0.844885

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.
- Similarly, the attribute will not be available if it conflicts with any of the following list: index, major_axis, minor_axis, items, labels.
- 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.
- The Series/Panel accesses are available starting in 0.13.0.

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 [23]: x = pd.DataFrame({'x': [1, 2, 3], 'y': [3, 4, 5]})

In [24]: x.iloc[1] = dict(x=9, y=99)

In [25]: x
Out[25]:
   x  y
0  1  3
1  9  99

13.3. Attribute Access
13.4 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 [26]: s[:5]
Out[26]:
2000-01-01 -0.282863
2000-01-02 -0.173215
2000-01-03 -2.104569
2000-01-04 -0.706771
2000-01-05  0.567020
Freq: D, Name: A, dtype: float64
```

```
In [27]: s[::2]
Out[27]:
2000-01-01 -0.282863
2000-01-03 -2.104569
2000-01-05  0.567020
2000-01-07  0.577046
Freq: 2D, Name: A, dtype: float64
```

```
In [28]: s[::-1]
Out[28]:
2000-01-08 -1.157892
2000-01-07  0.577046
2000-01-06  0.113648
2000-01-05  0.567020
2000-01-04 -0.706771
2000-01-03 -2.104569
2000-01-02 -0.173215
2000-01-01 -0.282863
Freq: -1D, Name: A, dtype: float64
```

Note that setting works as well:

```
In [29]: s2 = s.copy()
```

```
In [30]: s2[:5] = 0
```

```
In [31]: s2
Out[31]:
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  0.113648
2000-01-07  0.577046
2000-01-08 -1.157892
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 [32]: df[:3]
Out[32]:
       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
```

```
In [33]: df[::-1]
Out[33]:
       A     B     C     D
2000-01-08 -1.157892 -0.370647 -1.344312  0.844885
2000-01-07  0.577046  0.404705 -1.715002 -1.039268
2000-01-06  0.113648 -0.673690 -1.478427  0.524988
2000-01-05  0.567020 -0.424972  0.276232 -1.087401
2000-01-04 -0.706771  0.721555 -1.039575  0.271860
2000-01-03 -2.104569 -0.861849 -0.494929  1.071804
2000-01-02 -0.173215  1.212112  0.119209 -1.044236
2000-01-01 -0.282863  0.469112 -1.509059 -1.135632
```

### 13.5 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

```
In [34]: dfl = pd.DataFrame(np.random.randn(5,4), columns=list('ABCD'), index=pd.date_range('20130101',periods=5))
```

```
In [35]: dfl
Out[35]:
       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 [36]: dfl.loc[2:3]
```

```
TypeError: cannot do slice indexing on <class 'pandas.tseries.index.DatetimeIndex'> with these indexers [2] of <type 'int'>
```

**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 [34]: dfl = pd.DataFrame(np.random.randn(5,4), columns=list('ABCD'), index=pd.date_range('20130101',periods=5))
```

```
In [35]: dfl
Out[35]:
       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]: dfl.loc[2:3]
```

```
TypeError: cannot do slice indexing on <class 'pandas.tseries.index.DatetimeIndex'> with these indexers [2] of <type 'int'>
```

**Warning:** String likes in slicing can be convertible to the type of the index and lead to natural slicing.

```
In [36]: dfl.loc['20130102':'20130104']
Out[36]:
       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
```

### 13.5 Selection By Label
pandas provides a suite of methods in order to have purely label based indexing. This is a strict inclusion based protocol. At least 1 of the labels for which you ask, must be in the index or a KeyError will be raised! When slicing, the start bound is included, AND the stop bound is included. 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!)
- A boolean array

```python
In [37]: s1 = pd.Series(np.random.randn(6),index=list('abcdef'))
```

```python
In [38]: s1
Out[38]:
a    1.431256
b    1.340309
c   -1.170299
d   -0.226169
e    0.410835
f    0.813850
dtype: float64
```

```python
In [39]: s1.loc['c':]
Out[39]:
c   -1.170299
d   -0.226169
e    0.410835
f    0.813850
dtype: float64
```

```python
In [40]: s1.loc['b']
Out[40]: 1.3403088497993827
```

Note that setting works as well:

```python
In [41]: s1.loc['c'] = 0
```

```python
In [42]: s1
Out[42]:
a    1.431256
b    1.340309
c    0.000000
d    0.000000
e    0.000000
f    0.000000
dtype: float64
```

With a DataFrame

```python
In [43]: df1 = pd.DataFrame(np.random.randn(6,4),
....:                      index=list('abcdef'),
....:                      columns=list('ABCD'))
....:
```

Chapter 13. Indexing and Selecting Data
In [44]: df1
Out[44]:

<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>0.132003</td>
<td>-0.827317</td>
<td>-0.076467</td>
<td>-1.187678</td>
</tr>
<tr>
<td>b</td>
<td>1.130127</td>
<td>-1.436737</td>
<td>-1.413681</td>
<td>1.607920</td>
</tr>
<tr>
<td>c</td>
<td>1.024180</td>
<td>0.569605</td>
<td>0.875906</td>
<td>-2.211372</td>
</tr>
<tr>
<td>d</td>
<td>0.974466</td>
<td>-2.006747</td>
<td>-0.410001</td>
<td>-0.078638</td>
</tr>
<tr>
<td>e</td>
<td>0.545952</td>
<td>-1.219217</td>
<td>-1.226825</td>
<td>0.769804</td>
</tr>
<tr>
<td>f</td>
<td>-1.281247</td>
<td>-0.727707</td>
<td>-0.121306</td>
<td>-0.097883</td>
</tr>
</tbody>
</table>

In [45]: df1.loc[['a','b','d']:, ]
Out[45]:

<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>0.132003</td>
<td>-0.827317</td>
<td>-0.076467</td>
<td>-1.187678</td>
</tr>
<tr>
<td>b</td>
<td>1.130127</td>
<td>-1.436737</td>
<td>-1.413681</td>
<td>1.607920</td>
</tr>
<tr>
<td>d</td>
<td>0.974466</td>
<td>-2.006747</td>
<td>-0.410001</td>
<td>-0.078638</td>
</tr>
</tbody>
</table>

Accessing via label slices

In [46]: df1.loc['d':,'A':'C']
Out[46]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>d</td>
<td>0.974466</td>
<td>-2.006747</td>
<td>-0.410001</td>
</tr>
<tr>
<td>e</td>
<td>0.545952</td>
<td>-1.219217</td>
<td>-1.226825</td>
</tr>
<tr>
<td>f</td>
<td>-1.281247</td>
<td>-0.727707</td>
<td>-0.121306</td>
</tr>
</tbody>
</table>

For getting a cross section using a label (equiv to df.xs('a'))

In [47]: df1.loc['a']
Out[47]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>0.132003</td>
</tr>
<tr>
<td>b</td>
<td>-0.827317</td>
</tr>
<tr>
<td>c</td>
<td>-0.076467</td>
</tr>
<tr>
<td>d</td>
<td>-1.187678</td>
</tr>
</tbody>
</table>

Name: a, dtype: float64

For getting values with a boolean array

In [48]: df1.loc['a']>0
Out[48]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>True</td>
</tr>
<tr>
<td>b</td>
<td>False</td>
</tr>
<tr>
<td>c</td>
<td>False</td>
</tr>
<tr>
<td>d</td>
<td>False</td>
</tr>
</tbody>
</table>

Name: a, dtype: bool

In [49]: df1.loc[:,df1.loc['a']>0]
Out[49]:

<table>
<thead>
<tr>
<th>a</th>
</tr>
</thead>
<tbody>
<tr>
<td>a 0.132003</td>
</tr>
<tr>
<td>b 1.130127</td>
</tr>
<tr>
<td>c 1.024180</td>
</tr>
<tr>
<td>d 0.974466</td>
</tr>
<tr>
<td>e 0.545952</td>
</tr>
<tr>
<td>f -1.281247</td>
</tr>
</tbody>
</table>

For getting a value explicitly (equiv to deprecated df.get_value('a','A'))

# this is also equivalent to `df1.at['a','A']`
In [50]: df1.loc['a','A']
13.6 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 bounds is included, while the upper bound is excluded. Trying to use a non-integer, even a valid label will raise a 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

```python
In [51]: s1 = pd.Series(np.random.randn(5), index=list(range(0,10,2))
```

```python
In [52]: s1
Out[52]:
0  0.695775
2  0.341734
4  0.959726
6  -1.110336
8  -0.619976
dtype: float64
```

```python
In [53]: s1.iloc[:3]
Out[53]:
0  0.695775
2  0.341734
4  0.959726
dtype: float64
```

```python
In [54]: s1.iloc[3]
Out[54]: -1.1103361028911667
```

Note that setting works as well:

```python
In [55]: s1.iloc[:3] = 0
```

```python
In [56]: s1
Out[56]:
0  0.000000
2  0.000000
4  0.000000
6  -1.110336
8  -0.619976
dtype: float64
```

With a DataFrame
In [57]: df1 = pd.DataFrame(np.random.randn(6,4),
                   index=list(range(0,12,2)),
                   columns=list(range(0,8,2)))

In [58]: df1
Out[58]:
     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

In [59]: df1.iloc[:3]
Out[59]:
     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 [60]: df1.iloc[1:5,2:4]
Out[60]:
     4  6
2 -0.154951 -2.179861
4  1.462696 -1.743161
6  0.690579
8  0.014871
10  3.357427

Select via integer list

In [61]: df1.iloc[[1,3,5],[1,3]]
Out[61]:
     2   6
2 -0.154951 -2.179861
6  0.345352  0.690579
10 -1.236269 -0.487602

In [62]: df1.iloc[1:3, :]
Out[62]:
     0  2   4     6
2 -0.403310 -0.154951 0.301624 -2.179861
4 -1.369849 -0.954208 1.462696 -1.743161

In [63]: df1.iloc[:, 1:3]
Out[63]:
     2   4
0 -0.732339  0.687738
2 -0.154951  0.301624
4 -0.954208  1.462696
6 -0.345352  1.314232
8  2.396780  0.014871
10 -1.236269  0.896171

# this is also equivalent to `df1.iat[1,1]`
In [64]: df1.iloc[1,1]
For getting a cross section using an integer position (equiv to `df.xs(1)`)

```python
In [65]: df1.iloc[1]
Out[65]:
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.
# Only works in Pandas starting from v0.14.0.
In [66]: x = list('abcdef')

In [67]: x
Out[67]: ['a', 'b', 'c', 'd', 'e', 'f']

In [68]: x[4:10]
Out[68]: ['e', 'f']

In [69]: x[8:10]
Out[69]: []

In [70]: s = pd.Series(x)

In [71]: s
Out[71]:
0  a
1  b
2  c
3  d
4  e
5  f
dtype: object

In [72]: s.iloc[4:10]
Out[72]:
4  e
5  f
dtype: object

In [73]: s.iloc[8:10]
Out[73]: Series([], dtype: object)
```

**Note:** Prior to v0.14.0, `iloc` would not accept out of bounds indexers for slices, e.g. a value that exceeds the length of the object being indexed.

Note that this could result in an empty axis (e.g. an empty DataFrame being returned)

```
In [74]: dfl = pd.DataFrame(np.random.randn(5,2), columns=list('AB'))

In [75]: dfl
Out[75]:
         A    B
0  0.149508  0.394921
1 -0.154951 -0.316243
2  0.279227 -0.690723
3 -0.252198 -0.501610
4  0.186729 -0.754846
```
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 [76]: df1.iloc[:,2:3]
Out[76]:
Empty DataFrame
Columns: []
Index: [0, 1, 2, 3, 4]

In [77]: df1.iloc[:,1:3]
Out[77]:
       B
0  -2.182937
1   0.084844
2   1.519970
3   0.600178
4   0.132885

In [78]: df1.iloc[4:6]
Out[78]:
     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

### 13.7 Selecting Random Samples

A random selection of rows or columns from a Series, DataFrame, or Panel 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 [79]: s = pd.Series([0,1,2,3,4,5])

# When no arguments are passed, returns 1 row.
In [80]: s.sample()
Out[80]:
      5
 dtype: int64

# One may specify either a number of rows:
In [81]: s.sample(n=3)
Out[81]:
     1
     5
     0
 dtype: int64
# Or a fraction of the rows:
In [82]: s.sample(frac=0.5)
Out[82]:
3 3  
0 0  
2 2  
dtype: int64

By default, sample will return each row at most once, but one can also sample with replacement using the replace option:

In [83]: s = pd.Series([0,1,2,3,4,5])

# Without replacement (default):
In [84]: s.sample(n=6, replace=False)
Out[84]:
4 4  
1 1  
0 0  
5 5  
2 2  
3 3  
dtype: int64

# With replacement:
In [85]: s.sample(n=6, replace=True)
Out[85]:
4 4  
0 0  
2 2  
2 2  
2 2  
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 [86]: s = pd.Series([0,1,2,3,4,5])

In [87]: example_weights = [0, 0, 0.2, 0.2, 0.2, 0.4]

In [88]: s.sample(n=3, weights=example_weights)
Out[88]:
5 5  
2 2  
4 4  
dtype: int64

# Weights will be re-normalized automatically
In [89]: example_weights2 = [0.5, 0, 0, 0, 0, 0]

In [90]: s.sample(n=1, weights=example_weights2)
Out[90]:
0 0
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 [91]: df2 = pd.DataFrame({'col1':[9,8,7,6], 'weight_column':[0.5, 0.4, 0.1, 0]})
In [92]: df2.sample(n = 3, weights = 'weight_column')
Out[92]:
   col1  weight_column
0    9           0.5
1    8           0.4
2    7           0.1

`sample` also allows users to sample columns instead of rows using the `axis` argument.

In [93]: df3 = pd.DataFrame({'col1':[1,2,3], 'col2':[2,3,4]})
In [94]: df3.sample(n=1, axis=1)

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 [95]: df4 = pd.DataFrame({'col1':[1,2,3], 'col2':[2,3,4]})
# With a given seed, the sample will always draw the same rows.
In [96]: df4.sample(n=2, random_state=2)
Out[96]:
   col1  col2
0    1    2
1    2    3
2    3    4

2  3  4
1  2  3
2  3  4

**13.8 Setting With Enlargement**

New in version 0.13.

The `.loc/ ix/[]` operations can perform enlargement when setting a non-existant key for that axis.

In the Series case this is effectively an appending operation.

In [98]: se = pd.Series([1,2,3])
In [99]: se
Out[99]:
0  1
1  2
2  3
A DataFrame can be enlarged on either axis via `.loc`

```python
In [102]: dfi = pd.DataFrame(np.arange(6).reshape(3,2),
   ...:                 columns=['A','B'])
   ...:
In [103]: dfi
Out[103]:
   A  B
0  0  1
1  2  3
2  4  5
```

This is like an append operation on the DataFrame.

```python
In [104]: dfi.loc[:,'C'] = dfi.loc[:,'A']
```

**13.9 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`

```python
In [105]: dfi
Out[105]:
   A  B  C
0  0  1  0
1  2  3  2
2  4  5  4
```

```python
In [107]: dfi
Out[107]:
   A  B  C
0  0  1  0
1  2  3  2
2  4  5  4
3  5  5  5
```

```python
In [108]: s.iat[5]
Out[108]: 5
```
You can also set using these same indexers.

In [111]: df.at[dates[5], 'E'] = 7

In [112]: df.iat[3, 0] = 7

at may enlarge the object in-place as above if the indexer is missing.

In [113]: df.at[dates[-1]+1, 0] = 7

In [114]: df

Out[114]:
   A     B     C     D     E   0
0  2000-01-01 -0.282863 0.469112 -1.509059 -1.135632 NaN NaN
1  2000-01-02 -0.173215 1.212112 0.119209 -1.044236 NaN NaN
2  2000-01-03 -2.104569 -0.861849 -0.494929 1.071804 NaN NaN
3  2000-01-04  7.000000 0.721555 -1.039575 0.271860 NaN NaN
4  2000-01-05  0.567020 -0.424972 0.276232 -1.087401 NaN NaN
5  2000-01-06  0.113648 -0.673690 -1.478427 0.524988 7 NaN
6  2000-01-07  0.577046 0.404705 -1.715002 -1.039268 NaN NaN
7  2000-01-08 -1.157892 -0.370647 -1.344312 0.844885 NaN NaN
8  2000-01-09  NaN  NaN  NaN  NaN  NaN  7
9  2000-01-10  NaN  NaN  NaN  NaN  NaN  NaN

13.10 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.

Using a boolean vector to index a Series works exactly as in a numpy ndarray:

In [115]: s = pd.Series(range(-3, 4))

In [116]: s[s > 0]

Out[116]:
   0 -3
   1 -2
   2 -1
   3  0
   4  1
   5  2
   6  3
dtype: int64

In [117]: s[s > 0]

Out[117]:
   4  1
   5  2
   6  3
dtype: int64
In [118]: s[(s < -1) | (s > 0.5)]
Out[118]:
   0 -3
   1 -2
   4  1
   5  2
   6  3
dtype: int64

In [119]: s[~(s < 0)]
Out[119]:
   3  0
   4  1
   5  2
   6  3
dtype: int64

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):

In [120]: df[df['A'] > 0]
Out[120]:
    A      B     C     D      E
0  2000-01-04  7.000000  0.721555 -1.039575  0.271860  NaN  NaN
1  2000-01-05  0.567020 -0.424972  0.276232 -1.087401  NaN  NaN
2  2000-01-06 -0.113648 -0.673690 -1.478427  0.524988   7  NaN
3  2000-01-07  0.577046  0.404705 -1.715002 -1.039268 -1.039268  NaN  NaN

List comprehensions and map method of Series can also be used to produce more complex criteria:

In [121]: df2 = pd.DataFrame({'a' : ['one', 'one', 'two', 'three', 'one', 'six'],
                        'b' : ['x', 'y', 'y', 'x', 'y', 'x'],
                        'c' : np.random.randn(7)})

In [122]: criterion = df2['a'].map(lambda x: x.startswith('t'))

In [123]: df2[criterion]
Out[123]:
   a    b    c
2  two  1.450520
3  three  0.206053
4  two  -0.251905

# equivalent but slower
In [124]: df2[[x.startswith('t') for x in df2['a']]]
Out[124]:
   a    b    c
2  two  1.450520
3  three  0.206053
4  two  -0.251905

# Multiple criteria
In [125]: df2[criterion & (df2['b'] == 'x')]
Out[125]:
   a    b    c
3  three  0.206053

424 Chapter 13. Indexing and Selecting Data
Note, 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.

```
In [126]: df2.loc[criterion & (df2['b'] == 'x'),'b':'c']
Out[126]:
   b   c
3  x  0.206053
```

### 13.11 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:

```
In [127]: s = pd.Series(np.arange(5), index=np.arange(5)[::-1], dtype='int64')
In [128]: s
Out[128]:
4  0
3  1
2  2
1  3
0  4
dtype: int64

In [129]: s.isin([2, 4, 6])
Out[129]:
4  False
3  False
2  True
1  False
0  True
dtype: bool

In [130]: s[s.isin([2, 4, 6])]
Out[130]:
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:

```
In [131]: s[s.index.isin([2, 4, 6])]
Out[131]:
4  0
2  2
dtype: int64

# compare it to the following
In [132]: s[[2, 4, 6]]
Out[132]:
2  2
4  0
6  NaN
dtype: float64
```

In addition to that, MultiIndex allows selecting a separate level to use in the membership check:
In [133]: s_mi = pd.Series(np.arange(6),
       index=pd.MultiIndex.from_product([[0, 1], ['a', 'b', 'c']]))

In [134]: s_mi
Out[134]:
0  a  0
   b  1
   c  2
1  a  3
   b  4
   c  5
dtype: int32

In [135]: s_mi.iloc[s_mi.index.isin([(1, 'a'), (2, 'b'), (0, 'c')])]
Out[135]:
0  c  2
1  a  3
dtype: int32

In [136]: s_mi.iloc[s_mi.index.isin(['a', 'c', 'e'], level=1)]
Out[136]:
0  a  0
   c  2
1  a  3
   c  5
dtype: int32

DataFrame also has an isin method. When calling isin, pass a set of values as either an array or dict. If values is an array, 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.

In [137]: df = pd.DataFrame({'vals': [1, 2, 3, 4], 'ids': ['a', 'b', 'f', 'n'],
       'ids2': ['a', 'n', 'c', 'n']})

In [138]: values = ['a', 'b', 1, 3]

In [139]: df.isin(values)
Out[139]:
   ids ids2 vals
0  True  True  True
1  False  False  False
2  False  True  True
3  False  False  False

Oftentimes you’ll want to match certain values with certain columns. Just make values a dict where the key is the column, and the value is a list of items you want to check for.

In [140]: values = {'ids': ['a', 'b'], 'vals': [1, 3]}

In [141]: df.isin(values)
Out[141]:
   ids ids2 vals
0  True  True  True
1  False  False  False
2  False  True  True
3  False  False  False
Combine DataFrame’s \(\text{isin}\) with the \(\text{any()}\) and \(\text{all()}\) methods to quickly select subsets of your data that meet a given criteria. To select a row where each column meets its own criterion:

**In [142]:** values = {'ids': ['a', 'b'], 'ids2': ['a', 'c'], 'vals': [1, 3]}

**In [143]:** row_mask = df.isin(values).all(1)

**In [144]:** df[row_mask]

```
ids ids2 vals
0   a     a     1
```

### 13.12 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 [145]:** s[s > 0]

```
Out[145]:
3   1
2   2
1   3
0   4
dtype: int64
```

To return a Series of the same shape as the original

**In [146]:** s.where(s > 0)

```
Out[146]:
4  NaN
3   1
2   2
1   3
0   4
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. Equivalent is \(\text{df.where(df < 0)}\)

**In [147]:** df[df < 0]

```
Out[147]:
          A       B        C        D
2000-01-01 NaN      NaN -0.863838  NaN
2000-01-02 -1.048089 -0.025747 -0.988387  NaN
2000-01-03 NaN      NaN  NaN      -0.055758
2000-01-04 NaN   -0.489682  NaN      -0.034571
2000-01-05 -2.484478 -0.281461  NaN      NaN
2000-01-06 NaN    -0.977349  NaN      -0.064034
2000-01-07 -1.282782  NaN      -1.071357  NaN
2000-01-08 NaN      NaN   -0.744471  NaN
```

In addition, `where` takes an optional `other` argument for replacement of values where the condition is False, in the returned copy.

**In [148]:** df.where(df < 0, -df)

```
Out[148]:
          A       B        C        D
2000-01-01 NaN      NaN -0.863838  NaN
2000-01-02 -1.048089 -0.025747 -0.988387  NaN
2000-01-03 NaN      NaN  NaN      -0.055758
2000-01-04 NaN   -0.489682  NaN      -0.034571
2000-01-05 -2.484478 -0.281461  NaN      NaN
2000-01-06 NaN    -0.977349  NaN      -0.064034
2000-01-07 -1.282782  NaN      -1.071357  NaN
2000-01-08 NaN      NaN   -0.744471  NaN
```
You may wish to set values based on some boolean criteria. This can be done intuitively like so:

In [149]: s2 = s.copy()

In [150]: s2[s2 < 0] = 0

In [151]: s2
Out[151]:
        0  1  2  3
A  4  0  2  1
B  3  1  3  0
C  4  0  1  2
dtype: int64

In [152]: df2 = df.copy()

In [153]: df2[df2 < 0] = 0

In [154]: df2
Out[154]:
          A        B        C        D
2000-01-01  1.266143  0.299368  0.000000  0.408204
2000-01-02  0.000000  0.000000  0.000000  0.094055
2000-01-03  1.262731  1.289997  0.082423  0.000000
2000-01-04  0.536580  0.000000  0.369374  0.000000
2000-01-05  0.000000  0.000000  0.030711  0.109121
2000-01-06  1.126203  0.000000  1.474071  0.000000
2000-01-07  0.000000  0.781836  0.000000  0.441153
2000-01-08  2.353925  0.583787  0.000000  0.744471

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:

In [155]: df_orig = df.copy()

In [156]: df_orig.where(df > 0, -df, inplace=True);

In [157]: df_orig
Out[157]:
          A        B        C        D
2000-01-01  1.266143  0.299368  0.863838  0.408204
2000-01-02  1.048089  0.025747  0.988387  0.094055
2000-01-03  1.262731  1.289997  0.082423  0.055758
2000-01-04  0.536580  0.489682  0.369374  0.034571
2000-01-05  2.484478  0.281461  0.030711  0.109121
2000-01-06  1.126203  0.781836  1.071357  0.441153
2000-01-07  2.353925  0.583787  0.221471  0.744471
2000-01-08  1.282782  0.781836  1.071357  0.441153
2000-01-09  2.353925  0.583787  0.221471  0.744471
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 `.ix` (but on the contents rather than the axis labels).

```python
In [158]: df2 = df.copy()
In [159]: df2[df2[1:4] > 0] = 3
In [160]: df2
Out[160]:
   A     B     C     D
0 2000-01-01  1.266143  0.299368 -0.863838  0.408204
1 2000-01-02 -1.048089 -0.025747 -0.988387  3.000000
2 2000-01-03  3.000000  3.000000  3.000000 -0.055758
3 2000-01-04  3.000000 -0.489682  3.000000 -0.034571
4 2000-01-05 -2.484478 -0.281461  0.030711  0.109121
5 2000-01-06  1.126203 -0.977349  1.474071 -0.064034
6 2000-01-07 -1.282782  0.781836 -1.071357  0.441153
7 2000-01-08  2.353925  0.583787  0.221471 -0.744471
```

New in version 0.13.

Where can also accept `axis` and `level` parameters to align the input when performing the `where`.

```python
In [161]: df2 = df.copy()
In [162]: df2.where(df2>0,df2['A'],axis='index')
Out[162]:
   A     B     C     D
0 2000-01-01  1.266143  0.299368  1.266143  0.408204
1 2000-01-02 -1.048089 -1.048089 -1.048089  0.094055
2 2000-01-03  1.262731  1.289997  0.082423  1.262731
3 2000-01-04  0.536580  0.536580  0.369374  0.536580
4 2000-01-05 -2.484478 -2.484478  0.030711  0.109121
5 2000-01-06  1.126203  1.126203  1.474071  1.126203
6 2000-01-07 -1.282782  0.781836 -1.282782  0.441153
7 2000-01-08  2.353925  0.583787  0.221471  2.353925
```

This is equivalent (but faster than) the following.

```python
In [163]: df2 = df.copy()
In [164]: df.apply(lambda x, y: x.where(x>0,y), y=df['A'])
Out[164]:
   A     B     C     D
0 2000-01-01  1.266143  0.299368  1.266143  0.408204
1 2000-01-02 -1.048089 -1.048089 -1.048089  0.094055
2 2000-01-03  1.262731  1.289997  0.082423  1.262731
3 2000-01-04  0.536580  0.536580  0.369374  0.536580
4 2000-01-05 -2.484478 -2.484478  0.030711  0.109121
5 2000-01-06  1.126203  1.126203  1.474071  1.126203
6 2000-01-07 -1.282782  0.781836 -1.282782  0.441153
7 2000-01-08  2.353925  0.583787  0.221471  2.353925
```

mask

mask is the inverse boolean operation of `where`.

```python
In [165]: s.mask(s >= 0)
Out[165]:
```

13.12. The where() Method and Masking
13.13 The `query()` Method (Experimental)

New in version 0.13.

`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:

In [167]: n = 10

In [168]: df = pd.DataFrame(np.random.rand(n, 3), columns=list('abc'))

In [169]: df

Out[169]:
   a       b       c
0 0.687704  0.582314  0.281645
1 0.250846  0.610021  0.420121
2 0.624328  0.401816  0.932146
3 0.011763  0.022921  0.244186
4 0.590198  0.325680  0.890392
5 0.598892  0.296424  0.007312
6 0.634625  0.803069  0.123872
7 0.924168  0.325076  0.303746
8 0.116822  0.364564  0.454607
9 0.986142  0.751953  0.561512

# pure python
In [170]: df[(df.a < df.b) & (df.b < df.c)]

Out[170]:
   a       b       c
3 0.011763  0.022921  0.244186
8 0.116822  0.364564  0.454607

# query
In [171]: df.query('(a < b) & (b < c)')

Out[171]:
   a       b       c
Do the same thing but fall back on a named index if there is no column with the name `a`.

In [172]:
def = pd.DataFrame(np.random.randint(n / 2, size=(n, 2)), columns=list('bc'))

In [173]:
df.index.name = 'a'

In [174]:
df
Out[174]:
   b  c
a
0   0  4
1   2  2
2   1  4
3   3  3
4   0  4
5   1  1
6   0  3
7   2  4
8   3  1
9   3  2

In [175]:
df.query('a < b and b < c')
Out[175]:
Empty DataFrame
Columns: [b, c]
Index: []

If instead you don’t want to or cannot name your index, you can use the name `index` in your query expression:

In [176]:
def = pd.DataFrame(np.random.randint(n, size=(n, 2)), columns=list('bc'))

In [177]:
df
Out[177]:
   b  c
0   9  8
1   0  5
2   4  7
3   2  0
4   5  1
5   4  0
6   2  0
7   6  7
8   3  4
9   9  7

In [178]:
df.query('index < b < c')
Out[178]:
   b  c
2   4  7

Note: If the name of your index overlaps with a column name, the column name is given precedence. For example,

In [179]:
def = pd.DataFrame({'a': np.random.randint(5, size=5)})

In [180]:
df.index.name = 'a'
In [181]: df.query('a > 2')  # uses the column 'a', not the index
Out[181]:
   a
0  2
1  3
2  4

You can still use the index in a query expression by using the special identifier ‘index’:

In [182]: df.query('index > 2')
Out[182]:
   a
0  3
1  4

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.

13.13.1 MultiIndex query() Syntax

You can also use the levels of a DataFrame with a MultiIndex as if they were columns in the frame:

In [183]: n = 10
In [184]: colors = np.random.choice(['red', 'green'], size=n)
In [185]: foods = np.random.choice(['eggs', 'ham'], size=n)
In [186]: colors
Out[186]: array(['green', 'green', 'red', 'red', 'green', 'red', 'green', 'red', 'green', 'green'], dtype='|S5')
In [187]: foods
Out[187]: array(['eggs', 'eggs', 'ham', 'ham', 'eggs', 'ham', 'eggs', 'eggs'], dtype='|S4')
In [188]: index = pd.MultiIndex.from_arrays([colors, foods], names=['color', 'food'])
In [189]: df = pd.DataFrame(np.random.randn(n, 2), index=index)
In [190]: df
Out[190]:
   color  food
0   green  eggs  1.555563  -0.823761
      eggs   0.535420  -1.032853
1   red    ham  1.469725   1.304124
      ham   1.449735   0.203109
2  green   eggs  1.032011   0.969818
      ham  -0.962723   1.382083
3   red    eggs  1.938794   0.669142
green ham  -0.433567 -0.273610
green eggs -0.276099 -1.821168
red   eggs  0.680433 -0.308450

In [191]: df.query('color == "red"')
Out[191]:
        0  
color food
    red  ham       1.469725  1.304124
          ham       1.449735  0.203109
          eggs     -0.938794  0.669142
          eggs       0.680433 -0.308450
    red  eggs     -1.032011  0.969818
          ham     -0.962723  1.382083
          eggs     -0.938794  0.669142
          green eggs -1.032011  0.969818
          ham     -0.962723  1.382083
          eggs     -0.938794  0.669142
          eggs       0.680433 -0.308450
          green eggs -0.276099 -1.821168

If the levels of the MultiIndex are unnamed, you can refer to them using special names:

In [192]: df.index.names = [None, None]
In [193]: df
Out[193]:
        0  
color food
    red  ham       1.469725  1.304124
          ham       1.449735  0.203109
          eggs     -0.938794  0.669142
          eggs       0.680433 -0.308450
    red  eggs     -1.032011  0.969818
          ham     -0.962723  1.382083
          eggs     -0.938794  0.669142
          green eggs -1.032011  0.969818
          ham     -0.962723  1.382083
          eggs     -0.938794  0.669142
          eggs       0.680433 -0.308450
          green eggs -0.276099 -1.821168

In [194]: df.query('ilevel_0 == "red"')
Out[194]:
        0  
red  ham       1.469725  1.304124
          ham       1.449735  0.203109
          eggs     -0.938794  0.669142
          eggs       0.680433 -0.308450

The convention is ilevel_0, which means “index level 0” for the 0th level of the index.

13.13.2 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 [195]: df = pd.DataFrame(np.random.rand(n, 3), columns=list('abc'))
In [196]: df
Out[196]:
     a       b       c
0  0.449167  0.447421  0.557792
1  0.427877  0.690714  0.035221
2  0.543944  0.507917  0.468025
3  0.973561  0.723731  0.700486
4  0.515391  0.337711  0.107630

13.13. The query() Method (Experimental)
In [197]: df2 = pd.DataFrame(np.random.rand(n + 2, 3), columns=df.columns)

In [198]: df2
Out[198]:
   a      b      c
0 0.164291 0.785148 0.847700
1 0.953696 0.111044 0.252125
2 0.033633 0.892920 0.037910
3 0.662580 0.219559 0.243745
4 0.885036 0.790218 0.224283
5 0.736107 0.139168 0.302827
6 0.657803 0.713897 0.611185
7 0.136624 0.984960 0.195246
8 0.123436 0.627712 0.618673
9 0.371660 0.047902 0.480088
10 0.062993 0.185760 0.568018
11 0.483467 0.445289 0.309040

In [199]: expr = '0.0 <= a <= c <= 0.5'

In [200]: map(lambda frame: frame.query(expr), [df, df2])
Out[200]:
[Empty DataFrame
  Columns: [a, b, c]
  Index: [
  ], a b c
  2 0.033633 0.892920 0.037910
  7 0.136624 0.984960 0.195246
  9 0.371660 0.047902 0.480088]

### 13.13.3 query() Python versus pandas Syntax Comparison

Full numpy-like syntax

In [201]: df = pd.DataFrame(np.random.randint(n, size=(n, 3)), columns=list('abc'))

In [202]: df
Out[202]:
   a  b  c
0  8  8  1
1  1  1  9
2  9  9  8
3  7  0  1
4  8  6  6
5  8  2  8
6  3  2  2
7  9  4  8
8  7  2  7
9  9  4  8

In [203]: df.query('(a < b) & (b < c)')
Out[203]:
   a  b  c
0  8  8  1
2  9  9  8
3  7  0  1
4  8  6  6
5  8  2  8
6  3  2  2
7  9  4  8
8  7  2  7
9  9  4  8
Empty DataFrame
Columns: [a, b, c]
Index: []

In [204]: df[(df.a < df.b) & (df.b < df.c)]
Out[204]:
Empty DataFrame
Columns: [a, b, c]
Index: []

Slightly nicer by removing the parentheses (by binding making comparison operators bind tighter than &: |)

In [205]: df.query('a < b & b < c')
Out[205]:
Empty DataFrame
Columns: [a, b, c]
Index: []

Use English instead of symbols

In [206]: df.query('a < b and b < c')
Out[206]:
Empty DataFrame
Columns: [a, b, c]
Index: []

Pretty close to how you might write it on paper

In [207]: df.query('a < b < c')
Out[207]:
Empty DataFrame
Columns: [a, b, c]
Index: []

13.13.4 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.

# get all rows where columns "a" and "b" have overlapping values
In [208]: df = pd.DataFrame({'a': list('aabccddeeff'), 'b': list('aaaabbbcccc'),
                           'c': np.random.randint(5, size=12),
                           'd': np.random.randint(9, size=12)})

In [209]: df
Out[209]:
a  b  c  d
0  a  a  1  7
1  a  a  0  1
2  b  a  2  0
3  b  a  1  7
4  c  b  0  8
5  c  b  1  1
6  d  b  1  0
7  d  b  1  7
8  e  c  4  2
9  e  c  2  7
In [210]: df.query('a in b')
Out[210]:
   a   b   c   d
0  a   a   1   7
1  a   a   0   1
2  b   a   2   0
3  b   a   1   7
4  c   b   0   8
5  c   b   1   1

# How you'd do it in pure Python
In [211]: df[df.a.isin(df.b)]
Out[211]:
   a   b   c   d
0  a   a   1   7
1  a   a   0   1
2  b   a   2   0
3  b   a   1   7
4  c   b   0   8
5  c   b   1   1

In [212]: df.query('a not in b')
Out[212]:
   a   b   c   d
6  d   b   1   0
7  d   b   1   7
8  e   c   4   2
9  e   c   2   7
10 f   c   2   2
11 f   c   4   6

# pure Python
In [213]: df[~df.a.isin(df.b)]
Out[213]:
   a   b   c   d
6  d   b   1   0
7  d   b   1   7
8  e   c   4   2
9  e   c   2   7
10 f   c   2   2
11 f   c   4   6

You can combine this with other expressions for very succinct queries:

# rows where cols a and b have overlapping values and col c's values are less than col d's
In [214]: df.query('a in b and c < d')
Out[214]:
   a   b   c   d
0  a   a   1   7
1  a   a   0   1
2  b   a   1   7
4  c   b   0   8

# pure Python
In [215]: df[df.b.isin(df.a) & (df.c < df.d)]
Out[215]: 
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.

### 13.13.5 Special use of the `==` operator with list objects

Comparing a list of values to a column using `==/!=` works similarly to `in/not in`

```
In [216]: df.query('b == ["a", "b", "c"]')
```

```
Out[216]:
 a  b  c  d
0  a  a  1 7
1  a  a  0 1
2  b  a  2 0
3  b  a  1 7
4  c  b  0 8
5  c  b  1 1
6  d  b  1 0
7  d  b  1 7
8  e  c  4 2
9  e  c  2 7
10 f  c  2 2
11 f  c  4 6
```

```
# pure Python
In [217]: df[df.b.isin(['a', 'b', 'c'])]
```

```
Out[217]:
 a  b  c  d
0  a  a  1 7
1  a  a  0 1
2  b  a  2 0
3  b  a  1 7
4  c  b  0 8
5  c  b  1 1
6  d  b  1 0
7  d  b  1 7
8  e  c  4 2
9  e  c  2 7
10 f  c  2 2
11 f  c  4 6
```

```
In [218]: df.query('c == [1, 2]')
```

```
Out[218]:
```
In [219]: df.query('c != [1, 2]')
Out[219]:
   a  b  c  d
0  a  a  1  7
2  b  a  2  0
3  b  a  1  7
5  c  b  1  1
6  d  b  1  0
7  d  b  1  7
9  e  c  2  7
10 f  c  2  2

# using in/not in
In [220]: df.query('[1, 2] in c')
Out[220]:
   a  b  c  d
0  a  a  1  7
2  b  a  2  0
3  b  a  1  7
5  c  b  1  1
6  d  b  1  0
7  d  b  1  7
9  e  c  2  7
10 f  c  2  2

In [221]: df.query('[1, 2] not in c')
Out[221]:
   a  b  c  d
0  a  a  1  7
2  b  a  2  0
3  b  a  1  7
5  c  b  1  1
6  d  b  1  0
7  d  b  1  7
9  e  c  2  7
10 f  c  2  2

# pure Python
In [222]: df[df.c.isin([1, 2])]
Out[222]:
   a  b  c  d
0  a  a  1  7
2  b  a  2  0
3  b  a  1  7
5  c  b  1  1
6  d  b  1  0
7  d  b  1  7
9  e  c  2  7
10 f  c  2  2

## 13.13.6 Boolean Operators

You can negate boolean expressions with the word **not** or the ~ operator.
In [223]: df = pd.DataFrame(np.random.rand(n, 3), columns=list('abc'))

In [224]: df['bools'] = np.random.rand(len(df)) > 0.5

In [225]: df.query('~bools')
Out[225]:
   a    b    c  bools
0 0.023729 0.458852 0.284632  False
1 0.004236 0.442347 0.767020  False
2 0.890592 0.568747 0.332692  False
3 0.843864 0.902394 0.538418  False
4 0.428377 0.870859 0.380827  False
5 0.321819 0.559198 0.382567  False
6 0.119041 0.715950 0.448156  False
7 0.606506 0.300726 0.666418  False

In [226]: df.query('not bools')
Out[226]:
   a    b    c  bools
0 0.023729 0.458852 0.284632  False
1 0.004236 0.442347 0.767020  False
2 0.890592 0.568747 0.332692  False
3 0.843864 0.902394 0.538418  False
4 0.428377 0.870859 0.380827  False
5 0.321819 0.559198 0.382567  False
6 0.119041 0.715950 0.448156  False
7 0.606506 0.300726 0.666418  False

In [227]: df.query('not bools') == df[~df.bools]
Out[227]:
     a    b    c  bools
0  True  True  True  True
1  True  True  True  True
2  True  True  True  True
3  True  True  True  True
4  True  True  True  True
5  True  True  True  True
6  True  True  True  True
7  True  True  True  True
8  True  True  True  True
9  True  True  True  True

Of course, expressions can be arbitrarily complex too

# short query syntax
In [228]: shorter = df.query('a < b < c and (not bools) or bools > 2')

# equivalent in pure Python
In [229]: longer = df[(df.a < df.b) & (df.b < df.c) & (~df.bools) | (df.bools > 2)]

In [230]: shorter
Out[230]:
     a    b    c  bools
0 0.004236 0.442347 0.767020  False

In [231]: longer
Out[231]:
     a    b    c  bools
0 0.004236 0.442347 0.767020  False

In [232]: shorter == longer

13.13. The query() Method (Experimental)
Out[232]:
    a   b   c  bools
  2  True True True True

### 13.13.7 Performance of `query()`

`DataFrame.query()` using `numexpr` is slightly faster than Python for large frames.

![Graph showing the performance comparison between python and numexpr](image)

**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.

![Graph showing the performance comparison between python and numexpr](image)

This plot was created using a `DataFrame` with 3 columns each containing floating point values generated using `numpy.random.randn()`. 
13.14 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 [233]: 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 [234]: df2
Out[234]:
   a  b   c
0 one x -0.599770
1 one y -0.120145
2 two x -1.403265
3 two y  0.162169
4 two x  0.232777
5 three x  1.048589
6 four x  0.070084

In [235]: df2.duplicated('a')
Out[235]:
0   False
1   True
2  False
3   True
4   True
5   False
6   False
dtype: bool

In [236]: df2.duplicated('a', keep='last')
Out[236]:
0   True
1   False
2   True
3   True
4  False
5  False
6  False
dtype: bool

In [237]: df2.duplicated('a', keep=False)
Out[237]:
0   True
1    True
2    True
3    True
4    True
5    False
6    False
dtype: bool

In [238]: df2.drop_duplicates('a')
Out[238]:
   a   b    c
0  one  x  -0.599770
2  two  x  -1.403265
5  three  x   1.048589
6   four  x   0.070084

In [239]: df2.drop_duplicates('a', keep='last')
Out[239]:
   a   b    c
1  one  y  -0.120145
4  two  x   0.232777
5  three  x   1.048589
6   four  x   0.070084

In [240]: df2.drop_duplicates('a', keep=False)
Out[240]:
   a   b    c
5  three  x   1.048589
6   four  x   0.070084

Also, you can pass a list of columns to identify duplications.

In [241]: df2.duplicated(['a', 'b'])
Out[241]:
0    False
1    False
2    False
3    False
4     True
5    False
6    False
dtype: bool

In [242]: df2.drop_duplicates(['a', 'b'])
Out[242]:
   a   b    c
0  one  x  -0.599770
1  one  y  -0.120145
2  two  x  -1.403265
3  two  y   0.162169
5  three  x   1.048589
6   four  x   0.070084

To drop duplicates by index value, use `Index.duplicated` then perform slicing. Same options are available in `keep` parameter.

In [243]: df3 = pd.DataFrame({'a': np.arange(6),
                         'b': np.random.randn(6),
                         index=['a', 'a', 'b', 'c', 'b', 'a'])

442 Chapter 13. Indexing and Selecting Data
13.15 Dictionary-like `get()` method

Each of Series, DataFrame, and Panel have a `get` method which can return a default value.

```
In [249]: s = pd.Series([1,2,3], index=['a','b','c'])
In [250]: s.get('a')  # equivalent to s['a']
Out[250]: 1
In [251]: s.get('x', default=-1)
Out[251]: -1
```

13.16 The `select()` Method

Another way to extract slices from an object is with the `select` method of Series, DataFrame, and Panel. This method should be used only when there is no more direct way. `select` takes a function which operates on labels along `axis` and returns a boolean. For instance:

```
In [252]: df.select(lambda x: x == 'A', axis=1)
Out[252]:
```
A
2000-01-01 -0.226151
2000-01-02  1.380589
2000-01-03  1.185125
2000-01-04 -0.124870
2000-01-05 -0.926415
2000-01-06 -0.447053
2000-01-07  0.183787
2000-01-08 -1.544483

13.17 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,

```python
In [253]: dflookup = pd.DataFrame(np.random.rand(20, 4), columns = ['A','B','C','D'])
In [254]: dflookup.lookup(list(range(0,10,2)), ['B','C','A','B','D'])
Out[254]: array([ 0.9242, 0.3338, 0.7562, 0.6023, 0.7212])
```

13.18 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`:

```python
In [255]: index = pd.Index(['e', 'd', 'a', 'b'])
In [256]: index
Out[256]: Index(['e', 'd', 'a', 'b'], dtype='object')
In [257]: 'd' in index
Out[257]: True
```

You can also pass a name to be stored in the index:

```python
In [258]: index = pd.Index(['e', 'd', 'a', 'b'], name='something')
In [259]: index.name
Out[259]: 'something'
```

The name, if set, will be shown in the console display:

```python
In [260]: index = pd.Index(list(range(5)), name='rows')
In [261]: columns = pd.Index(['A', 'B', 'C'], name='cols')
In [262]: df = pd.DataFrame(np.random.randn(5, 3), index=index, columns=columns)
In [263]: df
```

Chapter 13. Indexing and Selecting Data
### 13.18.1 Setting metadata

New in version 0.13.0.

Indexes are “mostly immutable”, but it is possible to set and change their metadata, like the index name (or, for MultiIndex, levels and labels).

You can use the `rename`, `set_names`, `set_levels`, and `set_labels` 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.

```
In [265]: ind = pd.Index([1, 2, 3])

In [266]: ind.rename("apple")
Out[266]: Int64Index([1, 2, 3], dtype='int64', name=u'apple')

In [267]: ind
Out[267]: Int64Index([1, 2, 3], dtype='int64')

In [268]: ind.set_names(['apple'], inplace=True)

In [269]: ind.name = "bob"

In [270]: ind
Out[270]: Int64Index([1, 2, 3], dtype='int64', name=u'bob')
```

New in version 0.15.0.

`set_names`, `set_levels`, and `set_labels` also take an optional `level` argument.

```
In [271]: index = pd.MultiIndex.from_product([range(3), ['one', 'two']], names=['first', 'second'])

In [272]: index
Out[272]: MultiIndex(levels=[[0, 1, 2], [u'one', u'two']],
              labels=[[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]],
              names=[u'first', u'second'])

In [273]: index.levels[1]
```
Out[273]: Index(['one', 'two'], dtype='object', name='second')

In [274]: index.set_levels(['a', 'b'], level=1)
Out[274]:
MultiIndex(levels=[[0, 1, 2], ['a', 'b']],
labels=[[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]],
names=['first', 'second'])

13.18.2 Set operations on Index objects

Warning: In 0.15.0, the 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().

The two main operations are union (|), intersection (&) These can be directly called as instance methods or used via overloaded operators. Difference is provided via the .difference() method.

In [275]: a = pd.Index(['c', 'b', 'a'])

In [276]: b = pd.Index(['c', 'e', 'd'])

In [277]: a | b
Out[277]: Index(['a', 'b', 'c', 'd', 'e'], dtype='object')

In [278]: a & b
Out[278]: Index(['c'], dtype='object')

In [279]: a.difference(b)
Out[279]: Index(['a', 'b'], dtype='object')

Also available is the sym_diff (^) operation, which returns elements that appear in either idx1 or idx2 but not both. This is equivalent to the Index created by idx1.difference(idx2).union(idx2.difference(idx1)), with duplicates dropped.

In [280]: idx1 = pd.Index([1, 2, 3, 4])

In [281]: idx2 = pd.Index([2, 3, 4, 5])

In [282]: idx1.sym_diff(idx2)
Out[282]: Int64Index([1, 5], dtype='int64')

In [283]: idx1 ^ idx2
Out[283]: Int64Index([1, 5], dtype='int64')

13.19 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.

13.19.1 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, indexed DataFrame:
In [284]: data
Out[284]:
    a    b    c    d
0  bar  one   z   1
1  bar  two   y   2
2  foo  one   x   3
3  foo  two   w   4

In [285]: indexed1 = data.set_index('c')

In [286]: indexed1
Out[286]:
    a    b    d
     c
   z  bar  one  1
   y  bar  two  2
   x  foo  one  3
   w  foo  two  4

In [287]: indexed2 = data.set_index(['a', 'b'])

In [288]: indexed2
Out[288]:
   c    d
    a    b
   bar  one  1
       two  2
   foo  one  3
       two  4

The append keyword option allow you to keep the existing index and append the given columns to a MultiIndex:

In [289]: frame = data.set_index('c', drop=False)

In [290]: frame = frame.set_index(['a', 'b'], append=True)

In [291]: frame
Out[291]:
   c    d
    a    b
   bar  one  1
       two  2
   foo  one  3
       two  4

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 [292]: data.set_index('c', drop=False)
Out[292]:
    a    b    c    d
     c
   z  bar  one  1
   y  bar  two  2
   x  foo  one  3
   w  foo  two  4

In [293]: data.set_index(['a', 'b'], inplace=True)
In [294]: data
data =
c d
a b
bar one z 1
two y 2
foo one x 3
two w 4

**13.19.2 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 to `set_index`

In [295]: data
Out[295]:
c d
a b
bar one z 1
two y 2
foo one x 3
two w 4

In [296]: data.reset_index()
Out[296]:
a b c d
0 bar one z 1
1 bar two y 2
2 foo one x 3
3 foo two w 4

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 [297]: frame
Out[297]:
c d
c a b
z bar one z 1
y bar two y 2
x foo one x 3
w foo two w 4

In [298]: frame.reset_index(level=1)
Out[298]:
a c d
c b
z one bar z 1
y two bar y 2
x one foo x 3
w two foo w 4

`reset_index` takes an optional parameter `drop` which if true simply discards the index, instead of putting index values in the DataFrame’s columns.

**Note:** The `reset_index` method used to be called `delevel` which is now deprecated.
13.19.3 Adding an ad hoc index

If you create an index yourself, you can just assign it to the `index` field:

```python
data.index = index
```

13.20 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 [299]: dfmi = pd.DataFrame(['abcd',
        ....:     list('efgh'),
        ....:     list('ijkl'),
        ....:     list('mnop'),
    columns=pd.MultiIndex.from_product([['one','two'],
        ....:     ['first','second']]))

In [300]: dfmi
Out[300]:
     first  second
one  
   first  second
0     a     b     c     d
1     e     f     g     h
2     i     j     k     l
3     m     n     o     p

Compare these two access methods:

```python
In [301]: dfmi['one']['second']
Out[301]:
   0     b
   1     f
   2     j
   3     n
Name: second, dtype: object

In [302]: dfmi.loc[:,('one','second')]
Out[302]:
   0     b
   1     f
   2     j
   3     n
Name: (one, second), dtype: object
```

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 data frame that is singly-indexed. Then another python operation `dfmi_with_one['second']` selects the series indexed by ‘second’ happens. 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.

### 13.20.1 Why does the assignment when using chained indexing fail!

So, why does this show the `SettingWithCopy` warning / and possibly not work when you do chained indexing and assignment:

```
  dfmi['one']['second'] = value
```

Since the chained indexing is 2 calls, it is possible that either call may return a `copy` of the data because of the way it is sliced. Thus when setting, you are actually setting a `copy`, and not the original frame data. It is impossible for pandas to figure this out because their are 2 separate python operations that are not connected.

The `SettingWithCopy` warning is a ‘heuristic’ to detect this (meaning it tends to catch most cases but is simply a lightweight check). Figuring this out for real is way complicated.

The `.loc` operation is a single python operation, and thus can select a slice (which still may be a copy), but allows pandas to assign that slice back into the frame after it is modified, thus setting the values as you would think.

The reason for having the `SettingWithCopy` warning is this. Sometimes when you slice an array you will simply get a view back, which means you can set it no problem. However, even a single dtyped array can generate a copy if it is sliced in a particular way. A multi-dtyped DataFrame (meaning it has say `float` and `object` data), will almost always yield a copy. Whether a view is created is dependent on the memory layout of the array.

### 13.20.2 Evaluation order matters

Furthermore, in chained expressions, the order may determine whether a copy is returned or not. If an expression will set values on a copy of a slice, then a `SettingWithCopy` exception will be raised (this raise/warn behavior is new starting in 0.13.0)

You can control the action of a chained assignment via the option `mode.chained_assignment`, which can take the values ['`raise`', 'warn', None], where showing a warning is the default.

```
In [303]: 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 [304]: dfb['c'][dfb.a.str.startswith('o')] = 42
```

This however is operating on a copy and will not work.

```
>>> 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/.ix`.

This is the correct access method

```
In [305]: dfc = pd.DataFrame({'A':['aaa','bbb','ccc'],'B':[1,2,3]})

In [306]: dfc.loc[0,'A'] = 11

In [307]: dfc
Out[307]:
   A  B
0  11 1
1  bbb 2
2  ccc 3
```

This can work at times, but is not guaranteed, and so should be avoided

```
In [308]: dfc = dfc.copy()

In [309]: dfc['A'][0] = 111

In [310]: dfc
Out[310]:
   A  B
0  111 1
1  bbb 2
2  ccc 3
```

This will not work at all, and so should be avoided

```
>>> pd.set_option('mode.chained_assignment','raise')

>>> dfc.loc[0]['A'] = 1111
Traceback (most recent call last):
  ... SettingWithCopyException:
      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.
This section covers indexing with a MultiIndex and more 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

**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 should be a transparent change with only very limited API implications (See the Internal Refactoring)

See the cookbook for some advanced strategies

### 14.1 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 the 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

#### 14.1.1 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 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), or a crossed set of iterables (using MultiIndex.from_product). The Index constructor will attempt to return a MultiIndex when it is passed a list of tuples. The following examples demo 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))
```
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(levels=[[u'bar', u'baz', u'foo', u'qux'], [u'one', u'two']],
labels=[[0, 0, 1, 1, 2, 2, 3, 3], [0, 1, 0, 1, 0, 1, 0, 1]],
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 function:

In [8]: iterables = [['bar', 'baz', 'foo', 'qux'], ['one', 'two']] 

In [9]: pd.MultiIndex.from_product(iterables, names=['first', 'second'])
Out[9]:
MultiIndex(levels=[[u'bar', u'baz', u'foo', u'qux'], [u'one', u'two']],
labels=[[0, 0, 1, 1, 2, 2, 3, 3], [0, 1, 0, 1, 0, 1, 0, 1]],
names=['first', 'second'])

As a convenience, you can pass a list of arrays directly into Series or DataFrame to construct a MultiIndex automatical-

In [10]: arrays = [np.array(['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux']),
           np.array(['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two'])]

In [11]: s = pd.Series(np.random.randn(8), index=arrays)

In [12]: s
Out[12]:
bar  one   -0.861849
      two   -2.104569
baz  one   -0.494929

dtype: float64

When you want every pairing of the elements in two iterables, it can be easier to use the
MultiIndex.from_product function:
In [13]: df = pd.DataFrame(np.random.randn(8, 4), index=arrays)

In [14]: df
Out[14]:
   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   -0.370647 -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
dtype: float64

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 [15]: df.index.names
Out[15]: 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:

In [16]: df = pd.DataFrame(np.random.randn(3, 8), index=['A', 'B', 'C'], columns=index)

In [17]: df
Out[17]:

<table>
<thead>
<tr>
<th>first</th>
<th>bar</th>
<th>baz</th>
<th>foo</th>
<th>qux</th>
</tr>
</thead>
<tbody>
<tr>
<td>second</td>
<td>one</td>
<td>two</td>
<td>one</td>
<td>two</td>
</tr>
<tr>
<td>A</td>
<td>0.895717</td>
<td>0.805244</td>
<td>-1.206412</td>
<td>2.565646</td>
</tr>
<tr>
<td>B</td>
<td>0.410835</td>
<td>0.813850</td>
<td>0.132003</td>
<td>-0.827317</td>
</tr>
<tr>
<td>C</td>
<td>-1.413681</td>
<td>1.607920</td>
<td>1.024180</td>
<td>0.569605</td>
</tr>
</tbody>
</table>

first
second  two
A    -0.226169
B    -1.436737
C     -2.006747

In [18]: pd.DataFrame(np.random.randn(6, 6), index=index[:6], columns=index[:6])
Out[18]:

<table>
<thead>
<tr>
<th>first</th>
<th>bar</th>
<th>baz</th>
<th>foo</th>
</tr>
</thead>
<tbody>
<tr>
<td>second</td>
<td>one</td>
<td>two</td>
<td>one</td>
</tr>
<tr>
<td>first</td>
<td>second</td>
<td>one</td>
<td>two</td>
</tr>
<tr>
<td>bar</td>
<td>-0.410001</td>
<td>0.078638</td>
<td>0.545952</td>
</tr>
<tr>
<td>two</td>
<td>-1.281247</td>
<td>0.727707</td>
<td>-0.121306</td>
</tr>
<tr>
<td>baz</td>
<td>0.959726</td>
<td>-1.110336</td>
<td>0.619976</td>
</tr>
<tr>
<td>foo</td>
<td>0.176444</td>
<td>0.403310</td>
<td>-0.154951</td>
</tr>
<tr>
<td>two</td>
<td>-0.954208</td>
<td>1.462696</td>
<td>-1.743161</td>
</tr>
<tr>
<td>two</td>
<td>0.690579</td>
<td>0.995761</td>
<td>2.396780</td>
</tr>
</tbody>
</table>

We’ve “sparsified” the higher levels of the indexes to make the console output a bit easier on the eyes.

It’s worth keeping in mind that there’s nothing preventing you from using tuples as atomic labels on an axis:

14.1. Hierarchical indexing (MultiIndex)
In [19]: pd.Series(np.random.randn(8), index=tuples)
Out[19]:
(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.

Note that how the index is displayed by be controlled using the multi_sparse option in
pandas.set_printoptions:

In [20]: pd.set_option('display.multi_sparse', False)
In [21]: df
Out[21]:
   first  bar  bar  baz  baz  foo  foo  qux
second   one  two  one  two  one  two  one
   A   0.895717  0.805244 -1.206412  2.565646  1.431256  1.340309 -1.170299
     B   0.410835  0.813850  0.132003 -0.827317 -0.076467 -1.187678  1.130127
     C  -1.413681  1.607920  1.024180  0.569605  0.875906 -2.211372  0.974466
   first   qux
second   two
     A  -0.226169
     B  -1.436737
     C  -2.006747
In [22]: pd.set_option('display.multi_sparse', True)

14.1.2 Reconstructing the level labels

The method get_level_values will return a vector of the labels for each location at a particular level:

In [23]: index.get_level_values(0)
Out[23]: Index([u'bar', u'bar', u'baz', u'baz', u'foo', u'foo', u'qux'], dtype='object', name='first')
In [24]: index.get_level_values('second')
Out[24]: Index([u'one', u'two', u'one', u'two', u'one', u'two', u'one', u'two'], dtype='object', name='second')

14.1.3 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:
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.

Note: The repr of a MultiIndex shows ALL the defined levels of an index, even if they are not actually used. When slicing an index, you may notice this. For example:

# original multi-index
In [29]: df.columns
Out[29]:
MultiIndex(levels=[['bar', 'baz', 'foo', 'qux'], ['one', 'two']],
labels=[[0, 0, 1, 1, 2, 2, 3, 3], [0, 1, 0, 1, 0, 1, 0, 1]],
names=['first', 'second'])

# sliced
In [30]: df[['foo', 'qux']].columns
Out[30]:
MultiIndex(levels=[['bar', 'baz', 'foo', 'qux'], ['one', 'two']],
labels=[[2, 2, 3, 3], [0, 1, 0, 1]],
names=['first', 'second'])

This is done to avoid a recomputation of the levels in order to make slicing highly performant. If you want to see the actual used levels.

In [31]: df[['foo', 'qux']].columns.values
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([u'foo', u'foo', u'qux', u'qux'], dtype='object', name=u'first')

To reconstruct the multiindex with only the used levels
In [33]: pd.MultiIndex.from_tuples(df[['foo', 'qux']].columns.values)
Out[33]:
MultiIndex(levels=[[u'foo', u'qux']], codes=[[0, 0, 1, 1]],
          labels=[[0, 1, 0, 1]])

14.1.4 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:

In [34]: s + s[:-2]
Out[34]:
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 [35]: s + s[::2]
Out[35]:
bar one   -1.723698
    two    NaN
baz one   -0.989859
    two    NaN
foo one    1.443110
    two    NaN
qux one   -2.079150
    two    NaN
dtype: float64

`reindex` can be called with another MultiIndex or even a list or array of tuples:

In [36]: s.reindex(index[:3])
Out[36]:
first  second
bar one   -0.861849
    two  -2.104569
baz one   -0.494929
dtype: float64

In [37]: s.reindex([('foo', 'two'), ('bar', 'one'), ('qux', 'one'), ('baz', 'one')])
Out[37]:
foo two  -0.706771
bar one  -0.861849
qux one  -1.039575
baz one  -0.494929
dtype: float64
14.2 Advanced indexing with hierarchical index

Syntactically integrating MultiIndex in advanced indexing with .loc/.ix is a bit challenging, but we’ve made every effort to do so. For example, the following works as you would expect:

```python
In [38]: df = df.T

In [39]: df
Out[39]:
    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 [40]: df.loc['bar']
Out[40]:
    A      B      C
second
one  0.895717  0.410835 -1.413681
two  0.805244  0.813850  1.607920

In [41]: df.loc['bar', 'two']
Out[41]:
    A  B  C
one  0.805244  0.813850  1.607920
Name: (bar, two), dtype: float64
```

“Partial” slicing also works quite nicely.

```python
In [42]: df.loc['baz':'foo']
Out[42]:
    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

In [43]: df.loc[('baz', 'two'):('qux', 'one')]  # range of tuples
Out[43]:
    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
```

You can slice with a ‘range’ of values, by providing a slice of tuples.
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 [45]: df.ix[['bar', 'two'], ('qux', 'one')]
Out[45]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>first second</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>bar two</td>
<td>0.805244</td>
<td>0.813850</td>
<td>1.607920</td>
</tr>
<tr>
<td>qux one</td>
<td>-1.170299</td>
<td>1.130127</td>
<td>0.974466</td>
</tr>
</tbody>
</table>

### 14.2.1 Using slicers

New in version 0.14.0.

In 0.14.0 we added a new way to slice multi-indexed objects. You can slice a multi-index 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*. 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'),.....),:]
```

rather than this:

```python
df.loc[(slice('A1','A3'),......)]
```

**Warning:** You will need to make sure that the selection axes are fully lexsorted!

In [46]: def mklbl(prefix,n):
   ....:     return ['%s%s' % (prefix,i) for i in range(n)]
   ....:     
In [47]: miindex = pd.MultiIndex.from_product([mklbl('A',4),
   ....:                              mklbl('B',2),
   ....:                              mklbl('C',4),
   ....:                              mklbl('D',2)])
   ....:     
In [48]: micolumns = pd.MultiIndex.from_tuples([('a','foo'),('a','bar'),
   ....:                              ('b','foo'),('b','bah')],
   ....:                              names=['lvl0', 'lvl1'])
In [49]: 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 [50]: dfmi

Out[50]:

<table>
<thead>
<tr>
<th>lvl0</th>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td>lvl1</td>
<td>bar</td>
<td>foo</td>
</tr>
<tr>
<td>A0</td>
<td>B0</td>
<td>1</td>
</tr>
<tr>
<td>D1</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>C1</td>
<td>D0</td>
<td>9</td>
</tr>
<tr>
<td>D1</td>
<td>13</td>
<td>12</td>
</tr>
<tr>
<td>C2</td>
<td>D0</td>
<td>17</td>
</tr>
<tr>
<td>D1</td>
<td>21</td>
<td>20</td>
</tr>
<tr>
<td>C3</td>
<td>D0</td>
<td>25</td>
</tr>
</tbody>
</table>

[64 rows x 4 columns]

Basic multi-index slicing using slices, lists, and labels.

In [51]: dfmi.loc[(slice('A1','A3'),slice(None), ['C1','C3']),:]

Out[51]:

<table>
<thead>
<tr>
<th>lvl0</th>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<td>lvl1</td>
<td>bar</td>
<td>foo</td>
</tr>
<tr>
<td>A1</td>
<td>B0</td>
<td>73</td>
</tr>
<tr>
<td>D1</td>
<td>77</td>
<td>76</td>
</tr>
<tr>
<td>C3</td>
<td>D0</td>
<td>89</td>
</tr>
<tr>
<td>D1</td>
<td>93</td>
<td>92</td>
</tr>
<tr>
<td>B1</td>
<td>C1</td>
<td>105</td>
</tr>
<tr>
<td>D1</td>
<td>109</td>
<td>108</td>
</tr>
<tr>
<td>C3</td>
<td>D0</td>
<td>121</td>
</tr>
</tbody>
</table>

[24 rows x 4 columns]

You can use a pd.IndexSlice to have a more natural syntax using : rather than using slice(None)

In [52]: idx = pd.IndexSlice

In [53]: dfmi.loc[idx[:, :, ['C1','C3']],idx[:, 'foo']]

Out[53]:

<table>
<thead>
<tr>
<th>lvl0</th>
<th>a</th>
<th>b</th>
</tr>
</thead>
</table>

14.2. Advanced indexing with hierarchical index
It is possible to perform quite complicated selections using this method on multiple axes at the same time.

```python
In [54]: dfmi.loc['A1', (slice(None), 'foo')]
Out[54]:
       a  b
    lvl0
A0 B0 C1 D0  8  10
    lvl1
A0 B0 C1 D1 12 14
    A0 C1 D0 24 26
A0 D1 28 30

... ... ...

A3 B0 C1 D1 204 206
    A0 B0 C1 D0 8 10
    lvl1
A0 B0 C1 D1 12 14
    A0 C1 D0 24 26
A0 D1 28 30

[32 rows x 2 columns]
```

```python
In [55]: dfmi.loc[idx[:,:,['C1','C3']],idx[:,'foo']]
Out[55]:
       a  b
    lvl0
A0 B0 C1 D0  8  10
    lvl1
A0 B0 C1 D1 12 14
    A0 C1 D0 24 26
A0 D1 28 30

... ... ...

A3 B0 C1 D1 204 206
    A0 B0 C1 D0 8 10
    lvl1
A0 B0 C1 D1 12 14
    A0 C1 D0 24 26
A0 D1 28 30

[16 rows x 2 columns]
```
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 [56]: mask = dfm['a','foo']>200

In [57]: dfm.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

You can also specify the axis argument to .loc to interpret the passed slicers on a single axis.

In [58]: dfm.loc(axis=0)[:,:,['C1','C3']]
Out[58]:
  lvl0  a  b
  lvl1  bar  foo  bah  foo
A0  B0  C0  D0  1  0  3  2  
   D1  5  4  7  6  
C0  D0  10  10  10  10  
   B1  C1  D0  41  40  43  42  
   D1  45  44  46  46  
C3  D0  57  56  59  58  
   ... ... ... ... ...
A3  B0  C1  D1  205  204  207  206  
   C3  D0  217  216  219  218  
   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 = dfm.copy()

In [60]: df2 = dfm.copy()

In [61]: df2.loc(axis=0)[:,:,['C1','C3']] = -10

Out[61]:
  lvl0  a  b
  lvl1  bar  foo  bah  foo
A0  B0  C0  D0  1  0  3  2  
   D1  5  4  7  6  
C0  D0  10  10  10  10  
   B1  C1  D0  41  40  43  42  
   D1  45  44  46  46  
C3  D0  57  56  59  58  
   ... ... ... ... ...
A3  B0  C1  D1  205  204  207  206  
   C3  D0  217  216  219  218  
   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

14.2. Advanced indexing with hierarchical index 463
You can use a right-hand-side of an alignable object as well.

```
In [62]: df2 = dfmi.copy()

In [63]: df2.loc[idx[:,:,['C1','C3']]] = df2*1000

In [64]: df2
```

```
Out[64]:
A  B  C  D
0  1  2  3
1  4  5  6
2  7  8  9
3 10 11 12
4 13 14 15
5 16 17 18
6 19 20 21
7 22 23 24
8 25 26 27
9 28 29 30
10 31 32 33
11 34 35 36
12 37 38 39
13 40 41 42
14 43 44 45
15 46 47 48
16 49 50 51
17 52 53 54
18 55 56 57
```

### 14.2.2 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 [65]: df

Out[65]:
A  B  C
first second
bar  0.895717  0.410835 -1.41368
  one  0.805244  0.813850  1.607920
  two -1.206412  0.132003  1.024180
  baz  2.565646 -0.827317  0.569605
  two  1.431256  0.076467  0.875906
foo  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 [66]: df.xs('one', level='second')
Out[66]:
   A   B   C
first
tab 0.895717 0.410835 -1.413681
baz -1.206412 0.132003 1.024180
foo  1.431256 -0.076467 0.875906
qux -1.170299 1.130127 0.974466

# using the slicers (new in 0.14.0)
In [67]: df.loc[(slice(None),'one'),:]
Out[67]:
   A   B   C
first second
tab 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

You can also select on the columns with xs(), by providing the axis argument

In [68]: df = df.T

In [69]: df.xs('one', level='second', axis=1)
Out[69]:
   first  bar  baz  foo  qux
A         0.895717 -1.206412 1.431256 -1.170299
B         0.410835 0.132003 -0.076467 1.130127
C  -1.413681  1.024180 0.875906  0.974466

# using the slicers (new in 0.14.0)
In [70]: df.loc[:,(slice(None),'one')]
Out[70]:
   first  bar  baz  foo  qux
second one  one  one  one  one
A         0.895717 -1.206412 1.431256 -1.170299
B         0.410835 0.132003 -0.076467 1.130127
C  -1.413681  1.024180 0.875906  0.974466

xs() also allows selection with multiple keys

In [71]: df.xs(('one', 'bar'), level=('second', 'first'), axis=1)
Out[71]:
   first  bar  baz  foo  qux
A         0.895717 -1.206412 1.431256 -1.170299
B         0.410835 0.132003 -0.076467 1.130127
C  -1.413681  1.024180 0.875906  0.974466

# using the slicers (new in 0.14.0)
In [72]: df.loc[:,('bar','one')]
Out[72]:
   A 0.895717
   B 0.410835
   C -1.413681

14.2. Advanced indexing with hierarchical index 465
Name: (bar, one), dtype: float64

New in version 0.13.0.

You can pass drop_level=False to .xs() to retain the level that was selected

In [73]: df.xs('one', level='second', axis=1, drop_level=False)
Out[73]:
   first  bar  baz  foo  qux
second  one  one  one  one
   A  0.895717 -1.206412 1.431256 -1.170299
   B  0.410835  0.132003 -0.076467  1.130127
   C -1.413681  1.024180  0.875906  0.974466

versus the result with drop_level=True (the default value)

In [74]: df.xs('one', level='second', axis=1, drop_level=True)
Out[74]:
   first  bar  baz  foo  qux
   A  0.895717 -1.206412 1.431256 -1.170299
   B  0.410835  0.132003 -0.076467  1.130127
   C -1.413681  1.024180  0.875906  0.974466

### 14.2.3 Advanced reindexing and alignment

The parameter level has been added to the reindex and align methods of pandas objects. This is useful to broadcast values across a level. For instance:

In [75]: midx = pd.MultiIndex(levels=[['zero', 'one'], ['x','y']],
                        labels=[[1,1,0,0],[1,0,1,0]])

In [76]: df = pd.DataFrame(np.random.randn(4,2), index=midx)

In [77]: df
Out[77]:
    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 [78]: df2 = df.mean(level=0)

In [79]: df2
Out[79]:
   0   1
zero 1.271532  0.713416
one  1.060074 -0.109716

In [80]: df2.reindex(df.index, level=0)
Out[80]:
    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 [81]: df_aligned, df2_aligned = df.align(df2, level=0)

In [82]: df_aligned
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_aligned
Out[83]:
   0  1
one y 1.060074 -0.109716
     x 1.060074 -0.109716
zero y 1.271532  0.713416
       x 1.271532  0.713416

14.2.4 Swapping levels with swaplevel()

The swaplevel function can switch the order of two levels:

In [84]: df[:5]
Out[84]:
   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 [85]: df[:5].swaplevel(0, 1, axis=0)
Out[85]:
   0  1
   y one 1.519970 -0.493662
        x 0.600178  0.274230
   y zero 0.132885 -0.023688
        x 2.410179  1.450520

14.2.5 Reordering levels with reorder_levels()

The reorder_levels function generalizes the swaplevel function, allowing you to permute the hierarchical index levels in one step:

In [86]: df[:5].reorder_levels([1,0], axis=0)
Out[86]:
   0  1
   y one 1.519970 -0.493662
        x 0.600178  0.274230
   y zero 0.132885 -0.023688
        x 2.410179  1.450520
14.3 The need for sortedness with MultiIndex

Caveat emptor: the present implementation of MultiIndex requires that the labels be sorted for some of the slicing / indexing routines to work correctly. You can think about breaking the axis into unique groups, where at the hierarchical level of interest, each distinct group shares a label, but no two have the same label. However, the MultiIndex does not enforce this: you are responsible for ensuring that things are properly sorted. There is an important new method `sort_index` to sort an axis within a MultiIndex so that its labels are grouped and sorted by the original ordering of the associated factor at that level. Note that this does not necessarily mean the labels will be sorted lexicographically!

```python
In [87]: import random; random.shuffle(tuples)

In [88]: s = pd.Series(np.random.randn(8), index=pd.MultiIndex.from_tuples(tuples))

In [89]: s
Out[89]:
foo one  0.206053
qux two -0.251905
baz two -2.213588
  one  1.063327
  qux  1.266143
bar two  0.299368
  one -0.863838
foo two  0.408204
dtype: float64

In [90]: s.sort_index(level=0)
Out[90]:
bar one  -0.863838
  two  0.299368
baz one  1.063327
  two -2.213588
foo one  0.206053
  two  0.408204
qux one  1.266143
  two -0.251905
dtype: float64

In [91]: s.sort_index(level=1)
Out[91]:
bar one  -0.863838
  baz one  1.063327
  foo one  0.206053
  qux one  1.266143
  bar two  0.299368
  baz two -2.213588
  foo two  0.408204
  qux two -0.251905
dtype: float64

Note, you may also pass a level name to `sort_index` if the MultiIndex levels are named.

In [92]: s.index.set_names(['L1', 'L2'], inplace=True)

In [93]: s.sort_index(level='L1')
Out[93]:
L1  L2
bar one  -0.863838
```
two   0.299368
baz   one  1.063327
two   -2.213588
foo   one  0.206053
two   0.408204
qux   one  1.266143
two   -0.251905
dtype: float64

In [94]: s.sort_index(level='L2')
Out[94]:
   L1  L2
bar  one -0.863838
baz  one  1.063327
foo  one  0.206053
qux  one  1.266143
bar two  0.299368
baz two -2.213588
foo two  0.408204
qux two -0.251905
dtype: float64

Some indexing will work even if the data are not sorted, but will be rather inefficient and will also return a copy of the
data rather than a view:

In [95]: s['qux']
Out[95]:
   L2
two  -0.251905
one  1.266143
dtype: float64

In [96]: s.sort_index(level=1)['qux']
Out[96]:
   L2
one  1.266143
two -0.251905
dtype: float64

On higher dimensional objects, you can sort any of the other axes by level if they have a MultiIndex:

In [97]: df.T.sort_index(level=1, axis=1)
Out[97]:
   zero  one  zero  one
       x    x    y    y
0  2.410179  0.600178  0.132885  1.519970
1  1.450520  0.274230 -0.023688 -0.493662

The MultiIndex object has code to explicitly check the sort depth. Thus, if you try to index at a depth at which
the index is not sorted, it will raise an exception. Here is a concrete example to illustrate this:

In [98]: tuples = [('a', 'a'), ('a', 'b'), ('b', 'a'), ('b', 'b')]

In [99]: idx = pd.MultiIndex.from_tuples(tuples)

In [100]: idx.lexsort_depth
Out[100]: 2

In [101]: reordered = idx[[1, 0, 3, 2]]
In [102]: reordered. lexsort_depth
Out[102]: 1

In [103]: s = pd.Series(np.random.randn(4), index=reordered)

In [104]: s.ix['a':'a']
Out[104]:
    a   b  
  a -1.04809
  a  -0.02575

However:

```python
>>> s.ix[('a', 'b'):('b', 'a')]
Traceback (most recent call last)
...
KeyError: Key length (3) was greater than MultiIndex lexsort depth (2)
```

### 14.4 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.

```python
In [105]: index = pd.Index(np.random.randint(0, 1000, 10))

In [106]: index
Out[106]: Int64Index([214, 502, 712, 567, 786, 175, 993, 133, 758, 329], dtype='int64')

In [107]: positions = [0, 9, 3]

In [108]: index[positions]
Out[108]: Int64Index([214, 329, 567], dtype='int64')

In [109]: index.take(positions)
Out[109]: Int64Index([214, 329, 567], dtype='int64')

In [110]: ser = pd.Series(np.random.randn(10))

In [111]: ser.iloc[positions]
Out[111]:
    0   -0.179666
    9    1.824375
    3    0.392149

dtype: float64

In [112]: ser.take(positions)
Out[112]:
    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 [113]: frm = pd.DataFrame(np.random.randn(5, 3))

In [114]: frm.take([1, 4, 3])
Out[114]:
0  1    2
1 -1.237881 0.106854 -1.276829
4  0.629675 -1.425966  1.857704
3  0.979542 -1.633678  0.615855

In [115]: frm.take([0, 2], axis=1)
Out[115]:
0    2
0  0.595974 0.601544
1 -1.237881 -1.276829
2 -0.767101  1.499591
3  0.979542  0.615855
4  0.629675  1.857704

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.

In [116]: arr = np.random.randn(10)

In [117]: arr.take([False, False, True, True])
Out[117]: array([-1.1935, -1.1935,  0.6775,  0.6775])

In [118]: arr[[0, 1]]
Out[118]: array([-1.1935,  0.6775])

In [119]: ser = pd.Series(np.random.randn(10))

In [120]: ser.take([False, False, True, True])
Out[120]:
0  0.233141
0  0.233141
1 -0.223540
1 -0.223540
dtype: float64

In [121]: ser.ix[[0, 1]]
Out[121]:
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.

### 14.5 CategoricalIndex

New in version 0.16.1.

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.
In [122]: df = pd.DataFrame({'A': np.arange(6),
                      'B': list('aabbc')})

In [123]: df['B'] = df['B'].astype('category', categories=list('cab'))

In [124]: df
Out[124]:
A   B
0   0  a
1   1  a
2   2  b
3   3  b
4   4  c
5   5  a

In [125]: df.dtypes
Out[125]:
A     int32
B   category
dtype: object

In [126]: df.B.cat.categories
Out[126]: Index(['c', 'a', 'b'], dtype='object')

Setting the index, will create a CategoricalIndex

In [127]: df2 = df.set_index('B')

In [128]: df2.index
Out[128]: CategoricalIndex(['a', 'a', 'b', 'b', 'c', 'a'], categories=['c', 'a', 'b'], ordered=False, name='B', dtype='category')

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.

In [129]: df2.loc['a']
Out[129]:
A
   B
  a  0
  a  1
  a  5

These PRESERVE the CategoricalIndex

In [130]: df2.loc['a'].index
Out[130]: CategoricalIndex(['a', 'a', 'a'], categories=['c', 'a', 'b'], ordered=False, name='B')

Sorting will order by the order of the categories

In [131]: df2.sort_index()
Out[131]:
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 [132]: df2.groupby(level=0).sum()
Out[132]:
   A
B  4
  c  6
  a  5
  b  5
```

```python
In [133]: df2.groupby(level=0).sum().index
Out[133]: CategoricalIndex([u'c', u'a', u'b'], categories=[u'c', u'a', u'b'], ordered=False, name=u'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 [134]: df2.reindex(['a','e'])
Out[134]:
   A
B
  a  0
  a  1
  a  5
  e NaN
```

```python
In [135]: df2.reindex(['a','e']).index
Out[135]: Index([u'a', u'a', u'a', u'e'], dtype='object', name=u'B')
```

```python
In [136]: df2.reindex(pd.Categorical(['a','e'],categories=list('abcde')))
Out[136]:
   A
B
  a  0
  a  1
  a  5
  e NaN
```

```python
In [137]: df2.reindex(pd.Categorical(['a','e'],categories=list('abcde'))).index
Out[137]: CategoricalIndex([u'a', u'a', u'a', u'e'], categories=[u'a', u'e'], ordered=False, name=u'B', dtype='category')
```

**Warning:** Reshaping and Comparison operations on a CategoricalIndex must have the same categories or a TypeError will be raised.

```python
In [9]: df3 = pd.DataFrame({'A' : np.arange(6),
                      'B' : pd.Series(list('aabca')).astype('category')})
In [11]: df3 = df3.set_index('B')
```

```python
In [11]: df3.index
Out[11]: CategoricalIndex([u'a', u'a', u'b', u'b', u'c', u'a'], categories=[u'a', u'b', u'c'], ordered=False, name='B', dtype='category')
```

```python
In [12]: pd.concat([df2, df3])
TypeError: categories must match existing categories when appending
```

14.5. CategoricalIndex 473
14.6 Float64Index

Note: As of 0.14.0, Float64Index is backed by a native float64 dtype array. Prior to 0.14.0, Float64Index was backed by an object dtype array. Using a float64 dtype in the backend speeds up arithmetic operations by about 30x and boolean indexing operations on the Float64Index itself are about 2x as fast.

New in version 0.13.0.

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.

```
In [138]: indexf = pd.Index([1.5, 2, 3, 4.5, 5])

In [139]: indexf
Out[139]: Float64Index([1.5, 2.0, 3.0, 4.5, 5.0], dtype='float64')

In [140]: sf = pd.Series(range(5), index=indexf)

In [141]: sf
Out[141]:
1.5 0
2.0 1
3.0 2
4.5 3
5.0 4
dtype: int64
```

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)

```
In [142]: sf[3]
Out[142]: 2

In [143]: sf[3.0]
Out[143]: 2

In [144]: sf.ix[3]
Out[144]: 2

In [145]: sf.ix[3.0]
Out[145]: 2

In [146]: sf.loc[3]
Out[146]: 2

In [147]: sf.loc[3.0]
Out[147]: 2
```

The only positional indexing is via iloc

```
In [148]: sf.iloc[3]
Out[148]: 3
```

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
In [149]: sf[2:4]
Out[149]:
2  1
3  2
dtype: int64

In [150]: sf.ix[2:4]
Out[150]:
2  1
3  2
dtype: int64

In [151]: sf.loc[2:4]
Out[151]:
2  1
3  2
dtype: int64

In [152]: sf.iloc[2:4]
Out[152]:
3.0  2
4.5  3
dtype: int64

In float indexes, slicing using floats is allowed

In [153]: sf[2.1:4.6]
Out[153]:
3.0  2
4.5  3
dtype: int64

In [154]: sf.loc[2.1:4.6]
Out[154]:
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)

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

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 [155]: dfir = pd.concat([pd.DataFrame(np.random.randn(5,2),
       index=np.arange(5) * 250.0),
       pd.DataFrame(np.random.randn(6,2),
       index=np.arange(4,10) * 250.1),
       ....:
       ....:         columns=list('AB')),
       ....:         index=np.arange(5,10) * 250.0),
       ....:         columns=list('AB')),
Selection operations then will always work on a value basis, for all selection operators.

In [157]: dfir[0:1000.4]
Out[157]:
          A         B
0  0.997289  -1.693316
250 -0.179129  -1.598062
500  0.936914   0.912560
750 -1.003401   1.632781
1000 -0.724626   0.178219
1000.4  0.310610  -0.108002
1250.5 -0.974226  -1.147708
1500.6 -2.281374   0.760010
1750.7  0.742532   1.533318
2000.8  2.495362  -0.432771
2250.9 -0.068954   0.043520

You could then easily pick out the first 1 second (1000 ms) of data then.

In [160]: dfir[0:1000]
Out[160]:
          A         B
0  0.997289  -1.693316
250 -0.179129  -1.598062
500  0.936914   0.912560
750 -1.003401   1.632781
1000 -0.724626   0.178219

Of course if you need integer based selection, then use \texttt{iloc}.
In [161]: dfir.iloc[0:5]
Out [161]:
       A         B
0  0.997289  -1.693316
250 -0.179129  -1.598062
500  0.936914   0.912560
750 -1.003401   1.632781
1000 -0.724626   0.178219
15.1 Statistical functions

15.1.1 Percent Change

Series, DataFrame, and Panel all 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
```

```python
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 -0.21832 -1.0540  1.9871 -0.5102
4 -0.43912 -1.8164  0.6497 -4.8228
5 -0.12783 -3.0421 -5.8666 -1.7769
6 -2.59683 -1.9595 -2.1117 -3.7989
7 -0.11783 -2.1691  0.0361 -0.0677
8  2.49260 -1.3573 -1.2058 -1.5587
9 -1.01298  2.3246 -1.0037 -0.3718
```

15.1.2 Covariance

The Series object has a method `cov` to compute covariance between series (excluding NA/null values).
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]: 0.00068010881743109993

Analogously, DataFrame has a method \texttt{cov} to compute pairwise covariances among the series in the DataFrame, also excluding NA/null values.

\textbf{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.

In [8]: frame = pd.DataFrame(np.random.randn(1000, 5), columns=['a', 'b', 'c', 'd', 'e'])
In [9]: frame.cov()
Out[9]:
\begin{array}{cccccc}
\text{a} & \text{b} & \text{c} & \text{d} & \text{e} \\
\text{a} & 1.000882 & -0.003177 & -0.002698 & -0.006889 & 0.031912 \\
\text{b} & -0.003177 & 1.024721 & 0.000191 & 0.009212 & 0.000857 \\
\text{c} & -0.002698 & 0.000191 & 0.950735 & -0.031743 & -0.005087 \\
\text{d} & -0.006889 & 0.009212 & -0.031743 & 1.002983 & -0.047952 \\
\text{e} & 0.031912 & 0.000857 & -0.005087 & -0.047952 & 1.042487
\end{array}

DataFrame.cov also supports an optional \texttt{min\_periods} keyword that specifies the required minimum number of observations for each column pair in order to have a valid result.

In [10]: frame = pd.DataFrame(np.random.randn(20, 3), columns=['a', 'b', 'c'])
In [11]: frame.ix[:5, 'a'] = np.nan
In [12]: frame.ix[5:10, 'b'] = np.nan
In [13]: frame.cov()
Out[13]:
\begin{array}{ccc}
\text{a} & \text{b} & \text{c} \\
\text{a} & 1.210090 & -0.430629 & 0.018002 \\
\text{b} & -0.430629 & 1.240960 & 0.347188 \\
\text{c} & 0.018002 & 0.347188 & 1.301149
\end{array}
In [14]: frame.cov(min\_periods=12)
Out[14]:
\begin{array}{ccc}
\text{a} & \text{b} & \text{c} \\
\text{a} & 1.210090 & \text{NaN} & 0.018002 \\
\text{b} & \text{NaN} & 1.240960 & 0.347188 \\
\text{c} & 0.018002 & 0.347188 & 1.301149
\end{array}

\subsection{15.1.3 Correlation}

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.

**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.ix[::2] = np.nan

# Series with Series
In [17]: frame['a'].corr(frame['b'])
Out[17]: 0.013479040400098794

In [18]: frame['a'].corr(frame['b'], method='spearman')
Out[18]: -0.0072898851595406388

# Pairwise correlation of DataFrame columns
In [19]: frame.corr()
Out[19]:

```
  a   b   c   d   e
a  1.000000 0.013479 -0.049269 -0.042239 -0.028525
b  0.013479 1.000000 -0.020433 -0.011139 0.005654
c -0.049269 -0.020433 1.000000 0.018587 -0.054269
d -0.042239 -0.011139 0.018587 1.000000 -0.017060
e -0.028525 0.005654 -0.054269 -0.017060 1.000000
```

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.ix[:5, 'a'] = np.nan

In [22]: frame.ix[5:10, 'b'] = np.nan

In [23]: frame.corr()
Out[23]:

```
   a    b    c
a  1.000000 -0.076520 0.160092
b -0.076520  1.000000 0.135967
c  0.160092  0.135967  1.000000
```

In [24]: frame.corr(min_periods=12)
Out[24]:

```
   a    b    c
a  1.000000 NaN  0.160092
b  NaN  1.000000 0.135967
c  0.160092  0.135967  1.000000
```

A related method corrwith is implemented on DataFrame to compute the correlation between like-labeled Series contained in different DataFrame objects.

In [25]: index = ['a', 'b', 'c', 'd', 'e']

15.1. Statistical functions
In [26]: columns = ['one', 'two', 'three', 'four']

In [27]: df1 = pd.DataFrame(np.random.randn(5, 4), index=index, columns=columns)

In [28]: df2 = pd.DataFrame(np.random.randn(4, 4), index=index[:4], columns=columns)

In [29]: df1.corrwith(df2)
Out[29]:
      one    two    three    four
one  -0.125501  
two  -0.493244  
three  0.344056  
four  0.004183  
dtype: float64

In [30]: df2.corrwith(df1, axis=1)
Out[30]:
a     -0.675817  
b      0.458296  
c      0.190809  
d     -0.186275  
e       NaN  
dtype: float64

15.1.4 Data ranking

The rank method produces a data ranking with ties being assigned the mean of the ranks (by default) for the group:

In [31]: s = pd.Series(np.random.randn(5), index=list('abcde'))

In [32]: s['d'] = s['b']  # so there's a tie

In [33]: s.rank()
Out[33]:
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.

In [34]: df = pd.DataFrame(np.random.randn(10, 6))


In [36]: df
Out[36]:
     0         1         2         3         4         5
0 -0.904948 -1.163537 -1.457187  0.135463  1.457187  0.294650
1 -0.976288 -0.244652 -0.748406  0.999601  0.748406  0.800809
2  0.401965  1.460840  1.256057  1.308127  1.256057  0.876004
3  0.205954  0.395552  0.669304  0.038378  0.669304  1.140296
4 -0.477586 -0.730705 -1.129149 -0.601463  1.129149  0.211196
5 -1.092970 -0.689246  0.908114  0.204848  1.129149  0.211196
6  0.376892  0.959292  0.095572  0.593740  1.129149  0.211196
7  0.502307 -0.482318 -0.774277 -0.956030  0.211196  0.211196
8  0.095676 -0.395225 -0.624055 -0.739987  0.211196  0.211196
9 -1.211270 -0.739249 -1.148675 -0.896972  0.211196  0.211196
pandas: powerful Python data analysis toolkit, Release 0.17.0

```python
7  -1.002601  1.957794 -0.120708  0.094214  NaN  -1.467422
8  -0.547231  0.664402 -0.519424 -0.073254  NaN  -1.263544
9  -0.250277 -0.237428 -1.056443  0.419477  NaN   1.375064
```

```python
In [37]: df.rank(1)
Out[37]:
   0   1  2   3  4   5
0  4  3  1.5  5  1.5  6
1  2  6  4.5  1  4.5  3
2  1  6  3.5  5  3.5  2
3  4  5  1.5  3  1.5  6
4  5  3  1.5  4  1.5  6
5  1  2  5.0  3  NaN  4
6  4  5  3.0  1  NaN  2
7  2  5  3.0  4  NaN  1
8  2  5  3.0  4  NaN  1
9  2  3  1.0  4  NaN  5
```

`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

## 15.2 Moving (rolling) statistics / moments

For working with time series data, a number of functions are provided for computing common *moving* or *rolling* statistics. Among these are count, sum, mean, median, correlation, variance, covariance, standard deviation, skewness, and kurtosis. All of these methods are in the `pandas` namespace, but otherwise they can be found in `pandas.stats.moments`.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>rolling_count</td>
<td>Number of non-null observations</td>
</tr>
<tr>
<td>rolling_sum</td>
<td>Sum of values</td>
</tr>
<tr>
<td>rolling_mean</td>
<td>Mean of values</td>
</tr>
<tr>
<td>rolling_median</td>
<td>Arithmetic median of values</td>
</tr>
<tr>
<td>rolling_min</td>
<td>Minimum</td>
</tr>
<tr>
<td>rolling_max</td>
<td>Maximum</td>
</tr>
<tr>
<td>rolling_std</td>
<td>Unbiased standard deviation</td>
</tr>
<tr>
<td>rolling_var</td>
<td>Unbiased variance</td>
</tr>
<tr>
<td>rolling_skew</td>
<td>Unbiased skewness (3rd moment)</td>
</tr>
<tr>
<td>rolling_kurt</td>
<td>Unbiased kurtosis (4th moment)</td>
</tr>
<tr>
<td>rolling_quantile</td>
<td>Sample quantile (value at %)</td>
</tr>
<tr>
<td>rolling_apply</td>
<td>Generic apply</td>
</tr>
<tr>
<td>rolling_cov</td>
<td>Unbiased covariance (binary)</td>
</tr>
<tr>
<td>rolling_corr</td>
<td>Correlation (binary)</td>
</tr>
<tr>
<td>rolling_window</td>
<td>Moving window function</td>
</tr>
</tbody>
</table>

Generally these methods all have the same interface. The binary operators (e.g. `rolling_corr`) take two `Series` or `DataFrames`. Otherwise, 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)
• freq: optionally specify a frequency string or DateOffset to pre-conform the data to. Note that prior to pandas v0.8.0, a keyword argument time_rule was used instead of freq that referred to the legacy time rule constants
• how: optionally specify method for down or re-sampling. Default is min for rolling_min, max for rolling_max, median for rolling_median, and mean for all other rolling functions. See DataFrame.resample()'s how argument for more information.

These functions can be applied to ndarrays or Series objects:

In [38]: ts = pd.Series(np.random.randn(1000), index=pd.date_range('1/1/2000', periods=1000))
In [39]: ts = ts.cumsum()
In [40]: ts.plot(style='k--')
Out[40]: <matplotlib.axes._subplots.AxesSubplot at 0xaaeb6cec>
In [41]: pd.rolling_mean(ts, 60).plot(style='k')
Out[41]: <matplotlib.axes._subplots.AxesSubplot at 0xaaeb6cec>

They can also be applied to DataFrame objects. This is really just syntactic sugar for applying the moving window functions.
operator to all of the DataFrame’s columns:

In [42]: df = pd.DataFrame(np.random.randn(1000, 4), index=ts.index,
                      columns=['A', 'B', 'C', 'D'])

In [43]: df = df.cumsum()

In [44]: pd.rolling_sum(df, 60).plot(subplots=True)

Out[44]: array([<matplotlib.axes._subplots.AxesSubplot object at 0xaf37306c>,
              <matplotlib.axes._subplots.AxesSubplot object at 0xaaa03fac>,
              <matplotlib.axes._subplots.AxesSubplot object at 0xaae8344c>,
              <matplotlib.axes._subplots.AxesSubplot object at 0xaad01a6c>],
             dtype=object)

The `rolling_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:

In [45]: mad = lambda x: np.fabs(x - x.mean()).mean()

In [46]: pd.rolling_apply(ts, 60, mad).plot(style='k')

Out[46]: <matplotlib.axes._subplots.AxesSubplot object at 0xac92f06c>
The `rolling_window` function performs a generic rolling window computation on the input data. The weights used in the window are specified by the `win_type` keyword. The list of recognized types are:

- `boxcar`
- `triang`
- `blackman`
- `hamming`
- `bartlett`
- `parzen`
- `bohman`
- `blackmanharris`
- `nuttall`
- `barthann`
- `kaiser (needs beta)`
- `gaussian (needs std)`
- `general_gaussian (needs power, width)`
- `slepian (needs width)`.
In [47]: ser = pd.Series(np.random.randn(10), index=pd.date_range('1/1/2000', periods=10))

In [48]: pd.rolling_window(ser, 5, 'triang')

Out[48]:
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 rolling_mean.

In [49]: pd.rolling_window(ser, 5, 'boxcar')

Out[49]:
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 [50]: pd.rolling_mean(ser, 5)

Out[50]:
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

For some windowing functions, additional parameters must be specified:

In [51]: pd.rolling_window(ser, 5, 'gaussian', std=0.1)

Out[51]:
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

15.2. Moving (rolling) statistics / moments 487
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. This keyword is available in other rolling functions as well.

```python
In [52]: pd.rolling_window(ser, 5, 'boxcar')
Out[52]:
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 [53]: pd.rolling_window(ser, 5, 'boxcar', center=True)
Out[53]:
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
```

```python
In [54]: pd.rolling_mean(ser, 5, center=True)
Out[54]:
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
```

**Note:** In rolling sum mode (`mean=False`) there is no normalization done to the weights. 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 rolling mean calculation (`mean=True`) 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.
15.2.1 Binary rolling moments

`rolling_cov` and `rolling_corr` can compute moving window statistics about two `Series` or any combination of `DataFrame/Series` or `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 `Panel` whose items are the dates in question (see the next section).

For example:

```python
In [55]: df2 = df[:20]
In [56]: pd.rolling_corr(df2, df2['B'], window=5)
Out[56]:
       A         B         C         D
2000-01-01 NaN       NaN       NaN       NaN
2000-01-02 NaN       NaN       NaN       NaN
2000-01-03 NaN       NaN       NaN       NaN
2000-01-04 NaN       NaN       NaN       NaN
2000-01-05 -0.262853  1.000000  0.334449  0.193380
2000-01-06 -0.083745  1.000000 -0.521587 -0.556126
2000-01-07 -0.292940  1.000000 -0.658532 -0.458128
...     ...     ...     ...     ...
2000-01-14 0.519499  1.000000 -0.687277  0.192822
2000-01-15 0.048982  1.000000 -0.061463  0.542153
2000-01-16 0.217190  1.000000 -0.326034  0.162740
2000-01-17 0.641180  1.000000 -0.111487  0.561330
2000-01-18 0.130422  1.000000  0.632383  0.306438
2000-01-19 0.317278  1.000000  0.813656  0.563127
2000-01-20 0.293598  1.000000  0.742381  0.577043
[20 rows x 4 columns]
```

15.2.2 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 `Panel` whose items 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.

```python
In [57]: covs = pd.rolling_cov(df[['B','C','D']], df[['A','B','C']], 50, pairwise=True)
In [58]: covs[df.index[-50]]
Out[58]:
       A         B         C
B  2.667506  1.671711  1.938634
```

15.2. Moving (rolling) statistics / moments 489
In [59]: correls = pd.rolling_corr(df, 50)

In [60]: correls[df.index[-50]]

Out[60]:

<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>1.000000</td>
<td>0.604221</td>
<td>0.767429</td>
<td>-0.776170</td>
</tr>
<tr>
<td>B</td>
<td>0.604221</td>
<td>1.000000</td>
<td>0.461484</td>
<td>-0.381148</td>
</tr>
<tr>
<td>C</td>
<td>0.767429</td>
<td>0.461484</td>
<td>1.000000</td>
<td>-0.748863</td>
</tr>
<tr>
<td>D</td>
<td>-0.776170</td>
<td>-0.381148</td>
<td>-0.748863</td>
<td>1.000000</td>
</tr>
</tbody>
</table>

Note: Prior to version 0.14 this was available through `rolling_corr_pairwise` which is now simply syntactic sugar for calling `rolling_corr(..., pairwise=True)` and deprecated. This is likely to be removed in a future release.

You can efficiently retrieve the time series of correlations between two columns using `ix` indexing:

In [61]: correls.ix[:, 'A', 'C'].plot()

Out[61]: <matplotlib.axes._subplots.AxesSubplot at 0xa923fa4c>
15.3 Expanding window moment functions

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. As these calculations are a special case of rolling statistics, they are implemented in pandas such that the following two calls are equivalent:

```
In [62]: pd.rolling_mean(df, window=len(df), min_periods=1)[:5]
Out[62]:
   A    B    C    D
2000-01-01 -1.388345 3.317290 0.344542 -0.036968
2000-01-02 -1.123132 3.622300 1.675867 0.595300
2000-01-03 -0.628502 3.626503 2.455240 1.060158
2000-01-04 -0.768740 3.888917 2.451354 1.281874
2000-01-05 -0.824034 4.108035 2.556112 1.140723
```

```
In [63]: pd.expanding_mean(df)[:5]
Out[63]:
   A    B    C    D
2000-01-01 -1.388345 3.317290 0.344542 -0.036968
2000-01-02 -1.123132 3.622300 1.675867 0.595300
2000-01-03 -0.628502 3.626503 2.455240 1.060158
2000-01-04 -0.768740 3.888917 2.451354 1.281874
2000-01-05 -0.824034 4.108035 2.556112 1.140723
```

Like the rolling_ functions, the following methods are included in the pandas namespace or can be located in pandas.stats.moments.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>expanding_count</td>
<td>Number of non-null observations</td>
</tr>
<tr>
<td>expanding_sum</td>
<td>Sum of values</td>
</tr>
<tr>
<td>expanding_mean</td>
<td>Mean of values</td>
</tr>
<tr>
<td>expanding_median</td>
<td>Arithmetic median of values</td>
</tr>
<tr>
<td>expanding_min</td>
<td>Minimum</td>
</tr>
<tr>
<td>expanding_max</td>
<td>Maximum</td>
</tr>
<tr>
<td>expanding_std</td>
<td>Unbiased standard deviation</td>
</tr>
<tr>
<td>expanding_var</td>
<td>Unbiased variance</td>
</tr>
<tr>
<td>expanding_skew</td>
<td>Unbiased skewness (3rd moment)</td>
</tr>
<tr>
<td>expanding_kurt</td>
<td>Unbiased kurtosis (4th moment)</td>
</tr>
<tr>
<td>expanding_quantile</td>
<td>Sample quantile (value at %)</td>
</tr>
<tr>
<td>expanding_apply</td>
<td>Generic apply</td>
</tr>
<tr>
<td>expanding_cov</td>
<td>Unbiased covariance (binary)</td>
</tr>
<tr>
<td>expanding_corr</td>
<td>Correlation (binary)</td>
</tr>
</tbody>
</table>

Aside from not having a window parameter, these functions have the same interfaces as their rolling_ counterpart. 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.

- **freq**: optionally specify a frequency string or DateOffset to pre-conform the data to. Note that prior to pandas v0.8.0, a keyword argument time_rule was used instead of freq that referred to the legacy time rule constants.

**Note:** The output of the rolling_ and expanding_ functions do not return a NaN if there are at least min_periods non-null values in the current window. This differs from cumsum, cumprod, cummax, and cummin, which return NaN in the output wherever a NaN is encountered in the input.
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 `expanding_mean` output for the previous time series dataset:

```python
In [64]: ts.plot(style='k--')
Out[64]: <matplotlib.axes._subplots.AxesSubplot at 0xa85ea9cc>

In [65]: pd.expanding_mean(ts).plot(style='k')
Out[65]: <matplotlib.axes._subplots.AxesSubplot at 0xa85ea9cc>
```

## 15.4 Exponentially weighted moment functions

A related set of functions are exponentially weighted versions of several of the above statistics. A number of expanding EW (exponentially weighted) functions are provided:

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>ewma</code></td>
<td>EW moving average</td>
</tr>
<tr>
<td><code>ewmvar</code></td>
<td>EW moving variance</td>
</tr>
<tr>
<td><code>ewmstd</code></td>
<td>EW moving standard deviation</td>
</tr>
<tr>
<td><code>ewmcorr</code></td>
<td>EW moving correlation</td>
</tr>
<tr>
<td><code>ewmcov</code></td>
<td>EW moving covariance</td>
</tr>
</tbody>
</table>
In general, a weighted moving average is calculated as

\[ y_t = \frac{\sum_{i=0}^{t} w_i x_{t-i}}{\sum_{i=0}^{t} w_i}, \]

where \( x_t \) is the input at \( y_t \) is the result.

The EW functions support two variants of exponential weights: The default, \( \text{adjust=True} \), uses the weights \( w_i = (1 - \alpha)^i \). When \( \text{adjust=False} \) 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.

\[ y_t = \alpha' y_{t-1} + (1 - \alpha')x_t. \]

One must have \( 0 < \alpha \leq 1 \), but rather than pass \( \alpha \) directly, it’s easier to think about either the span, center of mass (com) or halflife of an EW moment:

\[ \alpha = \begin{cases} 
\frac{2}{s+1}, & s = \text{span} \\
\frac{1}{1+c}, & c = \text{center of mass} \\
1 - \exp\left(\frac{\log 0.5}{h}\right), & h = \text{half life}
\end{cases} \]

One must specify precisely one of the three to the EW functions. Span corresponds to what is commonly called a “20-day EW moving average” for example. Center of mass has a more physical interpretation. For example, span = 20 corresponds to com = 9.5. Halflife is the period of time for the exponential weight to reduce to one half.

Here is an example for a univariate time series:

```python
In [66]: plt.close('all')
In [67]: ts.plot(style='k--')
Out[67]: <matplotlib.axes._subplots.AxesSubplot at 0xa9ad15ac>
In [68]: pd.ewma(ts, span=20).plot(style='k')
Out[68]: <matplotlib.axes._subplots.AxesSubplot at 0xa9ad15ac>
```
All the EW functions have a `min_periods` argument, which has the same meaning it does for all the `expanding_`
and `rolling_` functions: no output values will be set until at least `min_periods` non-null values are encountered
in the (expanding) window. (This is a change from versions prior to 0.15.0, in which the `min_periods` argument
affected only the `min_periods` consecutive entries starting at the first non-null value.)

All the EW functions also have 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 po-
sitions, so that intermediate null values affect the result. When `ignore_na=True` (which reproduces the behavior
in versions prior to 0.15.0), 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 `ewmvar`, `ewmstd`, and `ewmcov` functions have a `bias` argument, specifying whether the result should con-
tain biased or unbiased statistics. For example, if `bias=True`, `ewmvar(x)` is calculated as

$\text{ewmvar}(x) = \text{ewma}(x^2) - \text{ewma}(x)^2$;

whereas if `bias=False` (the default), the biased variance statistics are scaled
by debiasing factors

\[
\frac{\left(\sum_{i=0}^{t} w_i\right)^2}{\left(\sum_{i=0}^{t} w_i\right)^2 - \sum_{i=0}^{t} w_i^2}.
\]

(For \(w_i = 1\), this reduces to the usual \(N/(N - 1)\) factor, with \(N = t + 1\).) See http://en.wikipedia.org/wiki/Weighted_arithmetic_mean#Weighted_sample_variance for further details.
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. It differs from the MaskedArray approach of, for example, `scikits.timeseries`. We are hopeful that NumPy will soon be able to provide a native NA type solution (similar to R) performant enough to be used in pandas.

See the [cookbook](#) for some advanced strategies

### 16.1 Missing data basics

#### 16.1.1 When / why does data become missing?

Some might quibble over our usage of *missing*. By “missing” we simply mean null or “not present for whatever reason”. Many data sets simply arrive with missing data, either because it exists and was not collected or it never existed. For example, in a collection of financial time series, some of the time series might start on different dates. Thus, values prior to the start date would generally be marked as missing.

In pandas, one of the most common ways that missing data is introduced into a data set is by reindexing. For example

```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]:
   one   two   three  four  five
   a  0.469112  -0.282863  -1.509059  bar   True
   c -1.135632   1.212112   -0.173215  bar    False
   e  0.119209  -1.044236  -0.861849  bar   True
   f -2.104569  -0.494929   1.071804  bar    False
   h  0.721555  -0.706771  -1.039575  bar   True

In [5]: df2 = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])

In [6]: df2
Out[6]:
   one   two   three  four  five
   a  0.469112  -0.282863  -1.509059  bar   True
   b  1.181614  -0.667086  -0.477062  bar    False
   c -1.135632   1.212112   -0.173215  bar    False
   d -1.044236  -0.173215   -0.861849  bar    False
   e  0.119209  -1.044236  -0.861849  bar   True
   f -2.104569  -0.494929   1.071804  bar    False
   g  0.721555  -0.706771  -1.039575  bar    False
   h  0.721555  -0.706771  -1.039575  bar    False
16.1.2 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 “null”.

Note: Prior to version v0.10.0, inf and -inf were also considered to be “null” in computations. This is no longer the case by default; use the `mode.use_inf_as_null` option to recover it.

To make detecting missing values easier (and across different array dtypes), pandas provides the `isnull()` and `notnull()` functions, which are also methods on `Series` and `DataFrame` objects:

```
In [7]: df2['one']
Out[7]:
a    0.469112
b    NaN
   ...  
h    0.721555
Name: one, dtype: float64

In [8]: pd.isnull(df2['one'])
Out[8]:
a   False
b   True
   ...  
h   False
Name: one, dtype: bool

In [9]: df2['four'].notnull()
Out[9]:
a   True
b   False
   ...  
h   True
```
Name: four, dtype: bool

In [10]: df2.isnull()
Out[10]:
    one   two   three   four   five
a  True  True  True  True  True
b  True  True  True  True  True
c  True  True  True  True  True
d  True  True  True  True  True
e  True  True  True  True  True
f  True  True  True  True  True
g  True  True  True  True  True
h  True  True  True  True  True

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
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

16.2 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 intercompatibility between NaT and NaN.

In [14]: df2 = df.copy()

In [15]: df2['timestamp'] = pd.Timestamp('20120101')

In [16]: df2
Out[16]:
    one    two    three    four    five  timestamp
a -0.469112 -0.282863 -1.509059    bar  True 2012-01-01
b -1.135632  1.212112  0.173215    bar False 2012-01-01
c -0.119209 -1.044236 -0.861849    bar  True 2012-01-01
d -2.104569 -0.494929  1.071804    bar False 2012-01-01
e -0.721555 -0.706771 -1.039575    bar  True 2012-01-01
f -0.282863 -0.494929  0.173215    bar False 2012-01-01
g -1.509059  1.212112 -0.173215    bar False 2012-01-01
h -1.044236 -1.071804 -0.861849    bar  True 2012-01-01

**16.3 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 [20]: s = pd.Series([1, 2, 3])

In [21]: s.loc[0] = None
```

```
In [22]: s
Out[22]:
0  NaN
1   2
2   3
dtype: float64
```

Likewise, datetime containers will always use NaT.

For object containers, pandas will use the value given:

```
In [23]: s = pd.Series(["a", "b", "c"])

In [24]: s.loc[0] = None

In [25]: s.loc[1] = np.nan
```

```
In [26]: s
Out[26]:
0   None
1  NaN
2    c
dtype: object
```
16.4 Calculations with missing data

Missing values propagate naturally through arithmetic operations between pandas objects.

```
In [27]: a
Out[27]:
   one  two
a  NaN -0.282863
b  NaN  1.212112
c  NaN -1.044236
d -2.104569 -0.494929
e  0.119209 -1.044236
f -2.104569 -0.706771
```

```
In [28]: b
Out[28]:
   one  two  three
a  NaN -0.282863 -1.509059
b  NaN  1.212112 -0.173215
c  NaN -1.044236 -0.861849
d -2.104569 -0.494929  1.071804
e  0.119209 -1.044236 -0.861849
f -2.104569 -0.706771  1.071804
```

```
In [29]: a + b
Out[29]:
   one  three  two
a  NaN      NaN -0.565727
b  NaN      NaN  2.424224
c  NaN      NaN -2.088472
d -4.209138 NaN  1.071804
e  0.238417 NaN -0.861849
f  NaN      NaN -1.413542
```

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 NA
- Methods like cumsum and cumprod ignore NA values, but preserve them in the resulting arrays

```
In [30]: df
Out[30]:
   one  two  three
a  NaN -0.282863 -1.509059
b  NaN  1.212112 -0.173215
c  NaN -1.044236 -0.861849
d -2.104569 -0.494929  1.071804
e  0.119209 -1.044236 -0.861849
f -2.104569 -0.706771  1.071804
```

```
In [31]: df['one'].sum()
Out[31]: -1.9853605075978744
```

```
In [32]: df.mean(1)
Out[32]:
a  -0.895961
b  0.519449
c  -0.595625
d  -0.509232
e  -0.873173
```
pandas: powerful Python data analysis toolkit, Release 0.17.0

```
dtype: float64

In [33]: df.cumsum()
Out[33]:
   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
h  NaN  -1.316688  -2.511893

16.4.1 NA values in GroupBy

NA groups in GroupBy are automatically excluded. This behavior is consistent with R, for example:

In [34]: df
Out[34]:
   one  two  three
a  NaN  -0.282863 -1.509059
b  NaN   1.212112  4.173215
c  0.119209 -1.042436  0.861849
d -2.104569 -0.494929  1.071804
h  NaN  -0.706771 -1.039575

In [35]: df.groupby('one').mean()
Out[35]:
   two  three
one  -2.104569 -0.494929  
     0.119209 -1.044236 -0.861849

See the groupby section here for more information.

16.5 Cleaning / filling missing data

pandas objects are equipped with various data manipulation methods for dealing with missing data.

16.5.1 Filling missing values: fillna

The fillna function can “fill in” NA values with non-null data in a couple of ways, which we illustrate:

Replace NA with a scalar value

In [36]: df2
Out[36]:
   one  two  three  four   five  timestamp
a  NaN -0.282863 -1.509059  bar  True     NaT
b  NaN   1.212112 -1.682273  bar False     NaT
c  0.119209  1.042436 -0.861849  bar  True 2012-01-01
d -2.104569 -0.494929  1.071804  bar False 2012-01-01
h  NaN  -0.706771 -1.039575  bar  True     NaT

In [37]: df2.fillna(0)
Out[37]:
   one  two  three  four   five  timestamp
a  NaN -0.282863 -1.509059  bar  True     0.0
b  NaN   1.212112 -1.682273  bar False     0.0
c  0.119209  1.042436 -0.861849  bar  True 2012-01-01
d -2.104569 -0.494929  1.071804  bar False 2012-01-01
h  NaN  -0.706771 -1.039575  bar  True     0.0
In [38]: df2['four'].fillna('missing')
Out[38]:
    a  bar
    c  bar
    e  bar
    f  bar
    h  bar
Name: four, dtype: object

Fill gaps forward or backward

Using the same filling arguments as reindexing, we can propagate non-null values forward or backward:

In [39]: df
Out[39]:
    one   two   three
   ---   ---   ---
   a  NaN -0.282863 -1.509059
   c  NaN  1.212112 -0.173215
   e  NaN  -1.044236 -0.861849
   f  NaN -0.494929  1.071804
   h  NaN -0.706771 -1.039575

In [40]: df.fillna(method='pad')
Out[40]:
    one   two   three
   ---   ---   ---
   a  NaN -0.282863 -1.509059
   c  NaN  1.212112 -0.173215
   e  NaN   NaN   NaN
   f  NaN   NaN   NaN
   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 [41]: df
Out[41]:
    one   two   three
   ---   ---   ---
   a  NaN -0.282863 -1.509059
   c  NaN  1.212112 -0.173215
   e  NaN   NaN   NaN
   f  NaN   NaN   NaN
   h  NaN -0.706771 -1.039575

In [42]: df.fillna(method='pad', limit=1)
Out[42]:
    one   two   three
   ---   ---   ---
   a  NaN -0.282863 -1.509059
   c  NaN  1.212112 -0.173215
   e  NaN  1.212112 -0.173215
   f  NaN   NaN   NaN
   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.

The `ffill()` function is equivalent to `fillna(method='ffill')` and `bfill()` is equivalent to `fillna(method='bfill')`

### 16.5.2 Filling with a PandasObject

New in version 0.12.

You can alsofillna 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 [43]: dff = pd.DataFrame(np.random.randn(10,3), columns=list('ABC'))
In [44]: dff.iloc[3:5,0] = np.nan
In [45]: dff.iloc[4:6,1] = np.nan
In [46]: dff.iloc[5:8,2] = np.nan
In [47]: dff
Out[47]:
   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  NaN
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 [48]: dff.fillna(dff.mean())
Out[48]:
   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  NaN
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 [49]: dff.fillna(dff.mean()[:, 'B':'C'])
```

```python
Out[49]:
   A       B       C
0  0.271860 -0.424972  0.567020
```

Chapter 16. Working with missing data
1 0.276232 -1.087401 -0.673690
2 0.113648 -1.478427 0.524988
3 NaN 0.577046 -1.715002
4 NaN -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

New in version 0.13.

Same result as above, but is aligning the ‘fill’ value which is a Series in this case.

In [50]: dff.where(pd.notnull(dff), dff.mean(), axis='columns')
Out[50]:
  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

16.5.3 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 the dropna method:

In [51]: df
Out[51]:
  one     two     three
a NaN -0.282863 -1.509059
c NaN 1.212112 -0.173215
e NaN 0.000000 0.000000
f NaN 0.000000 0.000000
h NaN -0.706771 -1.039575

In [52]: df.dropna(axis=0)
Out[52]:
Empty DataFrame
Columns: [one, two, three]
Index: []

In [53]: df.dropna(axis=1)
Out[53]:
  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

In [54]: df['one'].dropna()
Out[54]: Series([], Name: one, dtype: float64)
Series.dropna is a simpler method as it only has one axis to consider. DataFrame.dropna has considerably more options than Series.dropna, which can be examined in the API.

### 16.5.4 Interpolation

New in version 0.13.0: `interpolate()` and `interpolate()` have revamped interpolation methods and functionality.

New in version 0.17.0: The `limit_direction` keyword argument was added.

Both Series and DataFrame objects have an `interpolate` method that, by default, performs linear interpolation at missing datapoints.

```python
In [55]: ts
Out[55]:
2000-01-31    0.469112
2000-02-29      NaN
2000-03-31      NaN
2000-04-28      NaN
2000-05-31      NaN
2000-06-30      NaN
2000-07-31      NaN
   ...          ...
2007-10-31   -3.305259
2007-11-30   -5.485119
2007-12-31  -6.854968
2008-01-31  -7.809176
2008-02-29  -6.346480
2008-03-31  -8.089641
2008-04-30  -8.916232
Freq: BM, dtype: float64

In [56]: ts.count()
Out[56]: 61

In [57]: ts.interpolate().count()
Out[57]: 100

In [58]: ts.interpolate().plot()
Out[58]: <matplotlib.axes._subplots.AxesSubplot at 0x9c1d2cec>
Index aware interpolation is available via the `method` keyword:

```
In [59]: ts2
Out[59]:
2000-01-31   0.469112
2000-02-29    NaN
2002-07-31  -5.689738
2005-01-31    NaN
2008-04-30  -8.916232
dtype: float64

In [60]: ts2.interpolate()
Out[60]:
2000-01-31   0.469112
2000-02-29  -2.610313
2002-07-31  -5.689738
2005-01-31  -7.302985
2008-04-30  -8.916232
dtype: float64

In [61]: ts2.interpolate(method='time')
Out[61]:
2000-01-31   0.469112
2000-02-29   0.273272
2002-07-31  -5.689738
```

16.5. Cleaning / filling missing data
For a floating-point index, use `method='values'`:

In [62]: ser

Out[62]:
0   0
1   NaN
10  10
dtype: float64

In [63]: ser.interpolate()

Out[63]:
0   0
1   5
10  10
dtype: float64

In [64]: ser.interpolate(method='values')

Out[64]:
0   0
1   1
10  10
dtype: float64

You can also interpolate with a DataFrame:

In [65]: 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 [66]: df

Out[66]:
   A   B
0  1.0  0.25
1  2.1   NaN
2   NaN   NaN
3  4.7   4.00
4  5.6  12.20
5  6.8  14.40

In [67]: df.interpolate()

Out[67]:
   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 set 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. For example, 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.
Warning: These methods require scipy.

```
In [68]: df.interpolate(method='barycentric')
Out[68]:
   A    B
0  1.0  0.250
1  2.1 -7.660
2  3.5 -4.515
3  4.7  4.000
4  5.6 12.200
5  6.8 14.400

In [69]: df.interpolate(method='pchip')
Out[69]:
   A          B
0  1.000000  0.250000
1  2.100000  1.130135
2  3.429309  2.337586
3  4.700000  4.000000
4  5.600000 12.200000
5  6.800000 14.400000
```

When interpolating via a polynomial or spline approximation, you must also specify the degree or order of the approximation:

```
In [70]: df.interpolate(method='spline', order=2)
Out[70]:
   A          B
0  1.000000  0.250000
1  2.100000 -0.428598
2  3.404545  1.206900
3  4.700000  4.000000
4  5.600000 12.200000
5  6.800000 14.400000

In [71]: df.interpolate(method='polynomial', order=2)
Out[71]:
   A          B
0  1.000000  0.250000
1  2.100000 -4.161538
2  3.547059 -2.911538
3  4.700000  4.000000
4  5.600000 12.200000
5  6.800000 14.400000
```

Compare several methods:

```
In [72]: np.random.seed(2)

In [73]: ser = pd.Series(np.arange(1, 10.1, .25)**2 + np.random.randn(37))

In [74]: bad = np.array([4, 13, 14, 15, 16, 17, 18, 20, 29])

In [75]: ser[bad] = np.nan

In [76]: methods = ['linear', 'quadratic', 'cubic']

In [77]: df = pd.DataFrame({m: ser.interpolate(method=m) for m in methods})
```
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 [79]: ser = pd.Series(np.sort(np.random.uniform(size=100)))

# interpolate at new_index
In [80]: new_index = ser.index | pd.Index([49.25, 49.5, 49.75, 50.25, 50.5, 50.75])

In [81]: interp_s = ser.reindex(new_index).interpolate(method='pchip')

In [82]: interp_s[49:51]
```

```
   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
```
Interpolation Limits

Like other pandas fill methods, `interpolate` accepts a `limit` keyword argument. Use this argument to limit the number of consecutive interpolations, keeping NaN values for interpolations that are too far from the last valid observation:

```
In [83]: ser = pd.Series([np.nan, np.nan, 5, np.nan, np.nan, np.nan, 13])
```

```
In [84]: ser.interpolate(limit=2)
Out[84]:
0   NaN
1   NaN
2    5
3    7
4    9
5   NaN
6   13
dtype: float64
```

By default, `limit` applies in a forward direction, so that only NaN values after a non-NaN value can be filled. If you provide `‘backward’` or `‘both’` for the `limit_direction` keyword argument, you can fill NaN values before non-NaN values, or both before and after non-NaN values, respectively:

```
In [85]: ser.interpolate(limit=1)  # limit_direction == ‘forward’
Out[85]:
0   NaN
1   NaN
2    5
3    7
4   NaN
5   NaN
6   13
```

```
In [86]: ser.interpolate(limit=1, limit_direction='backward')
Out[86]:
0   NaN
1    5
2    5
3   NaN
4   NaN
5   11
6   13
```

```
In [87]: ser.interpolate(limit=1, limit_direction='both')
Out[87]:
0   NaN
1    5
2    5
3    7
4   NaN
5   11
```
16.5.5 Replacing Generic Values

Often times we want to replace arbitrary values with other values. New in v0.8 is the replace method in Series/DataFrame that 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 [88]: ser = pd.Series([0., 1., 2., 3., 4.])
In [89]: ser.replace(0, 5)
Out[89]:
0 5
1 1
2 2
3 3
4 4
dtype: float64
```

You can replace a list of values by a list of other values:

```python
In [90]: ser.replace([0, 1, 2, 3, 4], [4, 3, 2, 1, 0])
Out[90]:
0 4
1 3
2 2
3 1
4 0
dtype: float64
```

You can also specify a mapping dict:

```python
In [91]: ser.replace({0: 10, 1: 100})
Out[91]:
0 10
1 100
2 2
3 3
4 4
dtype: float64
```

For a DataFrame, you can specify individual values by column:

```python
In [92]: df = pd.DataFrame({'a': [0, 1, 2, 3, 4], 'b': [5, 6, 7, 8, 9]})
In [93]: df.replace({'a': 0, 'b': 5}, 100)
Out[93]:
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:
In [94]: ser.replace([1, 2, 3], method='pad')
Out[94]:
0 0
1 0
2 0
3 0
4 4
dtype: float64

16.5.6 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 `np.nan` (str -> str)

In [95]: d = {a: list(range(4)), 'b': list('ab..'), 'c': ['a', 'b', np.nan, 'd']}
In [96]: df = pd.DataFrame(d)
In [97]: df.replace('.', np.nan)
Out[97]:
da b c
0 0 a a
1 1 b b
2 2 NaN NaN
3 3 NaN d

Now do it with a regular expression that removes surrounding whitespace (regex -> regex)

In [98]: df.replace(r'\s*\.\s*', np.nan, regex=True)
Out[98]:
da b c
0 0 a a
1 1 b b
2 2 NaN NaN
3 3 NaN d

Replace a few different values (list -> list)

In [99]: df.replace([a, '.'], ['b', np.nan])
Out[99]:
da b c
0 0 b b
1 1 b b
2 2 NaN NaN
3 3 NaN d

list of regex -> list of regex

In [100]: df.replace([r'\.', r'(a)'], ['dot', r'\1stuff'], regex=True)
Out[100]:
da b c
0 0 {stuff stuff
1 1 b b

16.5. Cleaning / filling missing data
Only search in column ‘b’ (dict -> dict)

In [101]: df.replace({'b': '.'}, {'b': np.nan})
Out[101]:
   a  b  c
0  0  a  a
1  1  b  b
2  NaN NaN
3  NaN  d

Same as the previous example, but use a regular expression for searching instead (dict of regex -> dict)

In [102]: df.replace({'b': r'\s*\.*\s*'}, {'b': np.nan}, regex=True)
Out[102]:
   a  b  c
0  0  a  a
1  1  b  b
2  NaN NaN
3  NaN  d

You can pass nested dictionaries of regular expressions that use regex=True

In [103]: df.replace({'b': {'b': r''}}, regex=True)
Out[103]:
   a  b  c
0  0  a  a
1  1  b
2  .  NaN
3  .  d

or you can pass the nested dictionary like so

In [104]: df.replace(regex={'b': {r'\s*\.*\s*': np.nan}})
Out[104]:
   a  b  c
0  0  a  a
1  1  b
2  .  NaN
3  .  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

In [105]: df.replace({'b': r'\s*(\.)\s*'}, {'b': r'\1ty'}, regex=True)
Out[105]:
   a  b  c
0  0  a  a
1  1  b  b
2  .  ty  NaN
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 [106]: df.replace([r'\s*\.*\s*', r'a|b'], np.nan, regex=True)
Out[106]:
   a  b  c
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

```python
In [107]: df.replace(regex=[r'\s*\./\s*', r'a|b'], value=np.nan)
Out[107]:
   a  b  c
0  0  NaN  NaN
1  1  NaN  NaN
2  2  NaN  NaN
3  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.

### 16.5.7 Numeric Replacement

Similar to `DataFrame.fillna`

```python
In [108]: df = pd.DataFrame(np.random.randn(10, 2))
In [109]: df[np.random.rand(df.shape[0]) > 0.5] = 1.5
In [110]: df.replace(1.5, np.nan)
Out[110]:
   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 via lists works as well

```python
In [111]: df00 = df.values[0, 0]
In [112]: df.replace([1.5, df00], [np.nan, 'a'])
Out[112]:
   0   1
0  NaN  NaN
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
```
6 -0.498174 -1.060799
7 0.591667 -0.183257
8 1.01985 -1.482465
9 NaN NaN

In [113]: df[1].dtype
Out[113]: dtype('float64')

You can also operate on the DataFrame in place

In [114]: 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 type. 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 [115]: s = pd.Series([True, False, True])

In [116]: s.replace('a string', 'another string')
Out[116]:
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.

### 16.6 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 reindexing will cause missing data to be introduced into, say, a Series or DataFrame. Here they are:

<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:

```python
In [117]: s = pd.Series(np.random.randn(5), index=[0, 2, 4, 6, 7])

In [118]: s > 0
Out[118]:
0  True
2  True
4  True
```
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 [123]: reindexed = s.reindex(list(range(8))).fillna(0)
```

```
In [124]: reindexed[crit]
---------------------------------------------------------------------------
ValueError                      Traceback (most recent call last)
<ipython-input-124-2da204ed1ac7> in <module>()
----> 1 reindexed[crit]
/home/joris/scipy/pandas/pandas/core/series.pyc in __getitem__(self, key)
      586 key = list(key)
      587
<---> 588 if is_bool_indexer(key):
      589     key = check_bool_indexer(self.index, key)
      590
/home/joris/scipy/pandas/pandas/core/common.pyc in is_bool_indexer(key)
     2073     if not lib.is_bool_array(key):
     2074         if isnull(key).any():
<---> 2075             raise ValueError('cannot index with vector containing ' 'NA / NaN values')
     2076     return False

ValueError: cannot index with vector containing NA / NaN values
```

However, these can be filled in using `fillna` and it will work fine:

```
In [125]: reindexed[crit.fillna(False)]
```

```
Out[125]:
```

```
0  0.126504
2  0.696198
4  0.697416
```

16.6. Missing data casting rules and indexing
In [126]: reindexed[crit.fillna(True)]
Out[126]:
   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
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

Of these, the split step is the most straightforward. In fact, in many situations you may wish to split the data set into groups and do something with those groups yourself. In the apply step, we might wish to one of the following:

- **Aggregation**: computing a summary statistic (or statistics) about each group. Some examples:
  - Compute group sums or means
  - Compute group sizes / counts

- **Transformation**: perform some group-specific computations and return a like-indexed. Some examples:
  - Standardizing data (zscore) within 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:
  - Discarding data that belongs to groups with only a few members
  - Filtering 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 method 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:

```
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.
### 17.1 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 do the following:

```python
>>> grouped = obj.groupby(key)
>>> grouped = obj.groupby(key, axis=1)
>>> grouped = obj.groupby([key1, key2])
```

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
- A list of any of the above things

Collectively we refer to the grouping objects as the keys. For example, consider the following DataFrame:

```python
In [1]: 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)})
```

We could naturally group by either the A or B columns or both:

```python
In [3]: grouped = df.groupby('A')
```

```python
In [4]: grouped = df.groupby(['A', 'B'])
```

These will split the DataFrame on its index (rows). We could also split by the columns:

```python
In [5]: def get_letter_type(letter):
    ...:     if letter.lower() in 'aeiou':
    ...:         return 'vowel'
    ...:     else:
    ...:         return 'consonant'
    ...
```

```python
In [6]: grouped = df.groupby(get_letter_type, axis=1)
```
Starting with 0.8, pandas Index objects now supports 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:

```
In [7]: lst = [1, 2, 3, 1, 2, 3]
In [8]: s = pd.Series([1, 2, 3, 10, 20, 30], lst)
In [9]: grouped = s.groupby(level=0)
In [10]: grouped.first()
Out[10]:
   1  1
   2  2
   3  3
dtype: int64

In [11]: grouped.last()
Out[11]:
   1 10
   2 20
   3 30
dtype: int64

In [12]: grouped.sum()
Out[12]:
   1 11
   2 22
   3 33
dtype: int64
```

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.

### 17.1.1 GroupBy sorting

By default the group keys are sorted during the `groupby` operation. You may however pass `sort=False` for potential speedups:

```
In [13]: df2 = pd.DataFrame({'X' : ['B', 'B', 'A', 'A'], 'Y' : [1, 2, 3, 4]})
In [14]: df2.groupby(['X']).sum()
Out[14]:
   Y
   X
   A  7
   B  3

In [15]: df2.groupby(['X'], sort=False).sum()
Out[15]:
   Y
   X
   B  3
   A  7
```

### 17.1. Splitting an object into groups
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 the appeared in the original DataFrame:

```python
In [16]: df3 = pd.DataFrame({ 'X' : ['A', 'B', 'A', 'B'], 'Y' : [1, 4, 3, 2] })

In [17]: df3.groupby([ 'X' ]).get_group('A')
Out[17]:
 X  Y
 0 A  1
 2 A  3

In [18]: df3.groupby([ 'X' ]).get_group('B')
Out[18]:
 X  Y
 1 B  4
 3 B  2
```

### 17.1.2 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 [19]: df.groupby( 'A' ).groups
Out[19]: {'bar': [1L, 3L, 5L], 'foo': [0L, 2L, 4L, 6L, 7L]}

In [20]: df.groupby(get_letter_type, axis=1).groups
Out[20]: {'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 [21]: grouped = df.groupby([ 'A', 'B' ])  

In [22]: grouped.groups
Out[22]:
({'bar', 'one': [1L],  
('bar', 'three': [3L],  
('bar', 'two': [5L],  
('foo', 'one': [0L, 6L],  
('foo', 'three': [7L],  
('foo', 'two': [2L, 4L])

In [23]: len(grouped)
Out[23]: 6
```

`GroupBy` will tab complete column names (and other attributes)

```python
In [24]: df
Out[24]:
   gender  height    weight
0  2000-01-01 male  42.849980  157.500553
1  2000-01-02 male  49.607315  177.340407
2  2000-01-03 male  56.293531  171.524640
3  2000-01-04 male  48.421077  144.251986
4  2000-01-05 male  46.556882  152.526206
5  2000-01-06 female 68.448851  168.272968
6  2000-01-07 male  70.757698  136.431469
7  2000-01-08 female 58.909500  176.499753
```

522 Chapter 17. `Group By`: split-apply-combine
2000-01-09  female  76.435631  174.094104
2000-01-10  male  45.306120  177.540920

In [25]: gb = df.groupby('gender')

In [26]: gb.<TAB>

gb.agg   gb.boxplot   gb.cummin   gb.describe   gb.filter   gb.get_group   gb.height   gb.aggregate   gb.count   gb.cumprod   gb.dtype   gb.first   gb.groups   gb.hist   gb.apply   gb.cummax   gb.cumsum   gb.fillna   gb.gender   gb.head   gb.indices
gb.height   gb.iqr   gb.last   gb.median   gb.ngroups   gb.plot   gb.rank   gb.std   gb.transform

17.1.3 GroupBy with MultiIndex

With *hierarchically-indexed data*, it’s quite natural to group by one of the levels of the hierarchy.

In [27]: s
Out[27]:
    first    second
  bar    one   -0.575247
         two    0.254161
  baz    one   -1.143704
         two    0.215897
  foo    one    1.193555
         two   -0.077118
  qux    one   -0.408530
         two   -0.862495

dtype: float64

In [28]: grouped = s.groupby(level=0)

In [29]: grouped.sum()
Out[29]:
first
bar  -0.321085
baz  -0.927807
foo   1.116437
qux  -1.271025

dtype: float64

If the MultiIndex has names specified, these can be passed instead of the level number:

In [30]: s.groupby(level='second').sum()
Out[30]:
second
one  -0.933926
two  -0.469555

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:

In [31]: s.sum(level='second')
Out[31]:
second
one  -0.933926
two  -0.469555

dtype: float64

Also as of v0.6, grouping with multiple levels is supported.

17.1. Splitting an object into groups
In [32]: s
Out[32]:
first   second  third
bar     doo     one   1.346061
        two     1.511763
baz     bee     one   1.627081
        two    -0.990582
foo     bop     one   -0.441652
        two    1.211526
qux     bop     one   0.268520
        two    0.024580
dtype: float64

In [33]: s.groupby(level=['first', 'second']).sum()
Out[33]:
first   second
bar     doo   2.857824
baz     bee   0.636499
foo     bop   0.769873
qux     bop   0.293100
dtype: float64

More on the sum function and aggregation later.

17.1.4 DataFrame column selection in GroupBy

Once you have created the GroupBy object from a DataFrame, for example, 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:

In [34]: grouped = df.groupby(['A'])

In [35]: grouped_C = grouped['C']

In [36]: grouped_D = grouped['D']

This is mainly syntactic sugar for the alternative and much more verbose:

In [37]: df['C'].groupby(df['A'])
Out[37]: <pandas.core.groupby.SeriesGroupBy object at 0xb032fa2c>

Additionally this method avoids recomputing the internal grouping information derived from the passed key.

17.2 Iterating through groups

With the GroupBy object in hand, iterating through the grouped data is very natural and functions similarly to itertools.groupby:

In [38]: grouped = df.groupby('A')

In [39]: for name, group in grouped:
       .....:     print(name)
       .....:     print(group)
       .....:
bar
A   B   C   D
1    bar    one  -0.042379 -0.089329
3    bar    three -0.009920  0.945867
5    bar    two   0.495767  1.956030

foo
    A   B   C   D
0    foo    one -0.919854 -1.131345
2    foo    two  1.247642  0.337863
4    foo    two  0.290213  0.932132
6    foo    one  0.362949  0.017587
7    foo    three  1.548106  0.016692

In the case of grouping by multiple keys, the group name will be a tuple:

In [40]: for name, group in df.groupby(["A", "B"]):
   ....:     print(name)
   ....:     print(group)
   ....:
('bar', 'one')
    A   B   C   D
 1    bar    one -0.042379 -0.089329
('bar', 'three')
    A   B   C   D
 3    bar    three -0.009920  0.945867
('bar', 'two')
    A   B   C   D
 5    bar    two  0.495767  1.956030
('foo', 'one')
    A   B   C   D
 0    foo    one -0.919854 -1.131345
 6    foo    one  0.362949  0.017587
('foo', 'three')
    A   B   C   D
 7    foo    three  1.548106 -0.016692
('foo', 'two')
    A   B   C   D
 2    foo    two  1.247642  0.337863
 4    foo    two  0.290213  0.932132

It’s standard Python-fu but remember you can unpack the tuple in the for loop statement if you wish: for (k1, k2), group in grouped:

17.3 Selecting a group

A single group can be selected using GroupBy.get_group():

In [41]: grouped.get_group(‘bar’)
Out[41]:
    A   B   C   D
 1    bar    one -0.042379 -0.089329
 3    bar    three -0.009920  0.945867
 5    bar    two  0.495767  1.956030

Or for an object grouped on multiple columns:

In [42]: df.groupby([‘A’, ‘B’]).get_group((‘bar’, ‘one’))
Out[42]:

17.3. Selecting a group 525
17.4 Aggregation

Once the GroupBy object has been created, several methods are available to perform a computation on the grouped data.

An obvious one is aggregation via the `aggregate` or equivalently `agg` method:

```python
In [43]: grouped = df.groupby('A')

In [44]: grouped.aggregate(np.sum)
Out[44]:
   C   D
A
bar 0.443469 0.920834
foo 2.529056 -1.724719
```

```python
In [45]: grouped = df.groupby(['A', 'B'])

In [46]: grouped.aggregate(np.sum)
Out[46]:
   C   D
A B
bar one -0.042379 -0.089329
   three -0.009920 -0.945867
   two  0.495767  1.956030
foo one -0.556905 -1.113758
   three  1.548106 -0.016692
   two  1.537855 -0.594269
```

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 [47]: grouped = df.groupby(['A', 'B'], as_index=False)

In [48]: grouped.aggregate(np.sum)
Out[48]:
   A  B  C  D
0  bar one -0.042379 -0.089329
   three -0.009920 -0.945867
   two  0.495767  1.956030
1  foo one -0.556905 -1.113758
   three  1.548106 -0.016692
   two  1.537855 -0.594269
```

```python
In [49]: df.groupby('A', as_index=False).sum()
Out[49]:
   A  C  D
0  bar 0.443469 0.920834
1  foo 2.529056 -1.724719
```

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:
In [50]: df.groupby(['A', 'B']).sum().reset_index()
Out[50]:
   A     B      C      D
0  bar   one -0.04238  -0.08933
1  bar  three -0.00992  -0.94587
2  bar   two   0.49577   1.95603
3  foo   one -0.55699 -1.11376
4  foo  three  1.54811  -0.01669
5  foo   two  1.53786 -0.59427

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.

In [51]: grouped.size()
Out[51]:
   A     B
bar one  1
   three 1
   two  1
foo one 2
   three 1
   two  2
dtype: int64

In [52]: grouped.describe()
Out[52]:
    C      D
   0  1.00000  1.00000
   mean -0.04238 -0.08933
   std   NaN     NaN
   min  -0.04238 -0.08933
  25%  -0.04238 -0.08933
  50%  -0.04238 -0.08933
  75%  -0.04238 -0.08933
...   ...     ...
   5  0.76893 -0.29713
   std  0.67700  0.89802
   min  0.29021 -0.93213
  25%  0.52957 -0.61463
  50%  0.76893 -0.29713
  75%  1.00829  0.02036
   max  1.24764  0.33786
[48 rows x 2 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 ones that reduce the dimension of the returned objects, for example: `mean`, `sum`, `size`, `count`, `std`, `var`, `sem`, `describe`, `first`, `last`, `nth`, `min`, `max`. This is what happens when you do for example `DataFrame.sum()` and get back a Series.

`nth` can act as a reducer or a filter, see [here](#).
17.4.1 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:

In [53]: grouped = df.groupby('A')

In [54]: grouped['C'].agg([np.sum, np.mean, np.std])
Out[54]:

<table>
<thead>
<tr>
<th></th>
<th>sum</th>
<th>mean</th>
<th>std</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.443469</td>
<td>0.147823</td>
<td>0.301765</td>
</tr>
<tr>
<td>foo</td>
<td>2.529056</td>
<td>0.505811</td>
<td>0.966450</td>
</tr>
</tbody>
</table>

If a dict is passed, the keys will be used to name the columns. Otherwise the function’s name (stored in the function object) will be used.

In [55]: grouped['D'].agg({'result1': np.sum, 'result2': np.mean})

Out[55]:

<table>
<thead>
<tr>
<th></th>
<th>result2</th>
<th>result1</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.306945</td>
<td>1.490982</td>
</tr>
<tr>
<td>foo</td>
<td>-0.344944</td>
<td>-1.724719</td>
</tr>
</tbody>
</table>

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:

In [56]: grouped.agg([np.sum, np.mean, np.std])
Out[56]:

<table>
<thead>
<tr>
<th></th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>sum</td>
<td>mean</td>
</tr>
<tr>
<td>A</td>
<td>0.443469</td>
<td>0.147823</td>
</tr>
<tr>
<td>foo</td>
<td>2.529056</td>
<td>0.505811</td>
</tr>
</tbody>
</table>

Passing a dict of functions has different behavior by default, see the next section.

17.4.2 Applying different functions to DataFrame columns

By passing a dict to `aggregate` you can apply a different aggregation to the columns of a DataFrame:

In [57]: grouped.agg({'C': np.sum, 'D': lambda x: np.std(x, ddof=1)})

Out[57]:

<table>
<thead>
<tr>
<th></th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.443469</td>
<td>1.490982</td>
</tr>
<tr>
<td>foo</td>
<td>2.529056</td>
<td>0.645875</td>
</tr>
</tbody>
</table>

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`:

In [58]: grouped.agg({'C': 'sum', 'D': 'std'})
Out[58]:

<table>
<thead>
<tr>
<th></th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.443469</td>
<td>1.490982</td>
</tr>
</tbody>
</table>

A
17.4.3 Cython-optimized aggregation functions

Some common aggregations, currently only `sum`, `mean`, `std`, and `sem`, have optimized Cython implementations:

```
In [59]: df.groupby('A').sum()
Out[59]:
           C     D
A
bar  0.443469  0.920834
foo  2.529056 -1.724719
```

```
In [60]: df.groupby(['A', 'B']).mean()
Out[60]:
           C     D
A B
  bar one  -0.042379 -0.089329
   three  -0.009920 -0.945867
   two    0.495767  1.956030
  foo one  -0.278452 -0.556879
   three  1.548106  -0.016692
   two    0.768928  -0.297134
```

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).

17.5 Transformation

The `transform` method returns an object that is indexed the same (same size) as the one being grouped. Thus, the passed transform function should return a result that is the same size as the group chunk. For example, suppose we wished to standardize the data within each group:

```
In [61]: index = pd.date_range('10/1/1999', periods=1100)
In [62]: ts = pd.Series(np.random.normal(0.5, 2, 1100), index)
In [63]: ts = pd.rolling_mean(ts, 100, 100).dropna()
In [64]: ts.head()
Out[64]:
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 [65]: ts.tail()
Out[65]:
2002-09-30    0.660294
2002-10-01    0.631095
2002-10-02    0.673601
2002-10-03    0.709213
```
2002-10-04  0.719369
Freq: D, dtype: float64

In [66]: key = lambda x: x.year

In [67]: zscore = lambda x: (x - x.mean()) / x.std()

In [68]: transformed = ts.groupby(key).transform(zscore)

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 [69]: grouped = ts.groupby(key)

In [70]: grouped.mean()
Out[70]:
2000  0.442441
2001  0.526246
2002  0.459365
dtype: float64

In [71]: grouped.std()
Out[71]:
2000  0.131752
2001  0.210945
2002  0.128753
dtype: float64

# Transformed Data
In [72]: grouped_trans = transformed.groupby(key)

In [73]: grouped_trans.mean()
Out[73]:
2000  -1.229286e-16
2001  -3.406712e-16
2002   4.969951e-17
dtype: float64

In [74]: grouped_trans.std()
Out[74]:
2000  1
2001  1
2002  1
dtype: float64

We can also visually compare the original and transformed data sets.

In [75]: compare = pd.DataFrame({'Original': ts, 'Transformed': transformed})

In [76]: compare.plot()
Out[76]: <matplotlib.axes._subplots.AxesSubplot at 0xaa120dec>
Another common data transform is to replace missing data with the group mean.

In [77]: data_df
Out [77]:
   A       B       C
0  1.539708 -1.166480  0.533026
1  1.302092 -0.505754   NaN
2 -0.371983  1.104803 -0.651520
3 -1.309622  1.118697 -1.161657
4 -1.924296  0.396437  0.812436
5  0.815643  0.367816 -0.469478
6 -0.030651  1.376106 -0.645129
   ...     ...     ...  
993 0.012359  0.554602 -1.976159
994 0.042312 -1.628835  1.013822
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
[1000 rows x 3 columns]
In [78]: countries = np.array(['US', 'UK', 'GR', 'JP'])

In [79]: key = countries[np.random.randint(0, 4, 1000)]

In [80]: grouped = data_df.groupby(key)

# Non-NA count in each group
In [81]: grouped.count()
Out[81]:
   A  B  C
GR 209 217 189
JP 240 255 217
UK 216 231 193
US 239 250 217

In [82]: f = lambda x: x.fillna(x.mean())

In [83]: transformed = grouped.transform(f)

We can verify that the group means have not changed in the transformed data and that the transformed data contains no NAs.

In [84]: grouped_trans = transformed.groupby(key)

In [85]: grouped.mean()  # original group means
Out[85]:
   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 [86]: grouped_trans.mean()  # transformation did not change group means
Out[86]:
   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 [87]: grouped.count()  # original has some missing data points
Out[87]:
   A  B  C
GR 209 217 189
JP 240 255 217
UK 216 231 193
US 239 250 217

In [88]: grouped_trans.count()  # counts after transformation
Out[88]:
   A  B  C
GR 228 228 228
JP 267 267 267
UK 247 247 247
US 258 258 258

In [89]: grouped_trans.size()  # Verify non-NA count equals group size
Out[89]:

Chapter 17. Group By: split-apply-combine
17.6 Filtration

New in version 0.12.

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.

```python
In [91]: sf = pd.Series([1, 1, 2, 3, 3, 3])

In [92]: sf.groupby(sf).filter(lambda x: x.sum() > 2)
```

```
Out[92]:
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.

```python
In [93]: dff = pd.DataFrame({'A': np.arange(8), 'B': list('aabbbbcc'))}

In [94]: dff.groupby('B').filter(lambda x: len(x) > 2)
```

```
Out[94]:
```

17.6. Filtration
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 [95]:
dff.groupby('B').filter(lambda x: len(x) > 2, dropna=False)
Out[95]:
A  B
0 NaN NaN
1 NaN NaN
2 2 b
3 3 b
4 4 b
5 5 b
6 NaN NaN
7 NaN NaN

For dataframes with multiple columns, filters should explicitly specify a column as the filter criterion.

In [96]:
dff['C'] = np.arange(8)
In [97]:
dff.groupby('B').filter(lambda x: len(x['C']) > 2)
Out[97]:
A  B  C
2 2 b 2
3 3 b 3
4 4 b 4
5 5 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.

In [98]:
dff.groupby('B').head(2)
Out[98]:
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

17.7 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:

In [99]:
grouped = df.groupby('A')
In [100]: grouped.agg(lambda x: x.std())
Out[100]:
      C    D
A  bar  0.301765  1.490982
    foo  0.966450  0.645875

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:

In [101]: grouped.std()
Out[101]:
      C    D
A  bar  0.301765  1.490982
    foo  0.966450  0.645875

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:

In [102]: tsdf = pd.DataFrame(np.random.randn(1000, 3),
                      index=pd.date_range('1/1/2000', periods=1000),
                      columns=['A', 'B', 'C'])

In [103]: grouped = tsdf.groupby(lambda x: x.year)
In [104]: grouped.fillna(method='pad')
Out[104]:
       A     B     C
2000-01-01  NaN  NaN  NaN
2000-01-02 -0.353501 -0.080957 -0.876864
2000-01-03 -0.353501 -0.080957 -0.876864
2000-01-04  0.050976  0.044273 -0.559849
2000-01-05  0.050976  0.044273 -0.559849
2000-01-06  0.030091  0.186460 -0.680149
2000-01-07  0.030091  0.186460 -0.680149
      ...     ...     ...
2002-09-20  2.310215  0.157482 -0.064476
2002-09-21  2.310215  0.157482 -0.064476
2002-09-22  0.005011  0.053897 -1.026922
2002-09-23  0.005011  0.053897 -1.026922
2002-09-24 -0.456542 -1.849051  1.559856
2002-09-25 -0.456542 -1.849051  1.559856
2002-09-26  1.123162  0.354660  1.128135

[1000 rows x 3 columns]

In this example, we chopped the collection of time series into yearly chunks then independently called fillna on the groups.

New in version 0.14.1.

The nlargest and nsmallest methods work on Series style groupbys:

17.7. Dispatching to instance methods
In [106]: s = pd.Series([9, 8, 7, 5, 19, 1, 4.2, 3.3])

In [107]: g = pd.Series(list('abababab'))

In [108]: gb = s.groupby(g)

In [109]: gb.nlargest(3)
Out[109]:
   a 4  19.0
      0  9.0
      2  7.0
   b 1  8.0
      3  5.0
      7  3.3

dtype: float64

In [110]: gb.nsmallest(3)
Out[110]:
   a 6  4.2
      2  7.0
      0  9.0
   b 5  1.0
      7  3.3
      3  5.0

dtype: float64

17.8 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:

In [111]: df
Out[111]:
           A   B      C      D
0      foo  one  -0.919854  -1.131345
1       bar  one  -0.042379  -0.089329
2      foo  two   1.247642   0.337863
3       bar  three  -0.009920  -0.945867
4      foo  two   0.290213  -0.932132
5       bar  two   0.495767   1.956030
6       foo  one  0.362949   0.017587
7      foo  three  1.548106  -0.016692

In [112]: grouped = df.groupby('A')

# could also just call .describe()
In [113]: grouped['C'].apply(lambda x: x.describe())
Out[113]:
   A
bar    count 3.000000
         mean 0.147823
         std 0.301765
         min -0.042379
         25% -0.026149
The dimension of the returned result can also change:

In [114]: grouped = df.groupby('A')['C']

In [115]: def f(group):
   .....:     return pd.DataFrame({'original' : group,
   .....:                            'demeaned' : group - group.mean()})
   .....:

In [116]: grouped.apply(f)

Out[116]:
          demeaned  original
0 -1.425665   -0.919854
1 -0.190202   -0.042379
2  0.741831    1.247642
3 -0.157743   -0.009920
4 -0.215598    0.290213
5  0.347944    0.495767
6 -0.142862    0.362949
7  1.042295    1.548106

aply 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 [117]: def f(x):
   .....:     return pd.Series([ x, x**2 ], index = ['x', 'x^s'])
   .....:

In [118]: s

Out[118]:
          x  x^s
0     9.0  81.00
1     8.0  64.00
2     7.0  49.00
3     5.0  25.00

dtype: float64

In [119]: s.apply(f)

Out[119]:
          x  x^s
0     9.0  81.00
1     8.0  64.00
2     7.0  49.00
3     5.0  25.00

dtype: float64
Note: `apply` can act as a reducer, transformer, or filter function, depending on exactly what is passed to apply. 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.

Warning: In the current implementation `apply` calls `func` twice on the first group to decide whether it can take a fast or slow code path. This can lead to unexpected behavior if `func` has side-effects, as they will take effect twice for the first group.

In [120]: d = pd.DataFrame({"a":["x", "y"], "b":[1,2]})

In [121]: def identity(df):
......:     print df
......:     return df
......:

In [122]: d.groupby("a").apply(identity)

17.9 Other useful features

17.9.1 Automatic exclusion of “nuisance” columns

Again consider the example DataFrame we’ve been looking at:

In [123]: df

Out[123]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>foo</td>
<td>one</td>
<td>-0.919854</td>
<td>-1.131345</td>
</tr>
<tr>
<td>1</td>
<td>bar</td>
<td>one</td>
<td>-0.042379</td>
<td>-0.089329</td>
</tr>
<tr>
<td>2</td>
<td>foo</td>
<td>two</td>
<td>1.247642</td>
<td>0.337863</td>
</tr>
<tr>
<td>3</td>
<td>bar</td>
<td>three</td>
<td>-0.009920</td>
<td>-0.945867</td>
</tr>
<tr>
<td>4</td>
<td>foo</td>
<td>two</td>
<td>0.290213</td>
<td>-0.932132</td>
</tr>
<tr>
<td>5</td>
<td>bar</td>
<td>two</td>
<td>0.495767</td>
<td>1.956030</td>
</tr>
<tr>
<td>6</td>
<td>foo</td>
<td>one</td>
<td>0.362949</td>
<td>0.017587</td>
</tr>
<tr>
<td>7</td>
<td>foo</td>
<td>three</td>
<td>1.548106</td>
<td>-0.016692</td>
</tr>
</tbody>
</table>

Supposed we wished 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:

```python
In [124]: df.groupby('A').std()
Out[124]:
       C    D
A
bar  0.301765  1.490982
foo  0.966450  0.645875
```

### 17.9.2 NA and NaT group handling

If there are any NaN or NaT values in the grouping key, these will be automatically excluded. So 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).

### 17.9.3 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:

```python
In [125]: data = pd.Series(np.random.randn(100))
In [126]: factor = pd.qcut(data, [0, .25, .5, .75, 1.])
In [127]: data.groupby(factor).mean()
```

### 17.9.4 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 [128]: import datetime
In [129]: df = pd.DataFrame(
   .....:    'Branch' : 'A A A A A A A B'.split(),
   .....:    'Buyer' : 'Carl Mark 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(2013,12,2,12,0),
   .....:       datetime.datetime(2013,12,2,14,0),
   .....:        ]
```

17.9. Other useful features
...: }

In [130]: df
Out[130]:

<table>
<thead>
<tr>
<th>Branch</th>
<th>Buyer</th>
<th>Date</th>
<th>Quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Carl</td>
<td>2013-01-01</td>
<td>1</td>
</tr>
<tr>
<td>A</td>
<td>Mark</td>
<td>2013-01-01</td>
<td>3</td>
</tr>
<tr>
<td>A</td>
<td>Carl</td>
<td>2013-10-01</td>
<td>5</td>
</tr>
<tr>
<td>A</td>
<td>Carl</td>
<td>2013-10-02</td>
<td>1</td>
</tr>
<tr>
<td>A</td>
<td>Joe</td>
<td>2013-10-01</td>
<td>8</td>
</tr>
<tr>
<td>A</td>
<td>Joe</td>
<td>2013-10-02</td>
<td>1</td>
</tr>
<tr>
<td>A</td>
<td>Joe</td>
<td>2013-12-02</td>
<td>9</td>
</tr>
<tr>
<td>B</td>
<td>Carl</td>
<td>2013-12-02</td>
<td>3</td>
</tr>
</tbody>
</table>

Groupby a specific column with the desired frequency. This is like resampling.

In [131]: df.groupby([pd.Grouper(freq='1M', key='Date'), 'Buyer']).sum()
Out[131]:

<table>
<thead>
<tr>
<th>Date</th>
<th>Buyer</th>
<th>Quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013-01-31</td>
<td>Carl</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Mark</td>
<td>3</td>
</tr>
<tr>
<td>2013-10-31</td>
<td>Carl</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>Joe</td>
<td>9</td>
</tr>
<tr>
<td>2013-12-31</td>
<td>Carl</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>Joe</td>
<td>9</td>
</tr>
</tbody>
</table>

You have an ambiguous specification in that you have a named index and a column that could be potential groupers.

In [132]: df = df.set_index('Date')
In [133]: df['Date'] = df.index + pd.offsets.MonthEnd(2)
In [134]: df.groupby([pd.Grouper(freq='6M', key='Date'), 'Buyer']).sum()
Out[134]:

<table>
<thead>
<tr>
<th>Date</th>
<th>Buyer</th>
<th>Quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013-02-28</td>
<td>Carl</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Mark</td>
<td>3</td>
</tr>
<tr>
<td>2014-02-28</td>
<td>Carl</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>Joe</td>
<td>18</td>
</tr>
</tbody>
</table>

In [135]: df.groupby([pd.Grouper(freq='6M', level='Date'), 'Buyer']).sum()
Out[135]:

<table>
<thead>
<tr>
<th>Date</th>
<th>Buyer</th>
<th>Quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013-01-31</td>
<td>Carl</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Mark</td>
<td>3</td>
</tr>
<tr>
<td>2014-01-31</td>
<td>Carl</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>Joe</td>
<td>18</td>
</tr>
</tbody>
</table>

17.9.5 Taking the first rows of each group

Just like for a DataFrame or Series you can call head and tail on a groupby:

In [136]: df = pd.DataFrame([[1, 2], [1, 4], [5, 6]], columns=['A', 'B'])
In [137]: df
Out[137]:
   A  B
0  1  2
1  1  4
2  5  6

In [138]: g = df.groupby('A')

In [139]: g.head(1)
Out[139]:
   A  B
0  1  2
2  5  6

In [140]: g.tail(1)
Out[140]:
   A  B
1  1  4
2  5  6

This shows the first or last n rows from each group.

Warning: Before 0.14.0 this was implemented with a fall-through apply, so the result would incorrectly respect the as_index flag:

>>> g.head(1):  
# was equivalent to g.apply(lambda x: x.head(1))
   A  B
A
1  0  1  2
5  2  5  6

17.9.6 Taking the nth row of each group

To select from a DataFrame or Series the nth item, use the nth method. This is a reduction method, and will return a single row (or no row) per group if you pass an int for n:

In [141]: df = pd.DataFrame([[[1, np.nan], [1, 4], [5, 6], columns=['A', 'B'])

In [142]: g = df.groupby('A')

In [143]: g.nth(0)
Out[143]:
   B
A
1  NaN
5  6

In [144]: g.nth(-1)
Out[144]:
   B
A
1  4
5  6

In [145]: g.nth(1)
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`, for a Series this just needs to be truthy.

```python
# nth(0) is the same as g.first()
In [146]: g.nth(0, dropna='any')
Out[146]:
   B  A  1  4
   5  6

In [147]: g.first()
Out[147]:
   B  A  1  4
   5  6

# nth(-1) is the same as g.last()
In [148]: g.nth(-1, dropna='any')  # NaNs denote group exhausted when using dropna
Out[148]:
   B  A  1  4
   5  6

In [149]: g.last()
Out[149]:
   B  A  1  4
   5  6

In [150]: g.B.nth(0, dropna=True)
Out[150]:
   A  1  4
   5  6
Name: B, dtype: float64
```

As with other methods, passing `as_index=False`, will achieve a filtration, which returns the grouped row.

```python
In [151]: df = pd.DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=['A', 'B'])

In [152]: g = df.groupby('A', as_index=False)

In [153]: g.nth(0)
Out[153]:
   0  A  1  NaN
   2  B  5  6

In [154]: g.nth(-1)
Out[154]:

```
You can also select multiple rows from each group by specifying multiple nth values as a list of ints.

```python
In [155]: business_dates = pd.date_range(start='4/1/2014', end='6/30/2014', freq='B')
In [156]: df = pd.DataFrame(1, index=business_dates, columns=['a', 'b'])
# get the first, 4th, and last date index for each month
In [157]: df.groupby((df.index.year, df.index.month)).nth([0, 3, -1])
Out[157]:
    a  b
14-04-01 1 1
14-04-04 1 1
14-04-30 1 1
14-05-01 1 1
14-05-06 1 1
14-05-30 1 1
14-06-02 1 1
14-06-05 1 1
14-06-30 1 1
```

### 17.9.7 Enumerate group items

New in version 0.13.0.

To see the order in which each row appears within its group, use the `cumcount` method:

```python
In [158]: df = pd.DataFrame(list('aaabba'), columns=['A'])
In [159]: df
Out[159]:
    A
0  a
1  a
2  a
3  b
4  b
5  a
In [160]: df.groupby('A').cumcount()
Out[160]:
     0  1
0  0  1
1  1  2
2  2  3
3  3  4
5  3
```

```python
In [161]: df.groupby('A').cumcount(ascending=False)  # kwarg only
Out[161]:
     0  1
0  3  1
1  2  2
2  1  3
```

17.9. Other useful features
17.9.8 Plotting

Groupby also works with some plotting methods. For example, suppose we suspect that some features in a DataFrame my differ by group, in this case, the values in column 1 where the group is “B” are 3 higher on average.

```
In [162]: np.random.seed(1234)

In [163]: df = pd.DataFrame(np.random.randn(50, 2))

In [164]: df['g'] = np.random.choice(['A', 'B'], size=50)

In [165]: df.loc[df['g'] == 'B', 1] += 3
```

We can easily visualize this with a boxplot:

```
In [166]: df.groupby('g').boxplot()
Out[166]: OrderedDict([('A', {'boxes': [<matplotlib.lines.Line2D object at 0xb07dfe8c>, <matplotlib.lines.Line2D object at 0xb0e16d2c>, <matplotlib.lines.Line2D object at 0xb07327cc>, <matplotlib.lines.Line2D object at 0xb1d1e36c>], 'whiskers': [<matplotlib.lines.Line2D object at 0xb07f89cc>, <matplotlib.lines.Line2D object at 0xb0e16d2c>, <matplotlib.lines.Line2D object at 0xb07f47cc>, <matplotlib.lines.Line2D object at 0xb1d1e36c>], 'caps': [<matplotlib.lines.Line2D object at 0xb07f89cc>, <matplotlib.lines.Line2D object at 0xb0e16d2c>, <matplotlib.lines.Line2D object at 0xb07f47cc>, <matplotlib.lines.Line2D object at 0xb1d1e36c>], 'fliers': [<matplotlib.lines.Line2D object at 0xb07f89cc>, <matplotlib.lines.Line2D object at 0xb0e16d2c>, <matplotlib.lines.Line2D object at 0xb07f47cc>, <matplotlib.lines.Line2D object at 0xb1d1e36c>], 'median': [0.80688074], 'mean': [0.80688074], 'std': [0.72986017], 'var': [0.53277594], 'count': [50], 'n': [50], 'name': 'A'}), ('B', {'boxes': [<matplotlib.lines.Line2D object at 0xb1870e8c>, <matplotlib.lines.Line2D object at 0xb1870e8c>, <matplotlib.lines.Line2D object at 0xb1870e8c>, <matplotlib.lines.Line2D object at 0xb1870e8c>], 'whiskers': [<matplotlib.lines.Line2D object at 0xb1870e8c>, <matplotlib.lines.Line2D object at 0xb1870e8c>, <matplotlib.lines.Line2D object at 0xb1870e8c>, <matplotlib.lines.Line2D object at 0xb1870e8c>], 'caps': [<matplotlib.lines.Line2D object at 0xb1870e8c>, <matplotlib.lines.Line2D object at 0xb1870e8c>, <matplotlib.lines.Line2D object at 0xb1870e8c>, <matplotlib.lines.Line2D object at 0xb1870e8c>], 'fliers': [<matplotlib.lines.Line2D object at 0xb1870e8c>, <matplotlib.lines.Line2D object at 0xb1870e8c>, <matplotlib.lines.Line2D object at 0xb1870e8c>, <matplotlib.lines.Line2D object at 0xb1870e8c>], 'median': [1.04923162], 'mean': [1.04923162], 'std': [0.7957519], 'var': [0.62997986], 'count': [50], 'n': [50], 'name': 'B'})]
```

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.
17.10 Examples

17.10.1 Regrouping by factor

Regroup columns of a DataFrame according to their sum, and sum the aggregated ones.

```
In [167]: df = pd.DataFrame({
                         'a': [1, 0, 0, 0, 1, 1, 1, 1, 2, 2, 2, 2],
                         'b': [0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1],
                         'c': [1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0],
                         'd': [0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1],
                         })
```

```
In [168]: df.groupby(df.sum(), axis=1).sum()
```

```
metrics b_sum c_mean
a 0 2 0.5
1 2 0.5
2 2 0.5
```

17.10.2 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:

```
In [170]: def compute_metrics(x):
                   result = {'b_sum': x['b'].sum(), 'c_mean': x['c'].mean()}
                   return pd.Series(result, name='metrics')
```

```
In [171]: result = df.groupby('a').apply(compute_metrics)
```

```
metrics  b_sum  c_mean
a 0   2  0.5
1   2  0.5
2   2  0.5
```
In [174]: result.stack()
Out[174]:
   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
MERGE, JOIN, AND CONCATENATE

pandas provides various facilities for easily combining together Series, DataFrame, and Panel objects with various kinds of set logic for the indexes and relational algebra functionality in the case of join / merge-type operations.

18.1 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:

```
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', join_axes=None, ignore_index=False,
          keys=None, levels=None, names=None, verify_integrity=False)
```

- `objs`: list or dict of Series, DataFrame, or Panel 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)
- `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
- `join_axes`: list of Index objects. Specific indexes to use for the other n - 1 axes instead of performing inner/outer set logic
- `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. If keys passed, specific levels to use for the resulting 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
- `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.

Without a little bit of context and example many of these arguments don’t make much sense. Let’s take 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:
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 do stuff like select out each chunk by key:

In [7]: result.ix['y']
Out[7]:
   A  B  C  D
0  A0 B0 C0 D0
1  A1 B1 C1 D1
2  A2 B2 C2 D2
3  A3 B3 C3 D3

It’s not a stretch to see how this can be very useful. More detail on this functionality below.

**Note:** It is worth noting however, 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.

frames = [ process_your_file(f) for f in files ]
result = pd.concat(frames)

### 18.1.1 Set logic on the other axes

When gluing together multiple DataFrames (or Panels or...), for example, you have a choice of how to handle the other axes (other than the one being concatenated). This can be done in three ways:

- Take the (sorted) union of them all, `join='outer'`. This is the default option as it results in zero information loss.
• Take the intersection, `join='inner'`.
• Use a specific index (in the case of DataFrame) or indexes (in the case of Panel or future higher dimensional objects), i.e. the `join_axes` argument.

Here is an example of each of these methods. First, the default `join='outer'` behavior:

```
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)
```

<table>
<thead>
<tr>
<th>df1</th>
<th>df4</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>B</td>
<td>C</td>
</tr>
<tr>
<td>0</td>
<td>A0</td>
<td>B0</td>
</tr>
<tr>
<td>1</td>
<td>A1</td>
<td>E1</td>
</tr>
<tr>
<td>2</td>
<td>A2</td>
<td>E2</td>
</tr>
<tr>
<td>3</td>
<td>A3</td>
<td>E3</td>
</tr>
</tbody>
</table>

Note that the row indexes have been unioned and sorted. Here is the same thing with `join='inner'`:

```
In [10]: result = pd.concat([df1, df4], axis=1, join='inner')
```

```
<table>
<thead>
<tr>
<th>df1</th>
<th>df4</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>B</td>
<td>C</td>
</tr>
<tr>
<td>0</td>
<td>A0</td>
<td>B0</td>
</tr>
<tr>
<td>1</td>
<td>A1</td>
<td>E1</td>
</tr>
<tr>
<td>2</td>
<td>A2</td>
<td>E2</td>
</tr>
<tr>
<td>3</td>
<td>A3</td>
<td>E3</td>
</tr>
</tbody>
</table>
```

Lastly, suppose we just wanted to reuse the exact index from the original DataFrame:

```
In [11]: result = pd.concat([df1, df4], axis=1, join_axes=[df1.index])
```

```
<table>
<thead>
<tr>
<th>df1</th>
<th>df4</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>B</td>
<td>C</td>
</tr>
<tr>
<td>0</td>
<td>A0</td>
<td>B0</td>
</tr>
<tr>
<td>1</td>
<td>A1</td>
<td>E1</td>
</tr>
<tr>
<td>2</td>
<td>A2</td>
<td>E2</td>
</tr>
<tr>
<td>3</td>
<td>A3</td>
<td>E3</td>
</tr>
</tbody>
</table>
```

```
<table>
<thead>
<tr>
<th>df1</th>
<th>df4</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>B</td>
<td>C</td>
</tr>
<tr>
<td>2</td>
<td>A2</td>
<td>B2</td>
</tr>
<tr>
<td>3</td>
<td>A3</td>
<td>B3</td>
</tr>
</tbody>
</table>
```

```
<table>
<thead>
<tr>
<th>df1</th>
<th>df4</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>B</td>
<td>C</td>
</tr>
<tr>
<td>0</td>
<td>A0</td>
<td>B0</td>
</tr>
<tr>
<td>1</td>
<td>A1</td>
<td>E1</td>
</tr>
<tr>
<td>2</td>
<td>A2</td>
<td>E2</td>
</tr>
<tr>
<td>3</td>
<td>A3</td>
<td>E3</td>
</tr>
</tbody>
</table>
```
18.1.2 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 [12]: result = df1.append(df2)

In the case of DataFrame, the indexes must be disjoint but the columns do not need to be:

In [13]: result = df1.append(df4)
append may take multiple objects to concatenate:

In [14]: result = df1.append([df2, df3])

18.1.3 Ignoring indexes on the concatenation axis

For DataFrames which don’t have a meaningful index, you may wish to append them and ignore the fact that they may have overlapping indexes:

Note: Unlike list.append method, which appends to the original list and returns nothing, append here does not modify df1 and returns its copy with df2 appended.
To do this, use the `ignore_index` argument:

```
In [15]: result = pd.concat([df1, df4], ignore_index=True)
```

This is also a valid argument to `DataFrame.append`:

```
In [16]: result = df1.append(df4, ignore_index=True)
```

### 18.1.4 Concatenating with mixed ndims

You can concatenate a mix of Series and DataFrames. The Series will be transformed to DataFrames with the column name as the name of the Series.

```
In [17]: s1 = pd.Series(['X0', 'X1', 'X2', 'X3'], name='X')
```

```
In [18]: result = pd.concat([df1, s1], axis=1)
```
If unnamed Series are passed they will be numbered consecutively.

```
In [19]: s2 = pd.Series([‘_0’,'_1','_2','_3'])
```

```
In [20]: result = pd.concat([df1, s2, s2, s2], axis=1)
```

Passing `ignore_index=True` will drop all name references.

```
In [21]: result = pd.concat([df1, s1], axis=1, ignore_index=True)
```

### 18.1.5 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 inherits the parent Series’ name, when these existed.

```
In [22]: s3 = pd.Series([0, 1, 2, 3], name='foo')
```

```
In [23]: s4 = pd.Series([0, 1, 2, 3])
```
In [24]: s5 = pd.Series([0, 1, 4, 5])

In [25]: pd.concat([s3, s4, s5], axis=1)
Out[25]:
     foo 0 1
   0  0 0 0
   1  1 1 1
   2  2 2 4
   3  3 3 5

Through the keys argument we can override the existing column names.

In [26]: pd.concat([s3, s4, s5], axis=1, keys=['red', 'blue', 'yellow'])
Out[26]:
      red  blue  yellow
   0    0    0     0
   1    1    1     1
   2    2    2     4
   3    3    3     5

Let’s consider now a variation on the very first example presented:

In [27]: 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):

In [28]: pieces = {'x': df1, 'y': df2, 'z': df3}

In [29]: result = pd.concat(pieces)
```python
In [30]: result = pd.concat(pieces, keys=['z', 'y'])
```

The MultiIndex created has levels that are constructed from the passed keys and the index of the DataFrame pieces:
If you wish to specify other levels (as will occasionally be the case), you can do so using the `levels` argument:

```
In[32]: result = pd.concat(pieces, keys=['x', 'y', 'z'],
   ...:       levels=[['z', 'y', 'x', 'w']],
   ...:       names=['group_key'])
```

Yes, this is fairly esoteric, but is actually necessary for implementing things like GroupBy where the order of a categorical variable is meaningful.

### 18.1.6 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.

```
In[34]: s2 = pd.Series(['X0', 'X1', 'X2', 'X3'], index=['A', 'B', 'C', 'D'])
In[35]: 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 [36]: dicts = [{'A': 1, 'B': 2, 'C': 3, 'X': 4}, ....:          {'A': 5, 'B': 6, 'C': 7, 'Y': 8}]
In [37]: result = df1.append(dicts, ignore_index=True)
```

---

### 18.2 Database-style DataFrame 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 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 objects:

```python
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)
```

Here’s a description of what each argument is for:

- **left**: A DataFrame object
- **right**: Another DataFrame object
- **on**: Columns (names) to join on. Must be found in both the left and right DataFrame objects. If not passed and `left_index` and `right_index` are False, the intersection of the columns in the DataFrames will be inferred to be the join keys
- **left_on**: Columns from the left DataFrame to use as keys. Can either be column names or arrays with length equal to the length of the DataFrame
- **right_on**: Columns from the right DataFrame to use as keys. Can either be column names or arrays with length equal to the length of the DataFrame
- **left_index**: If True, use the index (row labels) from the left DataFrame as its join key(s). In the case of a DataFrame with a MultiIndex (hierarchical), the number of levels must match the number of join keys from the right DataFrame
- **right_index**: Same usage as `left_index` for the right DataFrame
- **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 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, `right_only` for observations whose merge key only appears in `right` DataFrame, and `both` if the observation’s merge key is found in both.

New in version 0.17.0.

The return type will be the same as `left`. If `left` is a DataFrame 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, with the calling DataFrame being implicitly considered the left object in the join.

The related DataFrame.join method, uses `merge` internally for the index-on-index and index-on-column(s) joins, but `joins on indexes` by default rather than trying to join on common columns (the default behavior for `merge`). If you are joining on index, you may wish to use DataFrame.join to save yourself some typing.

### 18.2.1 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 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 [38]: left = pd.DataFrame({
    ...:     'key': ['K0', 'K1', 'K2', 'K3'],
    ...:     'A': ['A0', 'A1', 'A2', 'A3'],
    ...:     'B': ['B0', 'B1', 'B2', 'B3']
    ...: })

In [39]: right = pd.DataFrame({
    ...:     'key': ['K0', 'K1', 'K2', 'K3'],
    ...:     'C': ['C0', 'C1', 'C2', 'C3'],
    ...:     'D': ['D0', 'D1', 'D2', 'D3']
    ...: })

In [40]: result = pd.merge(left, right, on='key')
```

Here is a more complicated example with multiple join keys:

```python
In [41]: left = pd.DataFrame({
    ...:     'key1': ['K0', 'K0', 'K1', 'K2'],
    ...:     'key2': ['K0', 'K1', 'K0', 'K1'],
    ...:     'A': ['A0', 'A1', 'A2', 'A3'],
    ...:     'B': ['B0', 'B1', 'B2', 'B3']
    ...: })

In [42]: right = pd.DataFrame({
    ...:     'key1': ['K0', 'K1', 'K1', 'K2'],
    ...:     'key2': ['K0', 'K0', 'K0', 'K0'],
    ...:     'C': ['C0', 'C1', 'C2', 'C3'],
    ...:     'D': ['D0', 'D1', 'D2', 'D3']
    ...: })

In [43]: 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>

For example:

```python
In [44]: result = pd.merge(left, right, how='left', on=['key1', 'key2'])
```

```python
In [45]: result = pd.merge(left, right, how='right', on=['key1', 'key2'])
```

```python
In [46]: result = pd.merge(left, right, how='outer', on=['key1', 'key2'])
```
18.2.2 The merge indicator

New in version 0.17.0.

merge now accepts the argument indicator. If True, a Categorical-type column called _merge will be added to the output object that takes on values:

<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>

In [48]: df1 = DataFrame({'col1':[0,1], 'col_left':['a','b']})

In [49]: df2 = DataFrame({'col1':[1,2,2],'col_right':[2,2,2]})

In [50]: merge(df1, df2, on='col1', how='outer', indicator=True)

Out[50]:

<table>
<thead>
<tr>
<th></th>
<th>col1</th>
<th>col_left</th>
<th>col_right</th>
<th>_merge</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>a</td>
<td>NaN</td>
<td>left_only</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>b</td>
<td>2</td>
<td>both</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>NaN</td>
<td>2</td>
<td>right_only</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>NaN</td>
<td>2</td>
<td>right_only</td>
</tr>
</tbody>
</table>

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 [51]: merge(df1, df2, on='col1', how='outer', indicator='indicator_column')

Out[51]:

<table>
<thead>
<tr>
<th></th>
<th>col1</th>
<th>col_left</th>
<th>col_right</th>
<th>_merge</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>a</td>
<td>NaN</td>
<td>left_only</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>b</td>
<td>2</td>
<td>both</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>NaN</td>
<td>2</td>
<td>right_only</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>NaN</td>
<td>2</td>
<td>right_only</td>
</tr>
</tbody>
</table>
18.2.3 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:

```python
In [52]: left = pd.DataFrame({
   ...:     'A': ['A0', 'A1', 'A2'],
   ...:     'B': ['B0', 'B1', 'B2'],
   ...:     'C': ['C0', 'C1', 'C2'],
   ...:     'D': ['D0', 'D1', 'D2'],
   ...:     'E': ['E0', 'E1', 'E2'],
   ...:     'F': ['F0', 'F1', 'F2'],
   ...:     'G': ['G0', 'G1', 'G2'],
   ...:     'H': ['H0', 'H1', 'H2'],
   ...:     'I': ['I0', 'I1', 'I2'],
   ...:     'J': ['J0', 'J1', 'J2'],
   ...:     'K': ['K0', 'K1', 'K2'],
   ...:     'L': ['L0', 'L1', 'L2'],
   ...:     'M': ['M0', 'M1', 'M2'],
   ...:     'N': ['N0', 'N1', 'N2'],
   ...:     'O': ['O0', 'O1', 'O2'],
   ...:     'P': ['P0', 'P1', 'P2'],
   ...:     'Q': ['Q0', 'Q1', 'Q2'],
   ...:     'R': ['R0', 'R1', 'R2'],
   ...:     'S': ['S0', 'S1', 'S2'],
   ...:     'T': ['T0', 'T1', 'T2'],
   ...:     'U': ['U0', 'U1', 'U2'],
   ...:     'V': ['V0', 'V1', 'V2'],
   ...:     'W': ['W0', 'W1', 'W2'],
   ...:     'X': ['X0', 'X1', 'X2'],
   ...:     'Y': ['Y0', 'Y1', 'Y2'],
   ...:     'Z': ['Z0', 'Z1', 'Z2'],
   ...:     'aa': ['aa0', 'aa1', 'aa2'],
   ...:     'bb': ['bb0', 'bb1', 'bb2'],
   ...:     'cc': ['cc0', 'cc1', 'cc2'],
   ...:     'dd': ['dd0', 'dd1', 'dd2'],
   ...:     'ee': ['ee0', 'ee1', 'ee2'],
   ...:     'ff': ['ff0', 'ff1', 'ff2'],
   ...:     'gg': ['gg0', 'gg1', 'gg2'],
   ...:     'hh': ['hh0', 'hh1', 'hh2'],
   ...:     'ii': ['ii0', 'ii1', 'ii2'],
   ...:     'jj': ['jj0', 'jj1', 'jj2'],
   ...:     'kk': ['kk0', 'kk1', 'kk2'],
   ...:     'll': ['ll0', 'll1', 'll2'],
   ...:     'mm': ['mm0', 'mm1', 'mm2'],
   ...:     'nn': ['nn0', 'nn1', 'nn2'],
   ...:     'oo': ['oo0', 'oo1', 'oo2'],
   ...:     'pp': ['pp0', 'pp1', 'pp2'],
   ...:     'qq': ['qq0', 'qq1', 'qq2'],
   ...:     'rr': ['rr0', 'rr1', 'rr2'],
   ...:     'ss': ['ss0', 'ss1', 'ss2'],
   ...:     'tt': ['tt0', 'tt1', 'tt2'],
   ...:     'uu': ['uu0', 'uu1', 'uu2'],
   ...:     'vv': ['vv0', 'vv1', 'vv2'],
   ...:     'ww': ['ww0', 'ww1', 'ww2'],
   ...:     'xx': ['xx0', 'xx1', 'xx2'],
   ...:     'yy': ['yy0', 'yy1', 'yy2'],
   ...:     'zz': ['zz0', 'zz1', 'zz2'],
   ...:     'aaa': ['aaa0', 'aaa1', 'aaa2'],
   ...:     'bbb': ['bbb0', 'bbb1', 'bbb2'],
   ...:     'ccc': ['ccc0', 'ccc1', 'ccc2'],
   ...:     'ddd': ['ddd0', 'ddd1', 'ddd2'],
   ...:     'eee': ['eee0', 'eee1', 'eee2'],
   ...:     'fff': ['fff0', 'fff1', 'fff2'],
   ...:     'ggg': ['ggg0', 'ggg1', 'ggg2'],
   ...:     'hhh': ['hhh0', 'hhh1', 'hhh2'],
   ...:     'iii': ['iii0', 'iii1', 'iii2'],
   ...:     'jjj': ['jjj0', 'jjj1', 'jjj2'],
   ...:     'kkk': ['kkk0', 'kkk1', 'kkk2'],
   ...:     'lll': ['lll0', 'lll1', 'lll2'],
   ...:     'mmm': ['mmm0', 'mmm1', 'mmm2'],
   ...:     'nnn': ['nnn0', 'nnn1', 'nnn2'],
   ...:     'onn': ['onn0', 'onn1', 'onn2'],
   ...:     'ppp': ['ppp0', 'ppp1', 'ppp2'],
   ...:     'qqq': ['qqq0', 'qqq1', 'qqq2'],
   ...:     'rrr': ['rrr0', 'rrr1', 'rrr2'],
   ...:     'sss': ['sss0', 'sss1', 'sss2'],
   ...:     'ttt': ['ttt0', 'ttt1', 'ttt2'],
   ...:     'uuu': ['uuu0', 'uuu1', 'uuu2'],
   ...:     'vvv': ['vvv0', 'vvv1', 'vvv2'],
   ...:     'www': ['www0', 'www1', 'www2'],
   ...:     'xxx': ['xxx0', 'xxx1', 'xxx2'],
   ...:     'yyy': ['yyy0', 'yyy1', 'yyy2'],
   ...:     'zzz': ['zzz0', 'zzz1', 'zzz2'],
   ...:     'aaaa': ['aaaa0', 'aaaa1', 'aaaa2'],
   ...:     'bbbb': ['bbbb0', 'bbbb1', 'bbbb2'],
   ...:     'cccc': ['cccc0', 'cccc1', 'cccc2'],
   ...:     'dddd': ['dddd0', 'dddd1', 'dddd2'],
   ...:     'eeee': ['eeee0', 'eeee1', 'eeee2'],
   ...:     'ffff': ['ffff0', 'ffff1', 'ffff2'],
   ...:     'gggg': ['gggg0', 'gggg1', 'gggg2'],
   ...:     'hhhh': ['hhhh0', 'hhhh1', 'hhhh2'],
   ...:     'iiii': ['iiii0', 'iiii1', 'iiii2'],
   ...:     'jjjj': ['jjjj0', 'jjjj1', 'jjjj2'],
   ...:     'kkkk': ['kkkk0', 'kkkk1', 'kkkk2'],
   ...:     'llll': ['llll0', 'llll1', 'llll2'],
   ...:     'mmmm': ['mmmm0', 'mmmm1', 'mmmm2'],
   ...:     'nnnn': ['nnnn0', 'nnnn1', 'nnnn2'],
   ...:     'onnn': ['onn0', 'onn1', 'onn2'],
   ...:     'pppp': ['ppp0', 'ppp1', 'ppp2'],
   ...:     'qqqq': ['qqq0', 'qqq1', 'qqq2'],
   ...:     'rrrr': ['rrr0', 'rrr1', 'rrr2'],
   ...:     'ssss': ['sss0', 'sss1', 'sss2'],
   ...:     'tttt': ['ttt0', 'ttt1', 'ttt2'],
   ...:     'uuuu': ['uuu0', 'uuu1', 'uuu2'],
   ...:     'vvvv': ['vvv0', 'vvv1', 'vvv2'],
   ...:     'wwww': ['www0', 'www1', 'www2'],
   ...:     'xxxxxxxx': ['xxxx0', 'xxxx1', 'xxxx2'],
   ...:     'yyyyy': ['yyyy0', 'yyyy1', 'yyyy2'],
   ...:     'zzzzz': ['zzz0', 'zzz1', 'zzz2']},
   ...:     index=['K0', 'K1', 'K2', 'K3', 'K4', 'K5', 'K6', 'K7', 'K8', 'K9'])

In [53]: right = pd.DataFrame({
   ...:     'A': ['A0', 'A1', 'A2'],
   ...:     'B': ['B0', 'B1', 'B2'],
   ...:     'C': ['C0', 'C1', 'C2'],
   ...:     'D': ['D0', 'D1', 'D2'],
   ...:     'E': ['E0', 'E1', 'E2'],
   ...:     'F': ['F0', 'F1', 'F2'],
   ...:     'G': ['G0', 'G1', 'G2'],
   ...:     'H': ['H0', 'H1', 'H2'],
   ...:     'I': ['I0', 'I1', 'I2'],
   ...:     'J': ['J0', 'J1', 'J2'],
   ...:     'K': ['K0', 'K1', 'K2', 'K3', 'K4', 'K5', 'K6', 'K7', 'K8', 'K9'])

In [54]: result = left.join(right)

In [55]: result = left.join(right, how='outer')

In [56]: result = left.join(right, how='inner')
```
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:

```py
In [57]: result = pd.merge(left, right, left_index=True, right_index=True, how='outer')
```

```py
In [58]: result = pd.merge(left, right, left_index=True, right_index=True, how='inner');
```

### 18.2.4 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:

```py
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:

```py
In [59]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
                          'B': ['B0', 'B1', 'B2', 'B3'],
                          'key': ['K0', 'K1', 'K0', 'K1']})
```
In [60]: right = pd.DataFrame({'C': ['C0', 'C1'],
                           'D': ['D0', 'D1']},
                          index=['K0', 'K1'])

In [61]: result = left.join(right, on='key')

In [62]: 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:

In [63]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
                           'B': ['B0', 'B1', 'B2', 'B3'],
                           'key1': ['K0', 'K0', 'K1', 'K2'],
                           'key2': ['K0', 'K1', 'K0', 'K1']})

In [64]: index = pd.MultiIndex.from_tuples([('K0', 'K0'), ('K1', 'K0'), ('K2', 'K0'), ('K2', 'K1')])

In [65]: 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 [66]: result = left.join(right, on=['key1', 'key2'])
`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 [67]: result = left.join(right, on=['key1', 'key2'], how='inner')
```

As you can see, this drops any rows where there was no match.

## 18.2.5 Joining a single Index to a Multi-index

New in version 0.14.0.

You can join a singly-indexed `DataFrame` with a level of a multi-indexed `DataFrame`. The level will match on the name of the index of the singly-indexed frame against a level name of the multi-indexed frame.

```
In [68]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2'],
                       'B': ['B0', 'B1', 'B2']},
                      index=Index(['K0', 'K1', 'K2'], name='key'))

In [69]: index = pd.MultiIndex.from_tuples([('K0', 'Y0'), ('K1', 'Y1'), ('K2', 'Y2'), ('K2', 'Y3')],
                                      names=['key', 'Y'])

In [70]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
                         'D': ['D0', 'D1', 'D2', 'D3']},
                         index=index)

In [71]: result = left.join(right, how='inner')
```
This is equivalent but less verbose and more memory efficient / faster than this.

```
In [72]: result = pd.merge(left.reset_index(), right.reset_index(),
...:                     on=['key'], how='inner').set_index(['key', 'Y'])
```

### 18.2.6 Joining with two multi-indexes

This is not implemented via `join` at-the-moment, however it can be done using the following.

```
In [73]: index = pd.MultiIndex.from_tuples([('K0', 'X0'), ('K0', 'X1'),
...:                                      ('K1', 'X2')],
...:                               names=['key', 'X'])
```

```
In [74]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2'],
...:                        'B': ['B0', 'B1', 'B2']},
...:                        index=index)
```

```
In [75]: result = pd.merge(left.reset_index(), right.reset_index(),
...:                     on=['key'], how='inner').set_index(['key', 'X', 'Y'])
```
18.2.7 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 [76]: left = pd.DataFrame({'k': ['K0', 'K1', 'K2'], 'v': [1, 2, 3]})

In [77]: right = pd.DataFrame({'k': ['K0', 'K0', 'K3'], 'v': [4, 5, 6]})

In [78]: result = pd.merge(left, right, on='k')

In [79]: result = pd.merge(left, right, on='k', suffixes=('l', 'r'))

DataFrame.join has lsuffix and rsuffix arguments which behave similarly.

In [80]: left = left.set_index('k')

In [81]: right = right.set_index('k')

In [82]: result = left.join(right, lsuffix='l', rsuffix='r')
18.2.8 Joining multiple DataFrame or Panel objects

A list or tuple of DataFrames can also be passed to `DataFrame.join` to join them together on their indexes. The same is true for `Panel.join`.

In [83]: right2 = pd.DataFrame({'v': [7, 8, 9]}, index=['K1', 'K1', 'K2'])

In [84]: result = left.join([right, right2])

18.2.9 Merging Ordered Data

New in v0.8.0 is the ordered_merge function for combining time series and other ordered data. In particular it has an optional `fill_method` keyword to fill/interpolate missing data:

In [85]: left = DataFrame({'k': ['K0', 'K1', 'K1', 'K2'],
                        'lv': [1, 2, 3, 4],
                        's': ['a', 'b', 'c', 'd']})

In [86]: right = DataFrame({'k': ['K1', 'K2', 'K4'],
                        'rv': [1, 2, 3]})

In [87]: result = ordered_merge(left, right, fill_method='ffill', left_by='s')
18.2.10 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 [88]:
   
   df1 = pd.DataFrame([[np.nan, 3., 5.], [-4.6, np.nan, np.nan],
   ....:                   [np.nan, 7., np.nan]])
   ....:                   index=[0, 1, 2])
   ....:

In [89]:
   
   df2 = pd.DataFrame([[42.6, np.nan, -8.2], [-5., 1.6, 4]],
   ....:                   index=[1, 2])
   ....:

For this, use the combine_first method:

In [90]:
   
   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 inplace:

In [91]:
   
   df1.update(df2)
### 18.2. Database-style DataFrame joining/merging

<table>
<thead>
<tr>
<th></th>
<th>df1</th>
<th>df2</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0  NaN  3.0  5.0</td>
<td>0  -2.6  NaN  -8.2</td>
<td>0  NaN  3.0  5.0</td>
</tr>
<tr>
<td>1</td>
<td>4.6  NaN  NaN</td>
<td>2  NaN  16  40</td>
<td>1  -2.6  NaN  -8.2</td>
</tr>
<tr>
<td>2</td>
<td>NaN  7.0  NaN</td>
<td>2  5.0  16  40</td>
<td>2  NaN  16  40</td>
</tr>
</tbody>
</table>
19.1 Reshaping by pivoting DataFrame objects

Data is often stored in CSV files or databases in so-called “stacked” or “record” format:

```python
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.util.testing as tm; tm.N = 3
def unpivot(frame):
    N, K = frame.shape
    data = {'value' : frame.values.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'])
df = unpivot(tm.makeTimeDataFrame())
```

To select out everything for variable A we could do:

```python
In [2]: df[df['variable'] == 'A']
Out[2]:
      date  variable  value
0  2000-01-03       A  0.469112
1  2000-01-04       A -0.282863
2  2000-01-05       A -1.509059
```

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, use the pivot function:
In [3]: df.pivot(index='date', columns='variable', values='value')
Out[3]:
    variable  A   B   C   D
date
2000-01-03  0.469112 -1.135632 0.119209 -2.104569
2000-01-04  -0.282863  1.212112 -1.044236 -0.494929
2000-01-05  -1.509059 -0.173215 -0.861849  1.071804

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:

In [4]: df['value2'] = df['value'] * 2
In [5]: pivoted = df.pivot('date', 'variable')
In [6]: pivoted
Out[6]:
    variable  A   B   C   D   A   B
value     
variable
2000-01-03  0.469112 -1.135632 0.119209 -2.104569 0.938225 -2.271265
2000-01-04  -0.282863  1.212112 -1.044236 -0.494929 -0.565727  2.424224
2000-01-05  -1.509059 -0.173215 -0.861849  1.071804 -3.018117 -0.346429

You of course can then select subsets from the pivoted DataFrame:

In [7]: pivoted['value2']
Out[7]:
    variable  A   B   C   D
value     
variable
2000-01-03  0.938225 -2.271265 0.238417 -4.209138
2000-01-04  -0.565727  2.424224 -2.088472 -0.989859
2000-01-05  -3.018117 -0.346429 -1.723698  2.143608

Note that this returns a view on the underlying data in the case where the data are homogeneously-typed.

19.2 Reshaping by stacking and unstacking

Closely related to the pivot function are the related stack and unstack functions currently available on Series and DataFrame. These functions are designed to work together with MultiIndex objects (see the section on hierarchical indexing). Here are essentially what these functions 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 from 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.

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
Out[12]:
   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]:
   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

In [16]: stacked.unstack(1)
Out[16]:
   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

In [17]: stacked.unstack(0)
Out[17]:
first   bar   baz
second
one   A  0.721555 -0.424972
      B -0.706771  0.567020
two   A -1.039575  0.276232
      B  0.271860 -1.087401

If the indexes have names, you can use the level names instead of specifying the level numbers:

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

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
2   a -0.370647
    b -1.157892
1   a -1.344312
    b  0.844885

In [22]: all(df.unstack().stack() == df.sort_index())
Out[22]: True

while the above code will raise a TypeError if the call to sort_index is removed.

19.2.1 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 [23]: columns = pd.MultiIndex.from_tuples([
    ....:     ('A', 'cat', 'long'), ('B', 'cat', 'long'),
    ....:     ('A', 'dog', 'short'), ('B', 'dog', 'short')
    ....: ],
    ....:     names=['exp', 'animal', 'hair_length'])
    ....: )
    ....: }
In [24]: df = pd.DataFrame(np.random.randn(4, 4), columns=columns)

In [25]: df
Out[25]:
exp    A    B    A    B
animal  cat  cat  dog  dog
hair_length  long  long  short  short
0  1.075770 -0.109050  1.643563 -1.469388
1  0.357021 -0.674600 -1.776904 -0.968914
2 -1.294524  0.413738  0.276662 -0.472035
3 -0.013960 -0.362543 -0.006154 -0.923061

In [26]: df.stack(level=['animal', 'hair_length'])
Out[26]:
exp  A  B
animal hair_length
0  cat  long  1.075770 -0.109050
   dog  short  1.643563 -1.469388
1  cat  long  0.357021 -0.674600
   dog  short -1.776904 -0.968914
2  cat  long -1.294524  0.413738
   dog  short  0.276662 -0.472035
3  cat  long -0.013960 -0.362543
   dog  short -0.006154 -0.923061

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]:
exp  A  B
animal hair_length
0  cat  long  1.075770 -0.109050
   dog  short  1.643563 -1.469388
1  cat  long  0.357021 -0.674600
   dog  short -1.776904 -0.968914
2  cat  long -1.294524  0.413738
   dog  short  0.276662 -0.472035
3  cat  long -0.013960 -0.362543
   dog  short -0.006154 -0.923061

19.2.2 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=['first', 'second'])
In [30]: df = pd.DataFrame(np.random.randn(8, 4), index=index, columns=columns)

In [31]: df2 = df.ix[[0, 1, 2, 4, 5, 7]]

In [32]: df2
Out[32]:
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 -1.413681  1.607920  1.024180  0.569605
foo  one -0.875906 -2.211372  0.974466 -2.006747
      two  0.875906 -2.211372  0.974466 -2.006747
qux  one  0.410835  0.132003 -0.827317  0.813850
      two -1.226825  0.769804 -1.281247 -0.727707

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       cat   dog
first second exp
bar  one  cat  0.895717 -1.206412
      dog  2.565646  0.805244
      two  cat  1.431256 -1.170299
      dog  1.340309  0.826169
baz  one  cat  0.410835  0.132003
      dog  0.813850  0.827317
foo  one  cat -1.413681  1.024180
      dog  1.607920  0.569605
      two  cat  0.875906 -2.006747
      dog  0.974466 -2.211372
qux  one  cat -1.226825 -0.727707
      dog  0.769804 -1.281247

In [34]: df2.stack('animal')
Out[34]:
exp   A   B
animal
first second animal
bar  one  cat  0.895717 -1.206412
      dog  2.565646  0.805244
      two  cat  1.431256 -1.170299
      dog  1.340309  0.826169
baz  one  cat  0.410835  0.132003
      dog  0.813850  0.827317
foo  one  cat -1.413681  1.024180
      dog  1.607920  0.569605
      two  cat  0.875906 -2.006747
      dog  0.974466 -2.211372
qux  one  cat -1.226825 -0.727707
      dog  0.769804 -1.281247

19.2.3 With a MultiIndex

Unstacking when the columns are a MultiIndex is also careful about doing the right thing:
In [35]: df[:3].unstack(0)
Out[35]:
  exp     A       B       A
animal   cat     dog     cat     dog
first    bar     baz     bar     baz     bar
second   one 0.895717 0.410835 0.81385 1.206412 0.132003 2.565646
two     1.431256 NaN     1.340309 NaN     -1.170299 NaN     -0.226169

exp
animal
first    baz
second
one    -0.827317
two    NaN

In [36]: df2.unstack(1)
Out[36]:
  exp     A       B       A
animal   cat     dog     cat     dog
second   one 0.895717 1.431256 0.805244 1.340309 -1.206412 -1.170299 2.565646
two     foo -1.413681 0.875906 1.607920 -2.211372 1.024180 0.974466 0.569605
first    qux NaN     -1.226825 NaN     0.769804 NaN     -1.281247 NaN

exp
animal
second   two
first
bar    -0.226169
baz    NaN
foo    -2.006747
qux    -0.727707

19.3 Reshaping by Melt

The `melt()` function is 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,

In [37]: cheese = pd.DataFrame({'first': ['John', 'Mary'],
                           'last': ['Doe', 'Bo'],
                           'height': [5.5, 6.0],
                           'weight': [130, 150]})

In [38]: cheese
Out[38]:
   first height last  weight
0  John   5.5   Doe    130
1  Mary   6.0     Bo    150
In [39]: pd.melt(cheese, id_vars=['first', 'last'])
Out[39]:
   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 [40]: pd.melt(cheese, id_vars=['first', 'last'], var_name='quantity')
Out[40]:
   first  last  quantity 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

Another way to transform is to use the \texttt{wide_to_long} panel data convenience function.

In [41]: dft = 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 : 0.1},
                        'X'     : dict(zip(range(3), np.random.randn(3)))})
....:

In [42]: dft["id"] = dft.index

In [43]: dft
Out[43]:
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 [44]: pd.wide_to_long(dft, ['A', 'B'], i="id", j="year")
Out[44]:
   X  A  B id year
0  0  a  d  1970 -0.121306  2.5
1  1  b  e  1970 -0.097883  1.2
2  2  c  f  1970  0.695775  0.7
3  0  a  d  1980 -0.121306  3.2
4  1  b  e  1980 -0.097883  1.3
5  2  c  f  1980  0.695775  0.1

19.4 Combining with stats and GroupBy

It should be no shock that combining \texttt{pivot} / \texttt{stack} / \texttt{unstack} with GroupBy and the basic Series and DataFrame statistical functions can produce some very expressive and fast data manipulations.

In [45]: df
Out[45]:
     exp
animal  cat  dog
first  second

580 Chapter 19. Reshaping and Pivot Tables
In [46]: df.stack().mean(1).unstack()
Out[46]:
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 [47]: df.groupby(level=1, axis=1).mean()
Out[47]:
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

In [48]: df.stack().groupby(level=1).mean()
Out[48]:
exp  A    B
second
one  0.071448  0.455513
two  -0.424186  -0.204486

In [49]: df.mean().unstack(0)
Out[49]:
exp  A    B
animal
cat  0.060843  0.018596
dog  -0.413580  0.232430

19.5 Pivot tables and cross-tabulations

The function pandas.pivot_table can be used to create spreadsheet-style pivot tables. See the cookbook for some advanced strategies.

It takes a number of arguments.
Consider a data set like this:

```
In [50]: import datetime
In [51]:
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)]})

In [52]: df
Out[52]:
   A   B   C       D       E       F
0  one A  foo  0.341734 -0.317441  2013-01-01
1  one B  foo  0.959726 -1.236269  2013-02-01
2  two C  foo -1.110336  0.896171  2013-03-01
3  three A  bar -0.619976 -0.487602  2013-04-01
4    one B  bar  0.149748 -0.082240  2013-05-01
5    one C  bar -0.732339 -2.182937  2013-06-01
6    two A  foo  0.687738  0.380396  2013-07-01
   ... ... ... ... ... ...
17  one C  bar -0.345352  0.206053  2013-06-15
18  two A  foo  1.314232 -0.251905  2013-07-15
19  three B  foo  0.690579 -2.213588  2013-08-15
20    one C  foo  0.995761  1.063327  2013-09-15
21    one A  bar  2.396780  1.266143  2013-10-15
22    two B  bar  0.014871  0.299368  2013-11-15
23    three C  bar  3.357427 -0.863838  2013-12-15
```

We can produce pivot tables from this data very easily:

```
In [53]: pd.pivot_table(df, values='D', index=['A', 'B'], columns=['C'])
Out[53]:
   C   bar   foo
A  B
   one A  1.120915 -0.514058
       B -0.338421  0.002759
       C -0.538846  0.699535
   three A -1.181568  NaN
         B  NaN  0.433512
         C  0.588783  NaN
   two A  NaN  1.000985
      B  0.158248  NaN
      C  NaN  0.176180
```

We can produce pivot tables from this data very easily:
In [54]: pd.pivot_table(df, values='D', index=['B'], columns=['A', 'C'], aggfunc=np.sum)
Out[54]:
    A    one    three    two
   C  bar  foo    bar    foo    bar    foo
  B  
    A  2.241830 -1.028115 -2.363137    NaN    NaN  2.001971
    B -0.676843  0.005518    NaN  0.867024  0.316495    NaN
    C -1.077692  1.399070  1.177566    NaN    NaN  0.352360

In [55]: pd.pivot_table(df, values=['D','E'], index=['B'], columns=['A', 'C'], aggfunc=np.sum)
Out[55]:
   D E
   A    one    three    two
   C  bar  foo    bar    foo    bar    foo
  B  
    A  2.241830 -1.028115 -2.363137    NaN    NaN  2.001971  2.786113
    B -0.676843  0.005518    NaN  0.867024  0.316495    NaN  1.368280
    C -1.077692  1.399070  1.177566    NaN    NaN  0.352360 -1.976883

    A    three    two
   C  foo  bar    foo    bar    foo
  B  
    A -0.043211  1.922577    NaN    NaN  0.128491
    B -1.103384    NaN -2.128743 -0.194294    NaN
    C  1.495717    NaN -0.263660    NaN  0.872482

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:

In [56]: pd.pivot_table(df, index=['A', 'B'], columns=['C'])
Out[56]:
   D E
   C    bar  foo    bar  foo
  A  
    one  1.120915 -0.514058  1.393057 -0.021605
    B -0.338421  0.002759  0.684140 -0.551692
    C -0.538846  0.699535 -0.988442  0.747859
  three  
    A -1.181568    NaN  0.961289    NaN
    B    NaN  0.433512    NaN -0.164372
    C  0.588783    NaN -0.131830    NaN
  two  
    A    NaN  1.009985    NaN  0.064245
    B  0.158248    NaN -0.097147    NaN
    C    NaN  0.176180    NaN  0.436241

Also, you can use Grouper for `index` and `columns` keywords. For detail of Grouper, see `Grouping with a Grouper specification`.

In [57]: pd.pivot_table(df, values='D', index=Grouper(freq='M', key='F'), columns='C')
Out[57]:
   C  bar  foo
  F  
    2013-01-31    NaN -0.514058
    2013-02-28    NaN  0.002759
    2013-03-31    NaN  0.176180
    2013-04-30 -1.181568    NaN
    2013-05-31 -0.338421    NaN

19.5. Pivot tables and cross-tabulations 583
You can render a nice output of the table omitting the missing values by calling `to_string` if you wish:

```python
In [58]: table = pd.pivot_table(df, index=['A', 'B'], columns=['C'])
In [59]: print(table.to_string(na_rep=''))
```

```
D   E
C   bar  foo  bar  foo
A   B
one A  1.120915 -0.514058 1.393057 -0.021605
     B -0.338421  0.002759  0.684140 -0.551692
     C -0.538846  0.699535 -0.988442  0.747859
three A -1.181568   0.961289
       B   0.433512 -1.064372
       C   0.588783 -0.131830
two A  1.000985  0.064245
      B  0.158248 -0.097147
     C  0.176180  0.436241
```

Note that `pivot_table` is also available as an instance method on DataFrame.

### 19.5.1 Cross tabulations

Use the `crosstab` function 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)

Any Series passed will have their name attributes used unless row or column names for the cross-tabulation are specified.

For example:

```python
In [60]: foo, bar, dull, shiny, one, two = 'foo', 'bar', 'dull', 'shiny', 'one', 'two'
In [61]: a = np.array([foo, foo, bar, bar, foo, foo], dtype=object)
In [62]: b = np.array([one, one, two, one, two, one], dtype=object)
In [63]: c = np.array([dull, dull, shiny, dull, dull, shiny], dtype=object)
```
19.5.2 Adding margins (partial aggregates)

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 [65]: df.pivot_table(index=['A', 'B'], columns='C', margins=True, aggfunc=np.std)
Out[65]:
```

<table>
<thead>
<tr>
<th></th>
<th>bar</th>
<th>foo</th>
<th>All</th>
<th>bar</th>
<th>foo</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>one</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>1.804346</td>
<td>1.210272</td>
<td>1.569879</td>
<td>0.179483</td>
<td>0.418374</td>
<td>0.858005</td>
</tr>
<tr>
<td>C</td>
<td>0.690376</td>
<td>1.353355</td>
<td>0.898998</td>
<td>1.083825</td>
<td>0.968138</td>
<td>1.101401</td>
</tr>
<tr>
<td>two</td>
<td>0.273641</td>
<td>0.418926</td>
<td>0.771139</td>
<td>1.689271</td>
<td>0.446140</td>
<td>1.422136</td>
</tr>
<tr>
<td>three</td>
<td>0.794212</td>
<td>NaN</td>
<td>2.049040</td>
<td>NaN</td>
<td>2.049040</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.363548</td>
<td>0.363548</td>
<td>1.625237</td>
<td>1.625237</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3.915454</td>
<td>1.035215</td>
<td>1.035215</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.819408</td>
<td>0.650439</td>
<td>1.059389</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

19.6 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 [66]: ages = np.array([10, 15, 13, 12, 23, 25, 28, 59, 60])
In [67]: pd.cut(ages, bins=3)
```

```
[(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]
```

Categories (3, object): [(9.95, 26.667] < (26.667, 43.333] < (43.333, 60]

If the bins keyword is an integer, then equal-width bins are formed. Alternatively we can specify custom bin-edges:

```python
In [68]: pd.cut(ages, bins=[0, 18, 35, 70])
```

```
[(0, 18], (0, 18], (0, 18], (0, 18], (18, 35], (18, 35], (18, 35], (18, 35], (35, 70], (35, 70]
```

Categories (3, object): [(0, 18] < (18, 35] < (35, 70]

19.7 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:
In [69]: df = pd.DataFrame({'key': list('bbacab'), 'data1': range(6)})

In [70]: pd.get_dummies(df['key'])
Out[70]:
   a  b  c
0  0  1  0
1  0  1  0
2  1  0  0
3  0  0  1
4  1  0  0
5  0  1  0

Sometimes it’s useful to prefix the column names, for example when merging the result with the original DataFrame:

In [71]: dummies = pd.get_dummies(df['key'], prefix='key')

In [72]: dummies
Out[72]:
   key_a  key_b  key_c
0       0       1       0
1       0       1       0
2       1       0       0
3       0       0       1
4       1       0       0
5       0       1       0

In [73]: df['data1'].join(dummies)
Out[73]:
   data1  key_a  key_b  key_c
0      0       0       1       0
1      1       0       1       0
2      2       1       0       0
3      3       0       0       1
4      4       1       0       0
5      5       0       1       0

This function is often used along with discretization functions like `cut`:

In [74]: values = np.random.randn(10)

In [75]: values
Out[75]:
array([ 0.4082, -1.0481, -0.0257, -0.9884,  0.0941,  1.2627,  1.29 ,
       0.0824, -0.0558,  0.5366])

In [76]: bins = [0, 0.2, 0.4, 0.6, 0.8, 1]

In [77]: pd.get_dummies(pd.cut(values, bins))
Out[77]:
   (0, 0.2]  (0.2, 0.4]  (0.4, 0.6]  (0.6, 0.8]  (0.8, 1]
0      0       0       1       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
See also `Series.str.get_dummies`.

New in version 0.15.0.

`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 [78]: df = pd.DataFrame({'A': ['a', 'b', 'a'], 'B': ['c', 'c', 'b'],
                      'C': [1, 2, 3]})
....:

In [79]: pd.get_dummies(df)
```

```
Out[79]:
   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.

```
In [80]: pd.get_dummies(df, columns=['A'])
```

```
Out[80]:
   B  C  A_a  A_b
0  c  1    1    0
1  c  2    0    1
2  b  3    1    0
```

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` keyword arguments. 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

```
In [81]: simple = pd.get_dummies(df, prefix='new_prefix')
```

```
In [82]: simple
```

```
Out[82]:
   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 [83]: from_list = pd.get_dummies(df, prefix=['from_A', 'from_B'])
```

```
In [84]: from_list
```

```
Out[84]:
   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 [85]: from_dict = pd.get_dummies(df, prefix={'B': 'from_B', 'A': 'from_A'})
```
In [86]: from_dict
Out[86]:

```
     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
```

19.8 Factorizing values

To encode 1-d values as an enumerated type use factorize:

In [87]: x = pd.Series(['A', 'A', np.nan, 'B', 3.14, np.inf])

In [88]: x
Out[88]:

```
0   A
1   A
2  NaN
3   B
4  3.14
5  inf
dtype: object
```

In [89]: labels, uniques = pd.factorize(x)

In [90]: labels
Out[90]: array([ 0, 0, -1, 1, 2, 3])

In [91]: uniques
Out[91]: Index([u'A', u'B', 3.14, inf], dtype='object')

Note that factorize is similar to numpy.unique, but differs in its handling of NaN:

Note: The following numpy.unique will fail under Python 3 with a TypeError because of an ordering bug. See also Here

In [92]: pd.factorize(x, sort=True)
Out[92]:

```
(array([ 2, 2, -1, 3, 0, 1]),
 Index([3.14, inf, u'A', u'B'], dtype='object'))
```

In [93]: np.unique(x, return_inverse=True)[::-1]
Out[93]: (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. This feature was introduced in version 0.15.
pandas has proven very successful as a tool for working with time series data, especially in the financial data analysis space. With the 0.8 release, we have further improved the time series API in pandas by leaps and bounds. Using the new NumPy `datetime64` dtype, we have 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.

In working with time series data, we will frequently seek to:

- generate sequences of fixed-frequency dates and time spans
- conform or convert time series to a particular frequency
- compute “relative” dates based on various non-standard time increments (e.g. 5 business days before the last business day of the year), or “roll” dates forward or backward

pandas provides a relatively compact and self-contained set of tools for performing the above tasks.

Create a range of dates:

```python
# 72 hours starting with midnight Jan 1st, 2011
In [1]: rng = date_range('1/1/2011', periods=72, freq='H')

In [2]: rng[:5]
Out[2]:
DateTimeIndex(['2011-01-01 00:00:00', '2011-01-01 01:00:00',
               '2011-01-01 02:00:00', '2011-01-01 03:00:00',
               '2011-01-01 04:00:00'], dtype='datetime64[ns]', freq='H')
```

Index pandas objects with dates:

```python
In [3]: ts = Series(randn(len(rng)), index=rng)

In [4]: ts.head()
Out[4]:
2011-01-01 00:00:00 0.469112
2011-01-01 01:00:00 -0.282863
2011-01-01 02:00:00 -1.509059
2011-01-01 03:00:00 -1.135632
2011-01-01 04:00:00 1.212112
Freq: H, dtype: float64
```

Change frequency and fill gaps:

```python
# to 45 minute frequency and forward fill
In [5]: converted = ts.asfreq('45Min', method='pad')
```
In [6]: converted.head()
Out[6]:
2011-01-01 00:00:00 0.469112
2011-01-01 00:45:00 0.469112
2011-01-01 01:30:00 -0.282863
2011-01-01 02:15:00 -1.509059
2011-01-01 03:00:00 -1.135632
Freq: 45T, dtype: float64

Resample:

# Daily means
In [7]: ts.resample('D', how='mean')
Out[7]:
2011-01-01 -0.319569
2011-01-02 -0.337703
2011-01-03 0.117258
Freq: D, dtype: float64

20.1 Overview

Following table shows the type of time-related classes pandas can handle and how to create them.

<table>
<thead>
<tr>
<th>Class</th>
<th>Remarks</th>
<th>How to create</th>
</tr>
</thead>
<tbody>
<tr>
<td>Timestamp</td>
<td>Represents a single time stamp</td>
<td>to_datetime, Timestamp</td>
</tr>
<tr>
<td>DatetimeIndex</td>
<td>Index of Timestamps</td>
<td>to_datetime, date_range, DatetimeIndex</td>
</tr>
<tr>
<td>Period</td>
<td>Represents a single time span</td>
<td>Period</td>
</tr>
<tr>
<td>PeriodIndex</td>
<td>Index of Period</td>
<td>period_range, PeriodIndex</td>
</tr>
</tbody>
</table>

20.2 Time Stamps vs. Time Spans

Time-stamped data is the most basic type of timeseries data that associates values with points in time. For pandas objects it means using the points in time.

In [8]: Timestamp(datetime(2012, 5, 1))
Out[8]: Timestamp('2012-05-01 00:00:00')

In [9]: Timestamp('2012-05-01')
Out[9]: 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:

In [10]: Period('2011-01')
Out[10]: Period('2011-01', 'M')

In [11]: Period('2012-05', freq='D')
Out[11]: Period('2012-05-01', 'D')

Timestamp and Period can be the index. Lists of Timestamp and Period are automatically coerced to DatetimeIndex and PeriodIndex respectively.
In [12]: dates = [Timestamp('2012-05-01'), Timestamp('2012-05-02'), Timestamp('2012-05-03')]

In [13]: ts = Series(np.random.randn(3), dates)

In [14]: type(ts.index)
Out[14]: pandas.tseries.index.DatetimeIndex

In [15]: ts.index
Out[15]: DatetimeIndex(['2012-05-01', '2012-05-02', '2012-05-03'], dtype='datetime64[ns]', freq=None)

In [16]: ts
Out[16]:
2012-05-01 -0.410001
2012-05-02 -0.078638
2012-05-03 0.545952
dtype: float64

In [17]: periods = [Period('2012-01'), Period('2012-02'), Period('2012-03')]

In [18]: ts = Series(np.random.randn(3), periods)

In [19]: type(ts.index)
Out[19]: pandas.tseries.period.PeriodIndex

In [20]: ts.index
Out[20]: PeriodIndex(['2012-01', '2012-02', '2012-03'], dtype='int64', freq='M')

In [21]: ts
Out[21]:
2012-01 -1.219217
2012-02 -1.226825
2012-03 0.769804
Freq: M, dtype: float64

Starting with 0.8, 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.

20.3 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:

In [22]: to_datetime(Series(['Jul 31, 2009', '2010-01-10', None]))
Out[22]:
0 2009-07-31
1 2010-01-10
2 NaT
dtype: datetime64[ns]

In [23]: to_datetime(['2005/11/23', '2010.12.31'])
Out[23]: 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 [24]: to_datetime(['04-01-2012 10:00'], dayfirst=True)
Out[24]: DatetimeIndex(['2012-01-04 10:00:00'], dtype='datetime64[ns]', freq=None)
```

```
In [25]: to_datetime(['14-01-2012', '01-14-2012'], dayfirst=True)
Out[25]: 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.

**Note:** Specifying a `format` argument will potentially speed up the conversion considerably and on versions later then 0.13.0 explicitly specifying a format string of ‘%Y%m%d’ takes a faster path still.

If you pass a single string to `to_datetime`, it returns single `Timestamp`. Also, `Timestamp` can accept the string input. Note that `Timestamp` doesn’t accept string parsing option like `dayfirst` or `format`, use `to_datetime` if these are required.

```
In [26]: to_datetime('2010/11/12')
Out[26]: Timestamp('2010-11-12 00:00:00')
```

```
In [27]: Timestamp('2010/11/12')
Out[27]: Timestamp('2010-11-12 00:00:00')
```

### 20.3.1 Invalid Data

**Note:** In version 0.17.0, the default for `to_datetime` is now `errors='raise'`, rather than `errors='ignore'`. This means that invalid parsing will raise rather that return the original input as in previous versions.

Pass `errors='coerce'` to convert invalid data to NaT (not a time):

```
# this is the default, raise when unparsable
In [28]: to_datetime(['2009/07/31', 'asd'], errors='raise')
```

```
ValueError
```

```
/home/joris/scipy/pandas/pandas/util/decorators.pyc in wrapper(*args, **kwargs)
     87             return func(*args, **kwargs)
     88         return wrapper
--> 89     return _deprecate_kwarg

/home/joris/scipy/pandas/pandas/concat.py in _concat(values, axis)
    520     return index_.append(index_.empty)
    521     return axis
--> 522     return (arg, errors, dayfirst, yearfirst, utc, box, format, name)

/home/joris/scipy/pandas/pandas/tseries/tools.py in _to_datetime(arg, errors, dayfirst, yearfirst, utc, box, format, exact, unit, infer_datetime_format)
    274     return _to_datetime(arg, errors=errors, dayfirst=dayfirst, yearfirst=yearfirst,
    275         utc=utc, box=box, format=format, exact=exact,
--> 276     return unit, infer_datetime_format=infer_datetime_format)
    277
    278
```

```
/home/joris/scipy/pandas/pandas/tseries/tools.py in _to_datetime(arg, errors, dayfirst, yearfirst, utc, box, format, exact, unit, infer_datetime_format)
    393     return _convert_listlike(arg, box, format, name=arg.name)
```

elif com.is_list_like(arg):
    return _convert_listlike(arg, box, format)
    return _convert_listlike(np.array([arg]), box, format)[0]

/home/joris/scipy/pandas/pandas/tseries/tools.pyc in _convert_listlike(arg, box, format, name)
    return DatetimeIndex._simple_new(values, name=name, tz=tz)
    except (ValueError, TypeError):
        raise e
    if arg is None:
        ValueError: Unknown string format

# return the original input when unparseable
In [29]: to_datetime(['2009/07/31', 'asd'], errors='ignore')
Out[29]: array(['2009/07/31', 'asd'], dtype=object)

# return NaT for input when unparseable
In [30]: to_datetime(['2009/07/31', 'asd'], errors='coerce')
Out[30]: DatetimeIndex(['2009-07-31', 'NaT'], dtype='datetime64[ns]', freq=None)

20.3.2 Epoch Timestamps

It's also possible to convert integer or float epoch times. The default unit for these is nanoseconds (since these are how
Timestamps are stored). However, often epochs are stored in another unit which can be specified:

Typical epoch stored units

In [31]: to_datetime([1349720105, 1349806505, 1349892905,
                        ....: 1349979305, 1350065705], unit='s')
Out[31]: 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)

In [32]: to_datetime([1349720105100, 1349720105200, 1349720105300,
                        ....: 1349720105400, 1349720105500], unit='ms')
Out[32]: 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)

These work, but the results may be unexpected.

In [33]: to_datetime([1])
Out[33]: DatetimeIndex(['1970-01-01 00:00:00.000000001'],
                        dtype='datetime64[ns]', freq=None)

In [34]: to_datetime([1, 3.14], unit='s')
Out[34]: DatetimeIndex(['1970-01-01 00:00:01', '1970-01-01 00:00:03.140000'],
                        dtype='datetime64[ns]',

Note: Epoch times will be rounded to the nearest nanosecond.
20.4 Generating Ranges of Timestamps

To generate an index with time stamps, you can use either the DatetimeIndex or Index constructor and pass in a list of datetime objects:

```python
In [35]: dates = [datetime(2012, 5, 1), datetime(2012, 5, 2), datetime(2012, 5, 3)]
In [36]: index = DatetimeIndex(dates)
```

```
In [37]: index # Note the frequency information
Out[37]: DatetimeIndex(['2012-05-01', '2012-05-02', '2012-05-03'], dtype='datetime64[ns]', freq=None)
```

```python
In [38]: index = Index(dates)
```

```
In [39]: index # Automatically converted to DatetimeIndex
Out[39]: DatetimeIndex(['2012-05-01', '2012-05-02', '2012-05-03'], dtype='datetime64[ns]', freq=None)
```

Practically, 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 pandas functions `date_range` and `bdate_range` to create timestamp indexes.

```python
In [40]: index = date_range('2000-1-1', periods=1000, freq='M')
```

```
In [41]: index
Out[41]:
               '2000-09-30', '2000-10-31',
               ... '2082-07-31', '2082-08-31', '2082-09-30', '2082-10-31',
               '2082-11-30', '2082-12-31', '2083-01-31', '2083-02-28',
               '2083-03-31', '2083-04-30'],
dtype='datetime64[ns]', length=1000, freq='M')
```

```python
In [42]: index = bdate_range('2012-1-1', periods=250)
```

```
In [43]: index
Out[43]:
DatetimeIndex(['2012-01-02', '2012-01-03', '2012-01-04', '2012-01-05',
               '2012-01-06', '2012-01-09', '2012-01-10', '2012-01-11',
               '2012-01-12', '2012-01-13',
               ... '2012-12-03', '2012-12-04', '2012-12-05', '2012-12-06',
               '2012-12-07', '2012-12-10', '2012-12-11', '2012-12-12',
               '2012-12-13', '2012-12-14'],
dtype='datetime64[ns]', length=250, freq='B')
```

Convenience functions like `date_range` and `bdate_range` utilize a variety of frequency aliases. The default frequency for `date_range` is a calendar day while the default for `bdate_range` is a business day.

```python
In [44]: start = datetime(2011, 1, 1)
In [45]: end = datetime(2012, 1, 1)
In [46]: rng = date_range(start, end)
In [47]: rng
Out[47]:
```

594 Chapter 20. Time Series / Date functionality
'2011-01-09', '2011-01-10',
'2011-12-23', '2011-12-24', '2011-12-25', '2011-12-26',
'2011-12-27', '2011-12-28', '2011-12-29', '2011-12-30',
'2011-12-31', '2012-01-01'],
dtype='datetime64[ns]', length=366, freq='D')

In [48]: rng = bdate_range(start, end)

In [49]: rng
Out[49]:
'2011-01-13', '2011-01-14',
'2011-12-19', '2011-12-20', '2011-12-21', '2011-12-22',
'2011-12-23', '2011-12-26', '2011-12-27', '2011-12-28',
'2011-12-29', '2011-12-30'],
dtype='datetime64[ns]', length=260, freq='B')

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:

In [50]: date_range(start, end, freq='BM')
Out[50]:
dtype='datetime64[ns]', freq='BM')

In [51]: date_range(start, end, freq='W')
Out[51]:
'2011-02-27', '2011-03-03', '2011-03-10', '2011-03-17',
'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')

In [52]: bdate_range(end=end, periods=20)
Out[52]:
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',
'2011-12-15', '2011-12-16', '2011-12-19', '2011-12-20',
'2011-12-21', '2011-12-22', '2011-12-23', '2011-12-26',
'2011-12-27', '2011-12-28', '2011-12-29', '2011-12-30'],
dtype='datetime64[ns]', freq='B')

20.4. Generating Ranges of Timestamps 595
In [53]: bdate_range(start=start, periods=20)
Out[53]:
dtype='datetime64[ns]', freq='B')

The start and end dates are strictly inclusive. So it will not generate any dates outside of those dates if specified.

20.5 DatetimeIndex

One of the main uses for DatetimeIndex is as an index for pandas objects. The DatetimeIndex class contains many timeseries 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 and tshift 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 has all the basic functionality of regular Index objects and a smorgasbord of advanced timeseries-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. So please be careful.

DatetimeIndex can be used like a regular index and offers all of its intelligent functionality like selection, slicing, etc.

In [54]: rng = date_range(start, end, freq='BM')
In [55]: ts = Series(randn(len(rng)), index=rng)
In [56]: ts.index
Out[56]:
dtype='datetime64[ns]', freq='BM')
In [57]: ts[:5].index
Out[57]:
               '2011-05-31'],
dtype='datetime64[ns]', freq='BM')
In [58]: ts[:2].index
Out [58]:
               '2011-09-30', '2011-11-30'],
dtype='datetime64[ns]', freq='2BM')

20.5.1 DatetimeIndex Partial String Indexing

You can pass in dates and strings that parse to dates as indexing parameters:

In [59]: ts['1/31/2011']
Out [59]: -1.2812473076599529

In [60]: ts[datetime(2011, 12, 25):]
Out [60]:
2011-12-30  0.687738
Freq: BM, dtype: float64

In [61]: ts['10/31/2011':'12/31/2011']
Out [61]:
2011-10-31  0.149748
2011-11-30 -0.732339
2011-12-30  0.687738
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 [62]: ts['2011']
Out [62]:
2011-01-31 -1.281247
2011-02-28 -0.727707
2011-03-31 -0.121306
2011-04-29 -0.097883
2011-05-31  0.695775
2011-06-30  0.341734
2011-07-29  0.959726
2011-08-31 -1.110336
2011-09-30 -0.619976
2011-10-31  0.149748
2011-11-30 -0.732339
2011-12-30  0.687738
Freq: BM, dtype: float64

In [63]: ts['2011-6']
Out [63]:
2011-06-30  0.341734
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. Here’s an example:

In [64]: dft = DataFrame(randn(100000,1),columns=['A'],index=date_range('20130101',periods=100000,freq='T'))

In [65]: dft
Out [65]:
A
In [66]: dft['2013']
Out[66]:
A
2013-01-01 00:00:00 0.176444
2013-01-01 00:01:00 0.403310
2013-01-01 00:02:00 -0.154951
2013-01-01 00:03:00 0.301624
2013-01-01 00:04:00 -2.179861
2013-01-01 00:05:00 -1.369849
2013-01-01 00:06:00 -0.954208
...
2013-03-11 10:33:00 -0.293083
2013-03-11 10:34:00 -0.059881
2013-03-11 10:35:00 1.252450
2013-03-11 10:36:00 0.046611
2013-03-11 10:37:00 0.059478
2013-03-11 10:38:00 -0.286539
2013-03-11 10:39:00 0.841669
[100000 rows x 1 columns]

This starts on the very first time in the month, and includes the last date & time for the month

In [67]: dft['2013-1':'2013-2']
Out[67]:
A
2013-01-01 00:00:00 0.176444
2013-01-01 00:01:00 0.403310
2013-01-01 00:02:00 -0.154951
2013-01-01 00:03:00 0.301624
2013-01-01 00:04:00 -2.179861
2013-01-01 00:05:00 -1.369849
2013-01-01 00:06:00 -0.954208
...
2013-03-11 10:33:00 -0.293083
2013-03-11 10:34:00 -0.059881
2013-03-11 10:35:00 1.252450
2013-03-11 10:36:00 0.046611
2013-03-11 10:37:00 0.059478
2013-03-11 10:38:00 -0.286539
2013-03-11 10:39:00 0.841669
[100000 rows x 1 columns]

...
This specifies a stop time **that includes all of the times on the last day**

```python
In [68]: dft['2013-1':'2013-2-28']
```

```
2013-01-01 00:00:00  0.176444
2013-01-01 00:01:00  0.403310
2013-01-01 00:02:00  -0.154951
2013-01-01 00:03:00  0.301624
2013-01-01 00:04:00  -2.179861
2013-01-01 00:05:00  -1.369849
2013-01-01 00:06:00  -0.954208
... ...
2013-02-28 23:53:00  0.103114
2013-02-28 23:54:00  -1.303422
2013-02-28 23:55:00  0.451943
2013-02-28 23:56:00  0.220534
2013-02-28 23:57:00  -1.624220
2013-02-28 23:58:00  0.093915
2013-02-28 23:59:00  -1.087454
```

This specifies an **exact** stop time (and is not the same as the above)

```python
In [69]: dft['2013-1':'2013-2-28 00:00:00']
```

```
2013-01-01 00:00:00  0.176444
2013-01-01 00:01:00  0.403310
2013-01-01 00:02:00  -0.154951
2013-01-01 00:03:00  0.301624
2013-01-01 00:04:00  -2.179861
2013-01-01 00:05:00  -1.369849
2013-01-01 00:06:00  -0.954208
... ...
2013-02-27 23:54:00  0.897051
2013-02-27 23:55:00  -0.309230
2013-02-27 23:56:00  1.944713
2013-02-27 23:57:00  0.369265
2013-02-27 23:58:00  0.053071
2013-02-27 23:59:00  -0.019734
2013-02-28 00:00:00  1.388189
```

We are stopping on the included end-point as it is part of the index

```python
In [70]: dft['2013-1-15':'2013-1-15 12:30:00']
```

```
2013-01-15 00:00:00  0.501288
2013-01-15 00:01:00  -0.605198
2013-01-15 00:02:00  0.215146
2013-01-15 00:03:00  0.924732
2013-01-15 00:04:00  -2.228519
2013-01-15 00:05:00  1.517331
```
Warning: The following selection will raise a KeyError; otherwise this selection methodology would be inconsistent with other selection methods in pandas (as this is not a slice, nor does it resolve to one)

dft['2013-1-15 12:30:00']

To select a single row, use .loc

In [71]: dft.loc['2013-1-15 12:30:00']
Out[71]:
A 0.193284
Name: 2013-01-15 12:30:00, dtype: float64

20.5.2 Datetime Indexing

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 frequency of the index. In contrast, indexing with datetime objects is exact, because the objects have exact meaning. These also follow the semantics of including both endpoints.

These datetime objects are specific hours, minutes, and seconds even though they were not explicitly specified (they are 0).

In [72]: dft[datetime(2013, 1, 1):datetime(2013,2,28)]
Out[72]:

   A
2013-01-01 00:00:00   0.176444
2013-01-01 00:01:00   0.403310
2013-01-01 00:02:00  -0.154951
2013-01-01 00:03:00   0.301624
2013-01-01 00:04:00  -2.179861
2013-01-01 00:05:00  -1.369849
2013-01-01 00:06:00  -0.954208
   ...  ...               ...
2013-02-27 23:54:00   0.897051
2013-02-27 23:55:00  -0.309230
2013-02-27 23:56:00   1.944713
2013-02-27 23:57:00   0.369265
2013-02-27 23:58:00   0.053071
2013-02-27 23:59:00  -0.019734
2013-02-28 00:00:00   1.388189

[83521 rows x 1 columns]

With no defaults.
20.5.3 Truncating & Fancy Indexing

A `truncate` convenience function is provided that is equivalent to slicing:

```python
In [74]: ts.truncate(before='10/31/2011', after='12/31/2011')
Out[74]:
2011-10-31 0.149748
2011-11-30 -0.732339
2011-12-30 0.687738
Freq: BM, dtype: float64
```

Even complicated fancy indexing that breaks the DatetimeIndex’s frequency regularity will result in a DatetimeIndex (but frequency is lost):

```python
In [75]: ts[[0, 2, 6]].index
Out[75]: DatetimeIndex(['2011-01-31', '2011-03-31', '2011-07-29'], dtype='datetime64[ns]', freq=None)
```

20.5.4 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</td>
</tr>
<tr>
<td>time</td>
<td>Returns datetime.time</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 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>Quarter of the date: Jan=Mar = 1, Apr-Jun = 2, etc.</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>
</tbody>
</table>

Furthermore, if you have a Series with datetimelike values, then you can access these properties via the .dt accessor, see the docs.

## 20.6 DateOffset objects

In the preceding examples, we created DatetimeIndex objects at various frequencies by passing in frequency strings like ‘M’, ‘W’, and ‘BM to the freq keyword. Under the hood, these frequency strings are being translated into an instance of pandas DateOffset, which represents a regular frequency increment. Specific offset logic like “month”, “business day”, or “one hour” is represented in its various subclasses.
<table>
<thead>
<tr>
<th>Class name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DateOffset</td>
<td>Generic offset class, defaults to 1 calendar day</td>
</tr>
<tr>
<td>BDay</td>
<td>business day (weekday)</td>
</tr>
<tr>
<td>CDay</td>
<td>custom business day (experimental)</td>
</tr>
<tr>
<td>Week</td>
<td>one week, optionally anchored on a day of the week</td>
</tr>
<tr>
<td>WeekOfMonth</td>
<td>the x-th day of the y-th week of each month</td>
</tr>
<tr>
<td>LastWeekOfMonth</td>
<td>the x-th day of the last week of each month</td>
</tr>
<tr>
<td>MonthEnd</td>
<td>calendar month end</td>
</tr>
<tr>
<td>MonthBegin</td>
<td>calendar month begin</td>
</tr>
<tr>
<td>BMonthEnd</td>
<td>business month end</td>
</tr>
<tr>
<td>BMonthBegin</td>
<td>business month begin</td>
</tr>
<tr>
<td>CBMonthEnd</td>
<td>custom business month end</td>
</tr>
<tr>
<td>CBMonthBegin</td>
<td>custom business month begin</td>
</tr>
<tr>
<td>QuarterEnd</td>
<td>calendar quarter end</td>
</tr>
<tr>
<td>QuarterBegin</td>
<td>calendar quarter begin</td>
</tr>
<tr>
<td>BQuarterEnd</td>
<td>business quarter end</td>
</tr>
<tr>
<td>BQuarterBegin</td>
<td>business quarter begin</td>
</tr>
<tr>
<td>FY5253Quarter</td>
<td>retail (aka 52-53 week) quarter</td>
</tr>
<tr>
<td>YearEnd</td>
<td>calendar year end</td>
</tr>
<tr>
<td>YearBegin</td>
<td>calendar year begin</td>
</tr>
<tr>
<td>BYearEnd</td>
<td>business year end</td>
</tr>
<tr>
<td>BYearBegin</td>
<td>business year begin</td>
</tr>
<tr>
<td>FY5253</td>
<td>retail (aka 52-53 week) year</td>
</tr>
<tr>
<td>BusinessHour</td>
<td>business hour</td>
</tr>
<tr>
<td>Hour</td>
<td>one hour</td>
</tr>
<tr>
<td>Minute</td>
<td>one minute</td>
</tr>
<tr>
<td>Second</td>
<td>one second</td>
</tr>
<tr>
<td>Milli</td>
<td>one millisecond</td>
</tr>
<tr>
<td>Micro</td>
<td>one microsecond</td>
</tr>
<tr>
<td>Nano</td>
<td>one nanosecond</td>
</tr>
</tbody>
</table>

The basic `DateOffset` takes the same arguments as `dateutil.relativedelta`, which works like:

```python
In [76]: d = datetime(2008, 8, 18, 9, 0)
In [77]: d + relativedelta(months=4, days=5)
Out[77]: datetime.datetime(2008, 12, 23, 9, 0)
```

We could have done the same thing with `DateOffset`:

```python
In [78]: from pandas.tseries.offsets import *
In [79]: d + DateOffset(months=4, days=5)
Out[79]: Timestamp('2008-12-23 09:00:00')
```

The key features of a `DateOffset` object are:

- it can be added / subtracted to/from a datetime object to obtain a shifted date
- it can be multiplied by an integer (positive or negative) so that the increment will be applied multiple times
- it has `rollforward` and `rollback` methods for moving a date forward or backward to the next or previous “offset date”

Subclasses of `DateOffset` define the `apply` function which dictates custom date increment logic, such as adding business days:
class BDay(DateOffset):
    """DateOffset increments between business days"""
    def apply(self, other):
        ...

In [80]: d - 5 * BDay()
Out[80]: Timestamp('2008-08-11 09:00:00')

In [81]: d + BMonthEnd()
Out[81]: Timestamp('2008-08-29 09:00:00')

The rollforward and rollback methods do exactly what you would expect:

In [82]: d
Out[82]: datetime.datetime(2008, 8, 18, 9, 0)

In [83]: offset = BMonthEnd()

In [84]: offset.rollforward(d)
Out[84]: Timestamp('2008-08-29 09:00:00')

In [85]: offset.rollback(d)
Out[85]: Timestamp('2008-07-31 09:00:00')

It’s definitely worth exploring the pandas.tseries.offsets module and the various docstrings for the classes. These operations (apply, rollforward and rollback) preserves time (hour, minute, etc) information by default. To reset time, use normalize=True keyword when creating the offset instance. If normalize=True, result is normalized after the function is applied.

In [86]: day = Day()

In [87]: day.apply(Timestamp('2014-01-01 09:00'))
Out[87]: Timestamp('2014-01-02 09:00:00')

In [88]: day = Day(normalize=True)

In [89]: day.apply(Timestamp('2014-01-01 09:00'))
Out[89]: Timestamp('2014-01-02 00:00:00')

In [90]: hour = Hour()

In [91]: hour.apply(Timestamp('2014-01-01 22:00'))
Out[91]: Timestamp('2014-01-01 23:00:00')

In [92]: hour = Hour(normalize=True)

In [93]: hour.apply(Timestamp('2014-01-01 22:00'))
Out[93]: Timestamp('2014-01-02 00:00:00')

In [94]: hour.apply(Timestamp('2014-01-01 23:00'))
Out[94]: Timestamp('2014-01-02 00:00:00')

20.6.1 Parametric offsets

Some of the offsets can be “parameterized” when created to result in different behaviors. For example, the Week offset for generating weekly data accepts a weekday parameter which results in the generated dates always lying on a particular day of the week:
In [95]: d
datetime.datetime(2008, 8, 18, 9, 0)

In [96]: d + Week()
Timestamp('2008-08-25 09:00:00')

In [97]: d + Week(weekday=4)
Timestamp('2008-08-22 09:00:00')

In [98]: (d + Week(weekday=4)).weekday()
4

In [99]: d - Week()
Timestamp('2008-08-11 09:00:00')

normalize option will be effective for addition and subtraction.

In [100]: d + Week(normalize=True)
Timestamp('2008-08-25 00:00:00')

In [101]: d - Week(normalize=True)
Timestamp('2008-08-11 00:00:00')

Another example is parameterizing YearEnd with the specific ending month:

In [102]: d + YearEnd()
Timestamp('2008-12-31 09:00:00')

In [103]: d + YearEnd(month=6)
Timestamp('2009-06-30 09:00:00')

20.6.2 Using offsets with Series / DatetimeIndex

Offsets can be used with either a Series or DatetimeIndex to apply the offset to each element.

In [104]: rng = date_range('2012-01-01', '2012-01-03')

In [105]: s = Series(rng)

In [106]: rng
 DatetimeIndex(['2012-01-01', '2012-01-02', '2012-01-03'],
dtype='datetime64[ns]', freq='D')

In [107]: rng + DateOffset(months=2)
 DatetimeIndex(['2012-03-01', '2012-03-02', '2012-03-03'],
dtype='datetime64[ns]', freq='D')

In [108]: s + DateOffset(months=2)
 Out[108]:
0   2012-03-01
1   2012-03-02
2   2012-03-03
dtype: datetime64[ns]

In [109]: s - DateOffset(months=2)
 Out[109]:
0   2011-11-01
1   2011-11-02
2   2011-11-03
dtype: datetime64[ns]

20.6. DateOffset objects 605
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.

```python
In [110]: s - Day(2)
Out[110]:
0   2011-12-30
1   2011-12-31
2   2012-01-01
dtype: datetime64[ns]

In [111]: td = s - Series(date_range('2011-12-29', '2011-12-31'))

In [112]: td
Out[112]:
0   3 days
1   3 days
2   3 days
dtype: timedelta64[ns]

In [113]: td + Minute(15)
Out[113]:
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 raise a `PerformanceWarning`.

```python
In [114]: rng + BQuarterEnd()
Out[114]: DatetimeIndex(['2012-03-30', '2012-03-30', '2012-03-30'], dtype='datetime64[ns]', freq=None)
```

### 20.6.3 Custom Business Days (Experimental)

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.

```python
In [115]: from pandas.tseries.offsets import CustomBusinessDay

# As an interesting example, let's look at Egypt where
# a Friday-Saturday weekend is observed.
In [116]: weekmask_egypt = 'Sun Mon Tue Wed Thu'

# They also observe International Workers' Day so let's
# add that for a couple of years
In [117]: holidays = ['2012-05-01', datetime(2013, 5, 1), np.datetime64('2014-05-01')]

In [118]: bday_egypt = CustomBusinessDay(holidays=holidays, weekmask=weekmask_egypt)

In [119]: dt = datetime(2013, 4, 30)

In [120]: dt + 2 * bday_egypt
Out[120]: Timestamp('2013-05-05 00:00:00')

In [121]: dts = date_range(dt, periods=5, freq=bday_egypt)
```
In [122]: Series(dts.weekday, dts).map(Series('Mon Tue Wed Thu Fri Sat Sun'.split()))
Out[122]:
2013-04-30 Tue
2013-05-02 Thu
2013-05-05 Sun
2013-05-06 Mon
2013-05-07 Tue
Freq: C, dtype: object

As of v0.14 holiday calendars can be used to provide the list of holidays. See the holiday calendar section for more information.

In [123]: from pandas.tseries.holiday import USFederalHolidayCalendar

In [124]: bday_us = CustomBusinessDay(calendar=USFederalHolidayCalendar())

# Friday before MLK Day
In [125]: dt = datetime(2014, 1, 17)

# Tuesday after MLK Day (Monday is skipped because it's a holiday)
In [126]: dt + bday_us
Out[126]: Timestamp('2014-01-21 00:00:00')

Monthly offsets that respect a certain holiday calendar can be defined in the usual way.

In [127]: from pandas.tseries.offsets import CustomBusinessMonthBegin

In [128]: bmth_us = CustomBusinessMonthBegin(calendar=USFederalHolidayCalendar())

# Skip new years
In [129]: dt = datetime(2013, 12, 17)

In [130]: dt + bmth_us
Out[130]: Timestamp('2014-01-02 00:00:00')

# Define date index with custom offset
In [131]: from pandas import DatetimeIndex

In [132]: DatetimeIndex(start='20100101', end='20120101', freq=bmth_us)
Out[132]:
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.

Note: This uses the numpy.busdaycalendar API introduced in Numpy 1.7 and therefore requires Numpy 1.7.0 or newer.
Warning: There are known problems with the timezone handling in Numpy 1.7 and users should therefore use this experimental(!) feature with caution and at their own risk. To the extent that the datetime64 and busdaycalendar APIs in Numpy have to change to fix the timezone issues, the behaviour of the CustomBusinessDay class may have to change in future versions.

20.6.4 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. 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, remaining is added to the next business day.

In [133]: bh = BusinessHour()

In [134]: bh
Out[134]: <BusinessHour: BH=09:00-17:00>

# 2014-08-01 is Friday
In [135]: Timestamp('2014-08-01 10:00').weekday()
Out[135]: 4

In [136]: Timestamp('2014-08-01 10:00') + bh
Out[136]: Timestamp('2014-08-01 11:00:00')

# Below example is the same as Timestamp('2014-08-01 09:00') + bh
In [137]: Timestamp('2014-08-01 08:00') + bh
Out[137]: Timestamp('2014-08-01 10:00:00')

# If the results is on the end time, move to the next business day
In [138]: Timestamp('2014-08-01 16:00') + bh
Out[138]: Timestamp('2014-08-04 09:00:00')

# Remainings are added to the next day
In [139]: Timestamp('2014-08-01 16:30') + bh
Out[139]: Timestamp('2014-08-04 09:30:00')

# Adding 2 business hours
In [140]: Timestamp('2014-08-01 10:00') + BusinessHour(2)
Out[140]: Timestamp('2014-08-01 12:00:00')

# Subtracting 3 business hours
In [141]: Timestamp('2014-08-01 10:00') + BusinessHour(-3)
Out[141]: Timestamp('2014-07-31 15:00:00')

Also, you can specify start and end time by keywords. Argument must be str which has hour:minute representation or datetime.time instance. Specifying seconds, microseconds and nanoseconds as business hour results in ValueError.

In [142]: bh = BusinessHour(start='11:00', end=time(20, 0))

In [143]: bh
Out[143]: <BusinessHour: BH=11:00-20:00>

In [144]: Timestamp('2014-08-01 13:00') + bh
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`.

```python
In [147]: bh = BusinessHour(start='17:00', end='09:00')
```

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
In [151]: BusinessHour().rollback(Timestamp('2014-08-02 15:00'))
```

# This adjusts a Timestamp to business hour edge
```python
In [153]: BusinessHour().rollforward(Timestamp('2014-08-02 15:00'))
```

# It is the same as BusinessHour().apply(Timestamp('2014-08-02 17:00')).
# And it is the same as BusinessHour().apply(Timestamp('2014-08-04 09:00'))
```python
In [155]: BusinessHour().apply(Timestamp('2014-08-02 15:00'))
```

# `BusinessDay` results (for reference)
```python
In [156]: BusinessHour().rollforward(Timestamp('2014-08-02'))
```

# It is the same as BusinessDay().apply(Timestamp('2014-08-02'))
# The result is the same as rollforward because BusinessDay never overlap.
```python
In [157]: BusinessHour().apply(Timestamp('2014-08-02'))
```
20.6.5 Offset Aliases

A number of string aliases are given to useful common time series frequencies. We will refer to these aliases as *offset aliases* (referred to as *time rules* prior to v0.8.0).

<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 (experimental)</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>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>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</td>
<td>year end frequency</td>
</tr>
<tr>
<td>BA</td>
<td>business year end frequency</td>
</tr>
<tr>
<td>AS</td>
<td>year start frequency</td>
</tr>
<tr>
<td>BAS</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>millisecond(s)</td>
</tr>
<tr>
<td>U, us</td>
<td>microsecond(s)</td>
</tr>
<tr>
<td>N</td>
<td>nanosecond(s)</td>
</tr>
</tbody>
</table>

20.6.6 Combining Aliases

As we have seen previously, the alias and the offset instance are fungible in most functions:

```
In [158]: date_range(start, periods=5, freq='B')
Out[158]:
               '2011-01-07'], dtype='datetime64[ns]', freq='B')
```

```
In [159]: date_range(start, periods=5, freq=BDay())
Out[159]:
               '2011-01-07'], dtype='datetime64[ns]', freq='B')
```

You can combine together day and intraday offsets:

```
In [160]: date_range(start, periods=10, freq='2h20min')
Out[160]:
```

Out[157]: Timestamp('2014-08-04 10:00:00')
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')

In [161]: date_range(start, periods=10, freq='1D10U')
Out[161]:
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')

20.6.7 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>(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`.

### 20.6.8 Legacy Aliases

Note that prior to v0.8.0, time rules had a slightly different look. These are deprecated in v0.17.0, and removed in future version.

<table>
<thead>
<tr>
<th>Legacy Time Rule</th>
<th>Offset Alias</th>
</tr>
</thead>
<tbody>
<tr>
<td>WEEKDAY</td>
<td>B</td>
</tr>
<tr>
<td>EOM</td>
<td>BM</td>
</tr>
<tr>
<td>W@MON</td>
<td>W-MON</td>
</tr>
<tr>
<td>W@TUE</td>
<td>W-TUE</td>
</tr>
<tr>
<td>W@WED</td>
<td>W-WED</td>
</tr>
<tr>
<td>W@THU</td>
<td>W-THU</td>
</tr>
<tr>
<td>W@FRI</td>
<td>W-FRI</td>
</tr>
<tr>
<td>W@SAT</td>
<td>W-SAT</td>
</tr>
<tr>
<td>W@SUN</td>
<td>W-SUN</td>
</tr>
<tr>
<td>Q@JAN</td>
<td>BQ-JAN</td>
</tr>
<tr>
<td>Q@FEB</td>
<td>BQ-FEB</td>
</tr>
<tr>
<td>Q@MAR</td>
<td>BQ-MAR</td>
</tr>
<tr>
<td>A@JAN</td>
<td>BA-JAN</td>
</tr>
<tr>
<td>A@FEB</td>
<td>BA-FEB</td>
</tr>
<tr>
<td>A@MAR</td>
<td>BA-MAR</td>
</tr>
<tr>
<td>A@APR</td>
<td>BA-APR</td>
</tr>
<tr>
<td>A@MAY</td>
<td>BA-MAY</td>
</tr>
<tr>
<td>A@JUN</td>
<td>BA-JUN</td>
</tr>
<tr>
<td>A@JUL</td>
<td>BA-JUL</td>
</tr>
<tr>
<td>A@AUG</td>
<td>BA-AUG</td>
</tr>
<tr>
<td>A@SEP</td>
<td>BA-SEP</td>
</tr>
<tr>
<td>A@OCT</td>
<td>BA-OCT</td>
</tr>
<tr>
<td>A@NOV</td>
<td>BA-NOV</td>
</tr>
<tr>
<td>A@DEC</td>
<td>BA-DEC</td>
</tr>
</tbody>
</table>

As you can see, legacy quarterly and annual frequencies are business quarters and business year ends. Please also note the legacy time rule for milliseconds `ms` versus the new offset alias for month start `MS`. This means that offset alias parsing is case sensitive.

### 20.6.9 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. Further, `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:
An example of how holidays and holiday calendars are defined:

```
In [162]: from pandas.tseries.holiday import Holiday, USMemorialDay,
   ....: AbstractHolidayCalendar, nearest_workday, MO
   ....:
In [163]: class ExampleCalendar(AbstractHolidayCalendar):
   ....:     rules = [
   ....:         USMemorialDay,
   ....:         Holiday('July 4th', month=7, day=4, observance=nearest_workday),
   ....:         Holiday('Columbus Day', month=10, day=1,
   ....:             offset=DateOffset(weekday=MO(2))), # same as 2*Week(weekday=2)
   ....:     ]
   ....:
In [164]: cal = ExampleCalendar()
In [165]: cal.holidays(datetime(2012, 1, 1), datetime(2012, 12, 31))
Out[165]: DatetimeIndex(['2012-05-28', '2012-07-04', '2012-10-08'],
    freq=None)
```

Using this calendar, creating an index or doing offset arithmetic skips weekends and holidays (i.e., Memorial Day/July 4th).

```
In [166]: DatetimeIndex(start='7/1/2012', end='7/10/2012',
   ....:     freq=CDay(calendar=cal)).to_pydatetime()
Out[166]:
array([datetime.datetime(2012, 7, 2, 0, 0),
   datetime.datetime(2012, 7, 3, 0, 0),
   datetime.datetime(2012, 7, 5, 0, 0),
   datetime.datetime(2012, 7, 6, 0, 0),
   datetime.datetime(2012, 7, 9, 0, 0),
   datetime.datetime(2012, 7, 10, 0, 0)],
   dtype=object)
```

```
In [167]: offset = CustomBusinessDay(calendar=cal)
In [168]: datetime(2012, 5, 25) + offset
Out[168]: Timestamp('2012-05-29 00:00:00')
In [169]: datetime(2012, 7, 3) + offset
Out[169]: Timestamp('2012-07-05 00:00:00')
In [170]: datetime(2012, 7, 3) + 2 * offset
Out[170]: Timestamp('2012-07-06 00:00:00')
In [171]: datetime(2012, 7, 6) + offset
Out[171]: Timestamp('2012-07-09 00:00:00')
```

Ranges are defined by the `start_date` and `end_date` class attributes of `AbstractHolidayCalendar`. The defaults are below.

### Table: Holiday Rules

<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>move 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>

20.6. DateOffset objects
In [172]: AbstractHolidayCalendar.start_date
Out[172]: Timestamp('1970-01-01 00:00:00')

In [173]: AbstractHolidayCalendar.end_date
Out[173]: Timestamp('2030-12-31 00:00:00')

These dates can be overwritten by setting the attributes as datetime/Timestamp/string.

In [174]: AbstractHolidayCalendar.start_date = datetime(2012, 1, 1)
In [175]: AbstractHolidayCalendar.end_date = datetime(2012, 12, 31)

In [176]: cal.holidays()
Out[176]: DatetimeIndex(['2012-05-28', '2012-07-04', '2012-10-08'], dtype='datetime64[ns]', freq=None)

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.

In [177]: from pandas.tseries.holiday import get_calendar, HolidayCalendarFactory,
.....: USLaborDay
.....:

In [178]: cal = get_calendar('ExampleCalendar')

In [179]: cal.rules
Out[179]:
[Holiday: MemorialDay (month=5, day=31, offset=<DateOffset: kwds={'weekday': MO(-1)>)),
Holiday: July 4th (month=7, day=4, observance=<function nearest_workday at 0x9dfb0cdc>),
Holiday: Columbus Day (month=10, day=1, offset=<DateOffset: kwds={'weekday': MO(+2)}>)]

In [180]: new_cal = HolidayCalendarFactory('NewExampleCalendar', cal, USLaborDay)

In [181]: new_cal.rules
Out[181]:
[Holiday: Labor Day (month=9, day=1, offset=<DateOffset: kwds={'weekday': MO(+1)}>),
Holiday: Columbus Day (month=10, day=1, offset=<DateOffset: kwds={'weekday': MO(+2)}>),
Holiday: July 4th (month=7, day=4, observance=<function nearest_workday at 0x9dfb0cdc>),
Holiday: MemorialDay (month=5, day=31, offset=<DateOffset: kwds={'weekday': MO(-1)}>)]

20.7 Time series-related instance methods

20.7.1 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 [182]: ts = ts[:5]

In [183]: ts.shift(1)
Out[183]:
2011-01-31    NaN
2011-02-28  -1.281247
2011-03-31  -0.727707
2011-04-29  -0.121306

Chapter 20. Time Series / Date functionality
The shift method accepts a \texttt{freq} argument which can accept a \texttt{DateOffset} class or other timedelta-like object or also a \texttt{offset alias}:

```
In [184]: ts.shift(5, freq=datetools.bday)
Out[184]:
2011-02-07   -1.281247
2011-03-07   -0.727707
2011-04-07   -0.121306
2011-05-06   -0.097883
2011-06-07    0.695775
Freq: BM, dtype: float64
```

```
In [185]: ts.shift(5, freq='BM')
Out[185]:
2011-06-30   -1.281247
2011-07-29   -0.727707
2011-08-31   -0.121306
2011-09-30   -0.097883
2011-10-31    0.695775
Freq: BM, dtype: float64
```

Rather than changing the alignment of the data and the index, DataFrame and Series objects also have a \texttt{tshift} convenience method that changes all the dates in the index by a specified number of offsets:

```
In [186]: ts.tshift(5, freq='D')
Out[186]:
2011-02-05   -1.281247
2011-03-05   -0.727707
2011-04-05   -0.121306
2011-05-04   -0.097883
2011-06-05    0.695775
Freq: BM, dtype: float64
```

Note that with \texttt{tshift}, the leading entry is no longer NaN because the data is not being realigned.

### 20.7.2 Frequency conversion

The primary function for changing frequencies is the \texttt{asfreq} function. For a DatetimeIndex, this is basically just a thin, but convenient wrapper around \texttt{reindex} which generates a date_range and calls \texttt{reindex}.

```
In [187]: dr = date_range('1/1/2010', periods=3, freq=3 * datetools.bday)

In [188]: ts = Series(randn(3), index=dr)

In [189]: ts
Out[189]:
2010-01-01   -0.659574
2010-01-06    1.494522
2010-01-11    -0.778425
Freq: 3B, dtype: float64

In [190]: ts.asfreq(BDay())
Out[190]:
2010-01-01   -0.659574
2010-01-04   NaN
```
asfreq provides a further convenience so you can specify an interpolation method for any gaps that may appear after the frequency conversion.

```
In [191]: ts.asfreq(BDay(), method='pad')
Out[191]:
2010-01-01 -0.659574
2010-01-04 -0.659574
2010-01-05 -0.659574
2010-01-06  1.494522
2010-01-07  1.494522
2010-01-08  1.494522
2010-01-11 -0.778425
Freq: B, dtype: float64
```

### 20.7.3 Filling forward / backward

Related to `asfreq` and `reindex` is the `fillna` function documented in the [missing data section](#).

### 20.7.4 Converting to Python datetimes

`DatetimeIndex` can be converted to an array of Python native `datetime.datetime` objects using the `to_pydatetime` method.

### 20.8 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.

```
In [192]: rng = date_range('1/1/2012', periods=100, freq='S')

In [193]: ts = Series(randint(0, 500, len(rng)), index=rng)

In [194]: ts.resample('5Min', how='sum')
Out[194]:
2012-01-01   25103
Freq: 5T, dtype: int32
```

The `resample` function is very flexible and allows you to specify many different parameters to control the frequency conversion and resampling operation.

The `how` parameter can be a function name or numpy array function that takes an array and produces aggregated values:
In [195]: ts.resample('5Min')  # default is mean
Out[195]:
2012-01-01  251.03
Freq: 5T, dtype: float64

In [196]: ts.resample('5Min', how='ohlc')
Out[196]:
<table>
<thead>
<tr>
<th></th>
<th>open</th>
<th>high</th>
<th>low</th>
<th>close</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012-01-01</td>
<td>308</td>
<td>460</td>
<td>9</td>
<td>205</td>
</tr>
</tbody>
</table>

In [197]: ts.resample('5Min', how=np.max)
Out[197]:
2012-01-01  460
Freq: 5T, dtype: int32

Any function available via dispatching can be given to the how parameter by name, including sum, mean, std, sem, max, min, median, first, last, ohlc.

For downsampling, closed can be set to 'left' or 'right' to specify which end of the interval is closed:

In [198]: ts.resample('5Min', closed='right')
Out[198]:
2011-12-31 23:55:00  308.000000
2012-01-01 00:00:00  250.454545
Freq: 5T, dtype: float64

In [199]: ts.resample('5Min', closed='left')
Out[199]:
2012-01-01  251.03
Freq: 5T, dtype: float64

Parameters like label and loffset are used to manipulate the resulting labels. label specifies whether the result is labeled with the beginning or the end of the interval. loffset performs a time adjustment on the output labels.

In [200]: ts.resample('5Min', label='left')
Out[200]:
2012-01-01  251.03
Freq: 5T, dtype: float64

In [201]: ts.resample('5Min', label='left', loffset='1s')
Out[201]:
2012-01-01 00:00:01  251.03
dtype: float64

The axis parameter can be set to 0 or 1 and allows you to resample the specified axis for a DataFrame.

kind can be set to 'timestamp' or 'period' to convert the resulting index to/from time-stamp 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.
20.8.1 Up Sampling

For upsampling, the fill_method and limit parameters can be specified to interpolate over the gaps that are created:

```python
# from secondly to every 250 milliseconds
In [203]: ts[:2].resample('250L')
Out[203]:
2012-01-01 00:00:00.000 308
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
Freq: 250L, dtype: float64

In [204]: ts[:2].resample('250L', fill_method='pad')
Out[204]:
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: int32

In [205]: ts[:2].resample('250L', fill_method='pad', limit=2)
Out[205]:
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 NaN
2012-01-01 00:00:01.000 204
Freq: 250L, dtype: float64
```

20.8.2 Sparse Resampling

Sparse timeseries are 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

```python
In [206]: rng = date_range('2014-1-1', periods=100, freq='D') + Timedelta('1s')
In [207]: ts = Series(range(100), index=rng)
If we want to resample to the full range of the series
In [208]: ts.resample('3T',how='sum')
Out[208]:
2014-01-01 00:00:00 0
2014-01-01 00:03:00 NaN
2014-01-01 00:06:00 NaN
2014-01-01 00:09:00 NaN
2014-01-01 00:12:00 NaN
2014-01-01 00:15:00 NaN
2014-01-01 00:18:00 NaN
..
We can instead only resample those groups where we have points as follows:

```
In [209]: from functools import partial

In [210]: from pandas.tseries.frequencies import to_offset

In [211]: def round(t, freq):
   ....:     freq = to_offset(freq)
   ....:     return Timestamp((t.value // freq.delta.value) * freq.delta.value)
   ....:

In [212]: ts.groupby(partial(round, freq='3T')).sum()
```

```
Out[212]:
2014-01-01  0
2014-01-02  1
2014-01-03  2
2014-01-04  3
2014-01-05  4
2014-01-06  5
2014-01-07  6
   ..
2014-04-04  93
2014-04-05  94
2014-04-06  95
2014-04-07  96
2014-04-08  97
2014-04-09  98
2014-04-10  99
```

dtype: int64

20.9 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`.

20.9.1 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 [213]: Period('2012', freq='A-DEC')
Out[213]: Period('2012', 'A-DEC')

In [214]: Period('2012-1-1', freq='D')
Out[214]: Period('2012-01-01', 'D')
```
In [215]: Period('2012-1-1 19:00', freq='H)
Out[215]: Period('2012-01-01 19:00', 'H')

In [216]: Period('2012-1-1 19:00', freq='5H')
Out[216]: 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 [217]: p = Period('2012', freq='A-DEC')

In [218]: p + 1
Out[218]: Period('2013', 'A-DEC')

In [219]: p - 3
Out[219]: Period('2009', 'A-DEC')

In [220]: p = Period('2012-01', freq='2M')

In [221]: p + 2
Out[221]: Period('2012-05', '2M')

In [222]: p - 1
Out[222]: Period('2011-11', '2M')

In [223]: p == Period('2012-01', freq='3M')
---------------------------------------------------------------------------
ValueError Traceback (most recent call last)
<ipython-input-223-196036327bc8> in <module>()
----> 1 p == Period('2012-01', freq='3M')
/home/joris/scipy/pandas/pandas/_period.so in pandas._period.Period.__richcmp__ (pandas/src/period.c:12559)()
ValueError: Input has different freq=3M from Period(freq=2M)

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.

In [224]: p = Period('2014-07-01 09:00', freq='H')

In [225]: p + Hour(2)
Out[225]: Period('2014-07-01 11:00', 'H')

In [226]: p + timedelta(minutes=120)
Out[226]: Period('2014-07-01 11:00', 'H')

In [227]: p + np.timedelta64(7200, 's')
Out[227]: Period('2014-07-01 11:00', 'H')

In [1]: p + Minute(5)
Traceback
...
ValueError: Input has different freq from Period(freq=H)

If Period has other freqs, only the same offsets can be added. Otherwise, ValueError will be raised.

In [228]: p = Period('2014-07', freq='M')

In [229]: p + MonthEnd(3)
Out[229]: Period('2014-10', 'M')

In [1]: p + 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:

In [230]: Period('2012', freq='A-DEC') - Period('2002', freq='A-DEC')
Out[230]: 10L

20.9.2 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:

In [231]: prng = period_range('1/1/2011', '1/1/2012', freq='M')

In [232]: prng
Out[232]:
PeriodIndex(
 '2012-01'],
dtype='int64', freq='M')

The PeriodIndex constructor can also be used directly:

In [233]: PeriodIndex(['2011-1', '2011-2', '2011-3'], freq='M')
Out[233]: PeriodIndex(['2011-01', '2011-02', '2011-03'], dtype='int64', freq='M')

Passing multiplied frequency outputs a sequence of Period which has multiplied span.

In [234]: PeriodIndex(start='2014-01', freq='3M', periods=4)

Just like DatetimeIndex, a PeriodIndex can also be used to index pandas objects:

In [235]: ps = Series(randn(len(prng)), prng)

In [236]: ps
Out[236]:
2011-01    -0.253355
2011-02    -1.426908
2011-03     1.548971
2011-04    -0.088718
2011-05    -1.771348
2011-06    -0.989328
2011-07    -1.584789
2011-08    -0.288786
2011-09    -2.029806
2011-10    -0.761200
2011-11    -1.603608
2011-12     1.756171
2012-01     0.256502
Freq: M, dtype: float64
PeriodIndex supports addition and subtraction with the same rule as Period.

In [237]: idx = period_range('2014-07-01 09:00', periods=5, freq='H')

In [238]: idx
Out[238]: 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='int64', freq='H')

In [239]: idx + Hour(2)
Out[239]: 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='int64', freq='H')

In [240]: idx = period_range('2014-07', periods=5, freq='M')

In [241]: idx
                    dtype='int64', freq='M')

In [242]: idx + MonthEnd(3)
                    dtype='int64', freq='M')

20.9.3 PeriodIndex Partial String Indexing

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.

In [243]: ps['2011-01']
Out[243]: -0.25335528290092818

In [244]: ps[datetime(2011, 12, 25):]
Out[244]:
2011-12  1.756171
2012-01  0.256502
Freq: M, dtype: float64

In [245]: ps['10/31/2011':'12/31/2011']
Out[245]:
2011-10  -0.761200
2011-11  -1.603608
2011-12  1.756171
Freq: M, dtype: float64

Passing a string representing a lower frequency than PeriodIndex returns partial sliced data.

In [246]: ps['2011']
Out[246]:
2011-01  -0.253355
2011-02  -1.426908
2011-03   1.548971
2011-04  -0.088718
2011-05  -1.771348
2011-06  -0.989328
2011-07  -1.584789
2011-08  -0.288786
2011-09  -2.029806
As with `DatetimeIndex`, the endpoints will be included in the result. The example below slices data starting from 10:00 to 11:59.

**In [250]:** dfp[\`2013-01-01 10H'\:'+2013-01-01 11H\']

**Out [250]:**

```python
2013-01-01 10:00  -0.745396
2013-01-01 10:01   0.141880
2013-01-01 10:02  -1.077754
2013-01-01 10:03  -1.301174
2013-01-01 10:04  -0.269628
2013-01-01 10:05  -0.456347
2013-01-01 10:06   0.157766
...  ... 
2013-01-01 11:53   0.168057
2013-01-01 11:54  -0.214306
2013-01-01 11:55  -0.069739
2013-01-01 11:56  -1.511809
2013-01-01 11:57   0.307021
2013-01-01 11:58  1.449776
2013-01-01 11:59   0.782537
```

[60 rows x 1 columns]
20.9.4 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 [251]: p = Period('2011', freq='A-DEC')
In [252]: p
Out[252]: 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 [253]: p.asfreq('M', how='start')
Out[253]: Period('2011-01', 'M')

In [254]: p.asfreq('M', how='end')
Out[254]: Period('2011-12', 'M')
```

The shorthands ‘s’ and ‘e’ are provided for convenience:

```
In [255]: p.asfreq('M', 's')
Out[255]: Period('2011-01', 'M')

In [256]: p.asfreq('M', 'e')
Out[256]: 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 [257]: p = Period('2011-12', freq='M')
In [258]: p.asfreq('A-NOV')
Out[258]: 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 [259]: p = Period('2012Q1', freq='Q-DEC')
In [260]: p.asfreq('D', 's')
Out[260]: Period('2012-01-01', 'D')
In [261]: p.asfreq('D', 'e')
Out[261]: Period('2012-03-31', 'D')
```

Q-MAR defines fiscal year end in March:

```
In [262]: p = Period('2011Q4', freq='Q-MAR')
In [263]: p.asfreq('D', 's')
Out[263]: Period('2011-01-01', 'D')
In [264]: p.asfreq('D', 'e')
Out[264]: Period('2011-03-31', 'D')
```

### 20.10 Converting between Representations

Timestamped data can be converted to PeriodIndex-ed data using `to_period` and vice-versa using `to_timestamp`:

```
In [265]: rng = date_range('1/1/2012', periods=5, freq='M')
In [266]: ts = Series(randn(len(rng)), index=rng)
In [267]: ts
Out[267]:
2012-01-31   -0.016142
2012-02-29    0.865782
2012-03-31    0.246439
2012-04-30   -1.199736
2012-05-31    0.407620
Freq: M, dtype: float64
In [268]: ps = ts.to_period()
In [269]: ps
Out[269]:
2012-01     -0.016142
2012-02     0.865782
2012-03     0.246439
2012-04    -1.199736
2012-05     0.407620
Freq: M, dtype: float64
In [270]: ps.to_timestamp()
Out[270]:
2012-01-01  -0.016142
2012-02-01  0.865782
2012-03-01  0.246439
2012-04-01 -1.199736
2012-05-01  0.407620
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 [271]: ps.to_timestamp('D', how='s')
Out[271]:
2012-01-01 -0.016142
2012-02-01 0.865782
2012-03-01 0.246439
2012-04-01 -1.199736
2012-05-01 0.407620
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 [272]: prng = period_range('1990Q1', '2000Q4', freq='Q-NOV')
In [273]: ts = Series(randn(len(prng)), prng)
In [274]: ts.index = (prng.asfreq('M', 'e') + 1).asfreq('H', 's') + 9
In [275]: ts.head()
Out[275]:
1990-03-01 09:00 -2.470970
1990-06-01 09:00 -0.929915
1990-09-01 09:00 1.385889
1990-12-01 09:00 -1.830966
1991-03-01 09:00 -0.328505
Freq: H, dtype: float64
```

### 20.11 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 [276]: span = period_range('1215-01-01', '1381-01-01', freq='D')

In [277]: span
Out[277]:
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='int64', length=60632, freq='D')
```

To convert from a int64 based YYYYMMDD representation:

```
In [278]: s = Series([20121231, 20141130, 99991231])

In [279]: s
Out[279]:
0  20121231
1  20141130
2  99991231
```
dtype: int64

In [280]: def conv(x):
.....: return Period(year = x // 10000, month = x//100 % 100, day = x%100, freq='D')
.....:

In [281]: s.apply(conv)
Out[281]:
0 2012-12-31
1 2014-11-30
2 9999-12-31
dtype: object

In [282]: s.apply(conv)[2]
Out[282]: Period('9999-12-31', 'D')

These can easily be converted to a PeriodIndex

In [283]: span = PeriodIndex(s.apply(conv))

In [284]: span
Out[284]: PeriodIndex(['2012-12-31', '2014-11-30', '9999-12-31'], dtype='int64', freq='D')

## 20.12 Time Zone Handling

Pandas provides rich support for working with timestamps in different time zones using pytz and dateutil libraries. dateutil support is new in 0.14.1 and currently only supported for fixed offset and tzfile zones. The default library is pytz. Support for dateutil is provided for compatibility with other applications e.g. if you use dateutil in other python packages.

### 20.12.1 Working with Time Zones

By default, pandas objects are time zone unaware:

In [285]: rng = date_range('3/6/2012 00:00', periods=15, freq='D')

In [286]: rng.tz
Out[286]: None

To supply the time zone, you can use the tz keyword to date_range and other functions. Dateutil time zone strings are distinguished from pytz time zones by starting with dateutil/.

- 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 timezones so there isn’t a fixed list available. For common zones, the names are the same as pytz.

# pytz
In [287]: rng_pytz = date_range('3/6/2012 00:00', periods=10, freq='D',
.....:      tz='Europe/London')
.....:

In [288]: rng_pytz.tz
Out[288]: <DstTzInfo 'Europe/London' LMT-1 day, 23:59:00 STD>
# dateutil

In [289]: rng_dateutil = date_range('3/6/2012 00:00', periods=10, freq='D',
       ....:     tz='dateutil/Europe/London')
       ....:

In [290]: rng_dateutil.tz
Out[290]: tzfile('/usr/share/zoneinfo/Europe/London')

# dateutil - utc special case

In [291]: rng_utc = date_range('3/6/2012 00:00', periods=10, freq='D',
       ....:     tz=dateutil.tz.tzutc())
       ....:

In [292]: rng_utc.tz
Out[292]: tzutc()

Note that the UTC timezone is a special case in dateutil and should be constructed explicitly as an instance of dateutil.tz.tzutc. You can also construct other timezones explicitly first, which gives you more control over which time zone is used:

# pytz

In [293]: tz_pytz = pytz.timezone('Europe/London')

In [294]: rng_pytz = date_range('3/6/2012 00:00', periods=10, freq='D',
       ....:     tz=tz_pytz)
       ....:

In [295]: rng_pytz.tz == tz_pytz
Out[295]: True

# dateutil

In [296]: tz_dateutil = dateutil.tz.gettz('Europe/London')

In [297]: rng_dateutil = date_range('3/6/2012 00:00', periods=10, freq='D',
       ....:     tz=tz_dateutil)
       ....:

In [298]: rng_dateutil.tz == tz_dateutil
Out[298]: True

Timestamps, like Python’s `datetime.datetime` object can be either time zone naive or time zone aware. Naive time series and DatetimeIndex objects can be localized using `tz_localize`:

In [299]: ts = Series(randn(len(rng)), rng)

In [300]: ts_utc = ts.tz_localize('UTC')

In [301]: ts_utc
Out[301]:
2012-03-06 00:00:00+00:00    0.758606
2012-03-07 00:00:00+00:00    2.190827
2012-03-08 00:00:00+00:00    0.706087
2012-03-09 00:00:00+00:00    1.798311
2012-03-10 00:00:00+00:00    1.228481
2012-03-11 00:00:00+00:00   -0.179494
2012-03-12 00:00:00+00:00    0.634073
2012-03-13 00:00:00+00:00    0.262123
2012-03-14 00:00:00+00:00    1.928233

628 Chapter 20. Time Series / Date functionality
Again, you can explicitly construct the timezone object first. You can use the `tz_convert` method to convert pandas objects to convert tz-aware data to another time zone:

```
In [302]: ts_utc.tz_convert('US/Eastern')
Out[302]:
2012-03-05 19:00:00-05:00 0.758606
2012-03-06 19:00:00-05:00 2.190827
2012-03-07 19:00:00-05:00 0.706087
2012-03-08 19:00:00-05:00 1.798831
2012-03-09 19:00:00-05:00 1.228481
2012-03-10 19:00:00-05:00 -0.179494
2012-03-11 20:00:00-04:00 0.634073
2012-03-12 20:00:00-04:00 0.262123
2012-03-13 20:00:00-04:00 1.928233
2012-03-14 20:00:00-04:00 0.322573
2012-03-15 20:00:00-04:00 -0.711113
2012-03-16 20:00:00-04:00 1.444272
2012-03-17 20:00:00-04:00 -0.352268
2012-03-18 20:00:00-04:00 0.213008
2012-03-19 20:00:00-04:00 -0.619340
Freq: D, dtype: float64
```

**Warning:** Be wary of conversions between libraries. For some zones `pytz` and `dateutil` have different definitions of the zone. This is more of a problem for unusual timezones than for ‘standard’ zones like `US/Eastern`.

**Warning:** Be aware that a timezone definition across versions of timezone 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:** It is incorrect to pass a timezone directly into the `datetime.datetime` constructor (e.g., `datetime.datetime(2011, 1, 1, tz=timezone('US/Eastern'))`). Instead, the datetime needs to be localized using the `localize` method on the timezone.

Under the hood, all timestamps are stored in UTC. Scalar values from a `DatetimeIndex` with a time zone will have their fields (day, hour, minute) 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 [303]: rng_eastern = rng_utc.tz_convert('US/Eastern')

In [304]: rng_berlin = rng_utc.tz_convert('Europe/Berlin')

In [305]: rng_eastern[5]
Out[305]: Timestamp('2012-03-10 19:00:00-0500', tz='US/Eastern', offset='D')

In [306]: rng_berlin[5]
Out[306]: Timestamp('2012-03-11 01:00:00+0100', tz='Europe/Berlin', offset='D')
```
Like Series, DataFrame, and DatetimeIndex, Timestamps can be converted to other time zones using `tz_convert`:

In [308]: rng_eastern[5]
Out[308]: Timestamp('2012-03-10 19:00:00-0500', tz='US/Eastern', offset='D')

In [309]: rng_berlin[5]
Out[309]: Timestamp('2012-03-11 01:00:00+0100', tz='Europe/Berlin', offset='D')

In [310]: rng_eastern[5].tz_convert('Europe/Berlin')
Out[310]: Timestamp('2012-03-11 01:00:00+0100', tz='Europe/Berlin')

Localization of Timestamps functions just like DatetimeIndex and Series:

In [311]: rng[5]
Out[311]: Timestamp('2012-03-11 00:00:00', offset='D')

In [312]: rng[5].tz_localize('Asia/Shanghai')
Out[312]: Timestamp('2012-03-11 00:00:00+0800', tz='Asia/Shanghai')

Operations between Series in different time zones will yield UTC Series, aligning the data on the UTC timestamps:

In [313]: eastern = ts_utc.tz_convert('US/Eastern')

In [314]: berlin = ts_utc.tz_convert('Europe/Berlin')

In [315]: result = eastern + berlin

In [316]: result
Out[316]:
2012-03-06 00:00:00+00:00  1.517212
2012-03-07 00:00:00+00:00  4.381654
2012-03-08 00:00:00+00:00  1.412174
2012-03-09 00:00:00+00:00  3.597662
2012-03-10 00:00:00+00:00  2.456962
2012-03-11 00:00:00+00:00 -0.358988
2012-03-12 00:00:00+00:00  1.268146
2012-03-13 00:00:00+00:00  0.524245
2012-03-14 00:00:00+00:00  3.856466
2012-03-15 00:00:00+00:00  0.645146
2012-03-16 00:00:00+00:00 -1.422226
2012-03-17 00:00:00+00:00  2.888544
2012-03-18 00:00:00+00:00 -0.704537
2012-03-19 00:00:00+00:00  0.426017
2012-03-20 00:00:00+00:00 -1.238679
Freq: D, dtype: float64

In [317]: result.index
Out[317]:
DatetimeIndex(['2012-03-06', '2012-03-07', '2012-03-08', '2012-03-09',
              '2012-03-10', '2012-03-11', '2012-03-12', '2012-03-13',
              '2012-03-14', '2012-03-15', '2012-03-16', '2012-03-17',
              '2012-03-18', '2012-03-19', '2012-03-20'],
            dtype='datetime64[ns, UTC]', freq='D')

To remove timezone from tz-aware DatetimeIndex, use `tz_localize(None)` or `tz_convert(None)`. `tz_localize(None)` will remove timezone holding local time representations. `tz_convert(None)` will re-
move timezone after converting to UTC time.

In [318]: didx = DatetimeIndex(start='2014-08-01 09:00', freq='H', periods=10, tz='US/Eastern')

In [319]: didx
Out[319]:
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 [320]: didx.tz_localize(None)
Out[320]:
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='H')

In [321]: didx.tz_convert(None)
Out[321]:
DatetimeIndex(['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',
 '2014-08-01 19:00:00', '2014-08-01 20:00:00',
 '2014-08-01 21:00:00', '2014-08-01 22:00:00'],
dtype='datetime64[ns]', freq='H')

# tz_convert(None) is identical with tz_convert('UTC').tz_localize(None)

In [322]: didx.tz_convert('UTC').tz_localize(None)
Out[322]:
DatetimeIndex(['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',
 '2014-08-01 19:00:00', '2014-08-01 20:00:00',
 '2014-08-01 21:00:00', '2014-08-01 22:00:00'],
dtype='datetime64[ns]', freq='H')

20.12.2 Ambiguous Times when Localizing

In some cases, localize cannot determine the DST and non-DST hours when there are duplicates. This often happens when reading files or database records that simply duplicate the hours. Passing ambiguous='infer' (infer_dst argument in prior releases) into tz_localize will attempt to determine the right offset. Below the top example will fail as it contains ambiguous times and the bottom will infer the right offset.

In [323]: rng_hourly = DatetimeIndex(['11/06/2011 00:00', '11/06/2011 01:00',
 ......: '11/06/2011 02:00', '11/06/2011 03:00'])

# This will fail as there are ambiguous times
In [324]: rng_hourly.tz_localize('US/Eastern')

---------------------------------------------------------------------------
AmbiguousTimeError Traceback (most recent call last)
In addition to 'infer', there are several other arguments supported. Passing an array-like of bools or 0s/1s where True represents a DST hour and False a non-DST hour, allows for distinguishing more than one DST transition (e.g., if you have multiple records in a database each with their own DST transition). Or passing ‘NaT’ will fill in transition times with not-a-time values. These methods are available in the DatetimeIndex constructor as well as tz_localize.

In [327]: rng_hourly_dst = np.array([1, 1, 0, 0, 0])

In [328]: rng_hourly.tz_localize('US/Eastern', ambiguous=rng_hourly_dst).tolist()
Out[328]:
[Timestamp('2011-11-06 00:00:00-0400', tz='US/Eastern'),
 Timestamp('2011-11-06 01:00:00-0400', tz='US/Eastern'),
 Timestamp('2011-11-06 01:00:00-0500', tz='US/Eastern'),
 Timestamp('2011-11-06 02:00:00-0500', tz='US/Eastern'),
 Timestamp('2011-11-06 03:00:00-0500', tz='US/Eastern')]

In [329]: rng_hourly.tz_localize('US/Eastern', ambiguous='NaT').tolist()
Out[329]:
[Timestamp('2011-11-06 00:00:00-0400', tz='US/Eastern'),
 NaT,
 NaT,
 Timestamp('2011-11-06 02:00:00-0500', tz='US/Eastern'),
 Timestamp('2011-11-06 03:00:00-0500', tz='US/Eastern')]

In [330]: didx = DatetimeIndex(start='2014-08-01 09:00', freq='H', periods=10, tz='US/Eastern')

In [331]: didx
Out[331]:

632 Chapter 20. Time Series / Date functionality
20.12.3 TZ aware Dtypes

New in version 0.17.0.

Series/DatetimeIndex with a timezone naive value are represented with a dtype of datetime64[ns].

```python
In [335]: s_naive = pd.Series(pd.date_range('20130101', periods=3))
```

```console
In [336]: s_naive
Out[336]:
0  2013-01-01
1  2013-01-02
2  2013-01-03
dtype: datetime64[ns]
```

Series/DatetimeIndex with a timezone aware value are represented with a dtype of datetime64[ns, tz].

```python
In [337]: s_aware = pd.Series(pd.date_range('20130101', periods=3, tz='US/Eastern'))
```

```console
In [338]: s_aware
Out[338]:
```

20.12. Time Zone Handling
Both of these Series can be manipulated via the `.dt` accessor, see [here](#).

For example, to localize and convert a naive stamp to timezone aware.

```python
In [339]: s_naive.dt.tz_localize('UTC').dt.tz_convert('US/Eastern')
Out[339]:
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]
```

Further more you can `.astype(...)` timezone aware (and naive). This operation is effectively a localize AND convert on a naive stamp, and a convert on an aware stamp.

```python
# localize and convert a naive timezone
In [340]: s_naive.astype('datetime64[ns, US/Eastern]')
Out[340]:
0 2013-01-01 05:00:00
1 2013-01-02 05:00:00
2 2013-01-03 05:00:00
dtype: datetime64[ns, US/Eastern]

# make an aware tz naive
In [341]: s_aware.astype('datetime64[ns]')
Out[341]:
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 the `.values` accessor on a Series, returns a numpy array of the data. These values are converted to UTC, as numpy does not currently support timezones (even though it *is* printing in the local timezone!).

```python
In [343]: s_naive.values
Out[343]:
array(['2013-01-01T01:00:00.000000000+0100',
      '2013-01-02T01:00:00.000000000+0100',
      '2013-01-03T01:00.000000000+0100'], dtype='datetime64[ns]')

In [344]: s_aware.values
Out[344]:
array(['2013-01-01T06:00:00.000000000+0100',
      '2013-01-02T06:00:00.000000000+0100',
      '2013-01-03T06:00.000000000+0100'], dtype='datetime64[ns]')
```

Further note that once converted to a numpy array these would lose the tz tenor.
In [345]: Series(s_aware.values)
Out[345]:
0 2013-01-01 05:00:00
1 2013-01-02 05:00:00
2 2013-01-03 05:00:00
dtype: datetime64[ns]

However, these can be easily converted

In [346]: pd.Series(s_aware.values).dt.tz_localize('UTC').dt.tz_convert('US/Eastern')
Out[346]:
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]
Note: Starting in v0.15.0, 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.

Timedeltas are differences in times, expressed in difference units, e.g. days, hours, minutes, seconds. They can be both positive and negative.

### 21.1 Parsing

You can construct a `Timedelta` scalar through various arguments:

```python
In [1]: Timedelta('1 days')
Out[1]: Timedelta('1 days 00:00:00')

In [2]: Timedelta('1 days 00:00:00')
Out[2]: Timedelta('1 days 00:00:00')

In [3]: Timedelta('1 days 2 hours')
Out[3]: Timedelta('1 days 02:00:00')

In [4]: Timedelta('-1 days 2 min 3us')
Out[4]: Timedelta('-2 days +23:57:59.999997')
```

# like `datetime.timedelta`

```python
# note: these MUST be specified as keyword arguments
In [5]: Timedelta(days=1,seconds=1)
Out[5]: Timedelta('1 days 00:00:01')
```

# integers with a unit

```python
In [6]: Timedelta(1,unit='d')
Out[6]: Timedelta('1 days 00:00:00')
```

# from a `timedelta/np.timedelta64`

```python
In [7]: Timedelta(timedelta(days=1,seconds=1))
Out[7]: Timedelta('1 days 00:00:01')
```

```python
In [8]: Timedelta(np.timedelta64(1,'ms'))
Out[8]: Timedelta('0 days 00:00:00.001000')
```

# negative Timedeltas have this string repr
# to be more consistent with datetime.timedelta conventions
In [9]: Timedelta('-1us')
Out[9]: Timedelta('-1 days +23:59:59.999999')

# a NaT
In [10]: Timedelta('nan')
Out[10]: NaT
In [11]: Timedelta('nat')
Out[11]: NaT

DateOffsets (Day, Hour, Minute, Second, Milli, Micro, Nano) can also be used in construction.
In [12]: Timedelta(Second(2))
Out[12]: Timedelta('0 days 00:00:02')

Further, operations among the scalars yield another scalar Timedelta
In [13]: Timedelta(Day(2)) + Timedelta(Second(2)) + Timedelta('00:00:00.000123')
Out[13]: Timedelta('2 days 00:00:02.000123')

21.1.1 to_timedelta

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), previously were (arg,box=True,unit='ns') as these are more logical.

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 will output a TimedeltaIndex
In [14]: to_timedelta('1 days 06:05:01.00003')
Out[14]: Timedelta('1 days 06:05:01.000030')
In [15]: to_timedelta('15.5us')
Out[15]: Timedelta('0 days 00:00:00.000015')
In [16]: to_timedelta(['1 days 06:05:01.00003', '15.5us', 'nan'])
Out[16]: TimedeltaIndex(['1 days 06:05:01.000030', '0 days 00:00:00.000015', NaT], dtype='timedelta64[ns]', freq=None)
In [17]: to_timedelta(np.arange(5),unit='s')
Out[17]: TimedeltaIndex(['00:00:00', '00:00:01', '00:00:02', '00:00:03', '00:00:04'], dtype='timedelta64[ns]')
In [18]: to_timedelta(np.arange(5),unit='d')
Out[18]: TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'], dtype='timedelta64[ns]')

21.2 Operations

You can operate on Series/DataFrames and construct timedelta64[ns] Series through subtraction operations on datetime64[ns] Series, or Timestamps.
In [19]: s = Series(date_range('2012-1-1', periods=3, freq='D'))

In [20]: td = Series([Timedelta(days=i) for i in range(3)])

In [21]: df = DataFrame(dict(A = s, B = td))

In [22]: df
Out[22]:
   A          B
0 2012-01-01 0 days
1 2012-01-02 1 days
2 2012-01-03 2 days

In [23]: df['C'] = df['A'] + df['B']

In [24]: df
Out[24]:
   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 [25]: df.dtypes
Out[25]:
A    datetime64[ns]
B     timedelta64[ns]
C    datetime64[ns]
dtype: object

In [26]: s - s.max()
Out[26]:
0   -2 days
1   -1 days
2    0 days
dtype: timedelta64[ns]

In [27]: s - datetime(2011,1,1,3,5)
Out[27]:
0  364 days 20:55:00
1  365 days 20:55:00
2  366 days 20:55:00
dtype: timedelta64[ns]

In [28]: s + timedelta(minutes=5)
Out[28]:
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 [29]: s + Minute(5)
Out[29]:
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 [30]: s + Minute(5) + Milli(5)
Operations with scalars from a `timedelta64[ns]` series

```python
In [31]: y = s - s[0]
```

```
In [32]: y
Out[32]:
0   NaT
1    1 days
2    2 days
dtype: timedelta64[ns]
```

Series of `timedelta`s with `NaT` values are supported

```python
In [33]: y = s - s.shift()
```

```
In [34]: y
Out[34]:
0   NaT
1    1 days
2    1 days
dtype: timedelta64[ns]
```

Elements can be set to `NaT` using `np.nan` analogously to `datetimes`

```python
In [35]: y[1] = np.nan
```

```
In [36]: y
Out[36]:
0   NaT
1   NaT
2    1 days
dtype: timedelta64[ns]
```

Operands can also appear in a reversed order (a singular object operated with a `Series`

```python
In [37]: s.max() - s
```

```
In [38]: datetime(2011,1,1,3,5) - s
```

```
In [39]: timedelta(minutes=5) + s
```
2012-01-03 00:05:00
dtype: datetime64[ns]

min, max and the corresponding idxmin, idxmax operations are supported on frames

In [40]: A = s - Timestamp('20120101') - Timedelta('00:05:05')

In [41]: B = s - Series(date_range('2012-1-2', periods=3, freq='D'))

In [42]: df = DataFrame(dict(A=A, B=B))

In [43]: df
Out[43]:
   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 [44]: df.min()
Out[44]:
   A         B
A  0 days 23:54:55 0 days
B  0 days 00:00:00 0 days
dtype: timedelta64[ns]

In [45]: df.min(axis=1)
Out[45]:
0 -1 days
1 -1 days
2 -1 days
dtype: timedelta64[ns]

In [46]: df.idxmin()
Out[46]:
   A 0
   B 0
dtype: int64

In [47]: df.idxmax()
Out[47]:
   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 [48]: df.min().max()
Out[48]: Timedelta('-1 days +23:54:55')

In [49]: df.min(axis=1).min()
Out[49]: Timedelta('-1 days +00:00:00')

In [50]: df.min().idxmax()
Out[50]: 'A'

In [51]: df.min(axis=1).idxmin()
Out[51]: 0

You can fillna on timedeltas. Integers will be interpreted as seconds. You can pass a timedelta to get a particular value.

21.2. Operations
In [52]: y.fillna(0)
Out[52]:
0  0 days
1  0 days
2  1 days
dtype: timedelta64[ns]

In [53]: y.fillna(10)
Out[53]:
0  0 days 00:00:10
1  0 days 00:00:10
2  1 days 00:00:00
dtype: timedelta64[ns]

In [54]: y.fillna(Timedelta('-1 days, 00:00:05'))
Out[54]:
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

In [55]: td1 = Timedelta('-1 days 2 hours 3 seconds')
In [56]: td1
Out[56]: Timedelta('-2 days +21:59:57')

In [57]: -1 * td1
Out[57]: Timedelta('1 days 02:00:03')

In [58]: - td1
Out[58]: Timedelta('1 days 02:00:03')

In [59]: abs(td1)
Out[59]: Timedelta('1 days 02:00:03')

21.3 Reductions

Numeric reduction operation for timedelta64[ns] will return Timedelta objects. As usual NaT are skipped during evaluation.

In [60]: y2 = Series(to_timedelta(['-1 days +00:00:05','nat','-1 days +00:00:05','1 days']))
In [61]: y2
Out[61]:
0  -1 days +00:00:05
1  NaT
2  -1 days +00:00:05
3  1 days 00:00:00
dtype: timedelta64[ns]

In [62]: y2.mean()
Out[62]: Timedelta('-1 days 06:00:01.666667')

In [63]: y2.median()
Out[63]: Timedelta('-1 days +00:00:05')

In [64]: y2.quantile(.1)
Out[64]: Timedelta('-1 days +00:00:05')

In [65]: y2.sum()
Out[65]: Timedelta('-1 days +00:00:10')

21.4 Frequency Conversion

New in version 0.13.

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 NaN -> nan. Note that division by the numpy scalar is true division, while astyping is equivalent of floor division.

In [66]: td = Series(date_range('20130101',periods=4)) - 
   ....: Series(date_range('20121201',periods=4))
   ....:

In [67]: td[2] += timedelta(minutes=5,seconds=3)

In [68]: td[3] = np.nan

In [69]: td
Out[69]:
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 [70]: td / np.timedelta64(1,'D')
Out[70]:
0     31.0
1     31.0
2     31.0
3       NaN
dtype: float64

In [71]: td.astype('timedelta64[D]')
Out[71]:
0     31
1     31
2     31
3       NaN
dtype: float64

# to seconds
In [72]: td / np.timedelta64(1,'s')
Out[72]:
0   2678400
1   2678400
2   2678703
3       NaN
21.5 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

In [77]: td.dt.days
Out[77]:
0  31
1  31

In [74]: td / np.timedelta64(1,'M')
Out[74]:
0  1.018501
1  1.018501
2  1.018617
3  NaN
dtype: float64

In [75]: td * -1
Out[75]:
0  -31 days +00:00:00
1  -31 days +00:00:00
2  -32 days +23:54:57
3   NaN

dtype: timedelta64[ns]

In [76]: td * Series([1,2,3,4])
Out[76]:
0   31 days 00:00:00
1   62 days 00:00:00
2   93 days 00:15:09
3       NaN

dtype: timedelta64[ns]

Dividing or multiplying a `timedelta64[ns]` Series by an integer or integer Series yields another `timedelta64[ns]` dtypes Series.

In [73]: td.astype('timedelta64[s]')
Out[73]:
0  2678400
1  2678400
2  2678703
3   NaN

dtype: float64

In [74]: td.astype('timedelta64[ms]')
Out[74]:
0  2678400
1  2678400
2  2678703
3   NaN

dtype: float64

# to months (these are constant months)
In [74]: td / np.timedelta64(1,'M')
Out[74]:
0  1.018501
1  1.018501
2  1.018617
3   NaN

dtype: float64

21.5 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.
You can access the value of the fields for a scalar `Timedelta` directly.

```python
In [79]: tds = Timedelta('31 days 5 min 3 sec')

In [80]: tds.days
Out[80]: 31L

In [81]: tds.seconds
Out[81]: 303L

In [82]: (-tds).seconds
Out[82]: 86097L
```

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 [83]: td.dt.components
Out[83]:
          days   hours  minutes  seconds  milliseconds  microseconds  nanoseconds
0         31      0       0        0            0             0            0
1         31      0       0        0            0             0            0
2         31      5       3        0            0             0            0
3        NaN     NaN     NaN      NaN           NaN           NaN           NaN

In [84]: td.dt.components.seconds
Out[84]:
          0  0  3  NaN
Name: seconds, dtype: float64
```

### 21.6 TimedeltaIndex

New in version 0.15.0.

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.

```python
In [85]: TimedeltaIndex(['1 days','1 days, 00:00:05',
                      np.timedelta64(2,'D'),timedelta(days=2,seconds=2)])
```
Similarly to `date_range`, you can construct regular ranges of a `TimedeltaIndex`:

```python
In [86]: timedelta_range(start='1 days', periods=5, freq='D')
Out[86]: TimedeltaIndex(['1 days', '2 days', '3 days', '4 days', '5 days'], dtype='timedelta64[ns]', freq='D')
```

```python
In [87]: timedelta_range(start='1 days', end='2 days', freq='30T')
Out[87]: 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')
```

## 21.6.1 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 [88]: s = Series(np.arange(100),
               index=timedelta_range('1 days', periods=100, freq='h'))
```

```python
In [89]: s
Out[89]:
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
1 days 06:00:00    6
   ...              ...
4 days 21:00:00   93
4 days 22:00:00   94
4 days 23:00:00   95
5 days 00:00:00   96
5 days 01:00:00   97
5 days 02:00:00   98
5 days 03:00:00   99
```

646 Chapter 21. Time Deltas
Selections work similarly, with coercion on string-likes and slices:

```python
In [90]: s['1 day':'2 day']
Out[90]:
1 days 00:00:00    0
2 days 00:00:00    1
1 days 02:00:00    2
2 days 02:00:00    3
1 days 04:00:00    4
2 days 04:00:00    5
1 days 06:00:00    6
..                     ...
2 days 17:00:00    41
2 days 18:00:00    42
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, dtype: int32
```

```python
In [91]: s['1 day 01:00:00']
Out[91]: 1
```

```python
In [92]: s[Timedelta('1 day 1h')]
Out[92]: 1
```

Furthermore you can use partial string selection and the range will be inferred:

```python
In [93]: s['1 day':'1 day 5 hours']
Out[93]:
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: int32
```

### 21.6.2 Operations

Finally, the combination of TimedeltaIndex with DatetimeIndex allow certain combination operations that are NaT preserving:

```python
In [94]: tdi = TimedeltaIndex(['1 days','pd.NaT','2 days'])
```

```python
In [95]: tdi.tolist()
Out[95]: [Timedelta('1 days 00:00:00'), NaT, Timedelta('2 days 00:00:00')]
```

```python
In [96]: dti = date_range('20130101',periods=3)
```

```python
In [97]: dti.tolist()
Out[97]: [Timestamp('2013-01-01 00:00:00', offset='D'),
          Timestamp('2013-01-02 00:00:00', offset='D'),
          Timestamp('2013-01-03 00:00:00', offset='D')]
```

21.6. TimedeltaIndex
**21.6.3 Conversions**

Similarly to frequency conversion on a `Series` above, you can convert these indices to yield another Index.

```python
In [100]: tdi / np.timedelta64(1,'s')
Out[100]: Float64Index([86400.0, nan, 172800.0], dtype='float64')

In [101]: tdi.astype('timedelta64[s]')
Out[101]: Float64Index([86400.0, nan, 172800.0], dtype='float64')
```

Scalars type ops work as well. These can potentially return a different type of index.

```python
# adding or timedelta and date -> datelike
In [102]: tdi + Timestamp('20130101')
Out[102]: 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 [103]: (Timestamp('20130101') - tdi).tolist()
Out[103]: [Timestamp('2012-12-31 00:00:00'), NaT, Timestamp('2012-12-30 00:00:00')]

# timedelta + timedelta -> timedelta
In [104]: tdi + Timedelta('10 days')
Out[104]: TimedeltaIndex(['11 days', NaT, '12 days'], dtype='timedelta64[ns]', freq=None)

# division can result in a Timedelta if the divisor is an integer
In [105]: tdi / 2
Out[105]: TimedeltaIndex(['0 days 12:00:00', NaT, '1 days 00:00:00'], dtype='timedelta64[ns]', freq=None)

# or a Float64Index if the divisor is a Timedelta
In [106]: tdi / tdi[0]
Out[106]: Float64Index([1.0, nan, 2.0], dtype='float64')
```

**21.7 Resampling**

Similar to timeseries resampling, we can resample with a `TimedeltaIndex`.

```python
In [107]: s.resample('D')
Out[107]:
Freq: D, dtype: float64
1 days   11.5
2 days   35.5
3 days   59.5
4 days   83.5
5 days   97.5
```
CHAPTER TWENTYTWO

CATEGORICAL DATA

New in version 0.15.

Note: While there was pandas.Categorical in earlier versions, the ability to use categorical data in Series and DataFrame is new.

This is an introduction to pandas categorical data type, including a short comparison with R's factor.

Categoricals are a pandas data type, which correspond to categorical variables in statistics: a variable, which can take on only a limited, and usually fixed, number of possible values (categories; levels in R). Examples are gender, social class, blood types, country affiliations, observation time or ratings 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:

1. 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.

2. 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.

3. 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.

22.1 Object Creation

Categorical Series or columns in a DataFrame can be created in several ways:

By specifying dtype="category" when constructing a Series:

```python
In [1]: s = pd.Series(['a','b','c','a'], dtype="category")
```

```python
In [2]: s
Out[2]:
0  a
1  b
```

```
By converting an existing Series or column to a category dtype:

```python
In [3]: df = pd.DataFrame({"A": ["a", "b", "c", "a"]})

In [4]: df["B"] = df["A"].astype('category')
```

```python
In [5]: df
Out[5]:
   A  B
0  a  a
1  b  b
2  c  c
3  a  a
```

By using some special functions:

```python
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)
```

```python
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     91  90 - 99
5     32  30 - 39
6     87  80 - 89
7     36  30 - 39
8      8   0 - 9
9
See documentation for cut().
```

By passing a pandas.Categorical object to a Series or assigning it to a DataFrame.

```python
In [10]: raw_cat = pd.Categorical(['a', 'b', 'c', 'a'], categories=['b', 'c', 'd'], ordered=False)

In [11]: s = pd.Series(raw_cat)
```

```python
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

You can also specify differently ordered categories or make the resulting data ordered, by passing these arguments to `astype()`:

In [16]: s = pd.Series(["a", "b", "c", "a"],
                   categories=["d", "c", "b", "a"],
                   ordered=True)

In [17]: s
Out[17]:
   0  NaN
   1   b
   2   c
   3  NaN

Note: In contrast to R’s `factor` function, categorical data is not converting input values to strings and 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.

To get back to the original Series or `numpy` array, use `Series.astype(original_dtype)` or `np.asarray(categorical)`:

In [20]: s = pd.Series(["a", "b", "c", "a", "a"])

In [21]: s
Out[21]:
   0  a
   1  b
   2  c
   3  a
   4  a

In [22]: s2 = s.astype('category')
In [23]: s2
Out[23]:
0  a
1  b
2  c
3  a
dtype: category
Categories (3, object): [a, b, c]

In [24]: s3 = s2.astype('string')

In [25]: s3
Out[25]:
0  a
1  b
2  c
3  a
dtype: object

In [26]: np.asarray(s2)
Out[26]: array(['a', 'b', 'c', 'a'], dtype=object)

If you have already codes and categories, you can use the from_codes() constructor to save the factorize step during normal constructor mode:

In [27]: splitter = np.random.choice([0,1], 5, p=[0.5,0.5])

In [28]: s = pd.Series(pd.Categorical.from_codes(splitter, categories=['train', 'test']))

22.2 Description

Using .describe() on categorical data will produce similar output to a Series or DataFrame of type string.

In [29]: cat = pd.Categorical(['a', 'c', 'c', np.nan], categories=['b', 'a', 'c'])

In [30]: df = pd.DataFrame({'cat':cat, 's':['a', 'c', 'c', np.nan]})

In [31]: df.describe()
Out[31]:
       cat    s
count    3    3
unique   2    2
top      c    c
freq     2    2

In [32]: df['cat'].describe()
Out[32]:
       count  unique  top  freq   Name: cat, dtype: object
22.3 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 in values.

```
In [33]: s = pd.Series(["a","b","c","a"], dtype="category")
In [34]: s.cat.categories
Out[34]: Index(["a", "b", "c", "a"], dtype=’object’)
In [35]: s.cat.ordered
Out[35]: False
```

It’s also possible to pass in the categories in a specific order:

```
In [36]: s = pd.Series(pd.Categorical(["a","b","c","a"], categories=["c","b","a"]))
In [37]: s.cat.categories
Out[37]: Index(["c", "b", "a"], dtype=’object’)
In [38]: s.cat.ordered
Out[38]: False
```

**Note:** New categorical data are NOT automatically ordered. You must explicitly pass `ordered=True` to indicate an ordered `Categorical`.

### 22.3.1 Renaming categories

Renaming categories is done by assigning new values to the `Series.cat.categories` property or by using the `Categorical.rename_categories()` method:

```
In [39]: s = pd.Series(["a","b","c","a"], dtype="category")
In [40]: s
Out[40]:
   0   a
   1   b
   2   c
   3   a
dtype: category
Categories (3, object): [a, b, c]
In [41]: s.cat.categories = ["Group %s" % g for g in s.cat.categories]
In [42]: s
Out[42]:
   0  Group a
   1  Group b
   2  Group c
   3  Group a
dtype: category
Categories (3, object): [Group a, Group b, Group c]
In [43]: s.cat.rename_categories([1,2,3])
Out[43]:
```
0 1
1 2
2 3
3 1
dtype: category
Categories (3, int64): [1, 2, 3]

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 operations, while most other operation under Series.cat per default return a new Series of dtype category.

Categories must be unique or a ValueError is raised:

```python
In [44]: try:
....:     s.cat.categories = [1,1,1]
....: except ValueError as e:
....:     print("ValueError: " + str(e))
....:
ValueError: Categorical categories must be unique
```

### 22.3.2 Appending new categories

Appending categories can be done by using the `Categorical.add_categories()` method:

```python
In [45]: s = s.cat.add_categories([4])
```

```python
In [46]: s.cat.categories
Out[46]: Index([u'Group a', u'Group b', u'Group c', 4], dtype='object')
```

```python
In [47]: s
Out[47]:
0  Group a
1  Group b
2  Group c
3  Group a
dtype: category
Categories (4, object): [Group a, Group b, Group c, 4]
```

### 22.3.3 Removing categories

Removing categories can be done by using the `Categorical.remove_categories()` method. Values which are removed are replaced by `np.nan`:

```python
In [48]: s = s.cat.remove_categories([4])
```

```python
In [49]: s
Out[49]:
0  Group a
1  Group b
2  Group c
3  Group a
dtype: category
Categories (3, object): [Group a, Group b, Group c]
22.3.4 Removing unused categories

Removing unused categories can also be done:

```
In [50]: s = pd.Series(pd.Categorical(['a','b','a'], categories=['a','b','c','d']))
```

```
In [51]: s
Out[51]:
  0 a
  1 b
  2 a
dtype: category
Categories (4, object): [a, b, c, d]
```

```
In [52]: s.cat.remove_unused_categories()
```

```
Out[52]:
  0 a
  1 b
  2 a
dtype: category
Categories (2, object): [a, b]
```

22.3.5 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 `Categorical.set_categories()`.

```
In [53]: s = pd.Series(['one','two','four', '-'], dtype='category')
```

```
In [54]: s
Out[54]:
  0 one
  1 two
  2 four
  3 -
dtype: category
Categories (4, object): [ -, four, one, two]
```

```
In [55]: s = s.cat.set_categories(['one','two','three','four'])
```

```
In [56]: s
Out[56]:
  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's S1 dtype and python strings). This can result in surprising behaviour!
22.4 Sorting and Order

Warning: The default for construction has changed in v0.16.0 to ordered=False, from the prior implicit ordered=True

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.

```python
In [57]: s = pd.Series(pd.Categorical(["a","b","c","a"], ordered=False))

In [58]: s.sort_values(inplace=True)

In [59]: s = pd.Series(["a","b","c","a"]).astype('category', ordered=True)

In [60]: s.sort_values(inplace=True)

In [61]: s
Out[61]:
0  a
3  a
1  b
2  c
dtype: category
Categories (3, object): [a < b < c]

In [62]: s.min(), s.max()
Out[62]: ('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.

```python
In [63]: s.cat.as_ordered()
Out[63]:
0  a
3  a
1  b
2  c
dtype: category
Categories (3, object): [a < b < c]

In [64]: s.cat.as_unordered()
Out[64]:
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:

```python
In [65]: s = pd.Series([1,2,3,1], dtype="category")

In [66]: s = s.cat.set_categories([2,3,1], ordered=True)

In [67]: s
```
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 [71]: s = pd.Series([1,2,3,1], dtype="category")

In [72]: s = s.cat.reorder_categories([2,3,1], ordered=True)

In [73]: s
Out[73]:
  0  1
  1  2
  2  3
  3  1
dtype: category
Categories (3, int64): [2 < 3 < 1]

In [74]: s.sort_values(inplace=True)

In [75]: s
Out[75]:
  1  2
  2  3
  0  1
  3  1
dtype: category
Categories (3, int64): [2 < 3 < 1]

In [76]: s.min(), s.max()
Out[76]: (2, 1)
```

22.4.1 Reordering
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`.

### 22.4.2 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 [77]: dfs = pd.DataFrame({'A' : pd.Categorical(list('bbeebbaa'), categories=['e','a','b'], ordered=True),
       .....:
       'B' : [1,2,1,2,2,1,2,1] })
.....:

In [78]: dfs.sort_values(by=['A', 'B'])
Out[78]:
  A  B
0  a  1
1  a  2
2  e  1
3  e  2
4  b  1
5  b  1
6  b  2
7  b  2
```

Reordering the categories changes a future sort.

```python
In [79]: dfs['A'] = dfs['A'].cat.reorder_categories(['a','b','e'])

In [80]: dfs.sort_values(by=['A', 'B'])
Out[80]:
  A  B
0  a  1
1  a  2
2  e  1
3  e  2
4  b  1
5  b  1
6  b  2
7  b  2
```

### 22.5 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 an TypeError because custom categories ordering could be interpreted in two ways: one with taking into account the ordering and one without.

```python
In [81]: cat = pd.Series([1,2,3]).astype("category", categories=[3,2,1], ordered=True)

In [82]: cat_base = pd.Series([2,2,2]).astype("category", categories=[3,2,1], ordered=True)

In [83]: cat_base2 = pd.Series([2,2,2]).astype("category", ordered=True)

In [84]: cat
Out[84]:
0 1
1 2
2 3
dtype: category
Categories (3, int64): [3 < 2 < 1]

In [85]: cat_base
Out[85]:
0 2
1 2
2 2
dtype: category
Categories (3, int64): [3 < 2 < 1]

In [86]: cat_base2
Out[86]:
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 [87]: cat > cat_base
Out[87]:
0   True
1  False
2  False
dtype: bool

In [88]: cat > 2
Out[88]:
0   True
1  False
2  False
dtype: bool

Equality comparisons work with any list-like object of same length and scalars:

**22.5. Comparisons**
In [89]: cat == cat_base
Out[89]:
0 False
1 True
2 False
dtype: bool

In [90]: cat == np.array([1,2,3])
Out[90]:
0 True
1 True
2 True
dtype: bool

In [91]: cat == 2
Out[91]:
0 False
1 True
2 False
dtype: bool

This doesn’t work because the categories are not the same:

In [92]: try:
   ....:     cat > cat_base2
   ....: except TypeError as e:
   ....:     print("TypeError: " + str(e))
   ....:
TypeError: Categoricals can only be compared if 'categories' are the same

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 [93]: base = np.array([1,2,3])

In [94]: try:
   ....:     cat > base
   ....: except TypeError as e:
   ....:     print("TypeError: " + str(e))
   ....:
TypeError: Cannot compare a Categorical for op __gt__ with type <type 'numpy.ndarray'>. If you want to compare values, use 'np.asarray(cat) <op> other'.

In [95]: np.asarray(cat) > base
Out[95]: array([False, False, False], dtype=bool)

### 22.6 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 [96]: s = pd.Series(pd.Categorical(["a","b","c","c"], categories=['c','a','b','d']))

In [97]: s.value_counts()
Out[97]:

Groupby will also show “unused” categories:

```python
In [98]: cats = pd.Categorical(["a", "b", "b", "b", "c", "c"], categories=["a", "b", "c", "d"])
In [99]: df = pd.DataFrame({"cats": cats, "values": [1, 2, 2, 2, 3, 4, 5]})
In [100]: df.groupby("cats").mean()
```

```
Out[100]:
          values
cats   
a     1
b     2
c     4
d  NaN
```

```python
In [101]: cats2 = pd.Categorical(["a", "a", "b", "b"], categories=["a", "b", "c"])
In [102]: df2 = pd.DataFrame({"cats": cats2, "B": ["c", "d", "c", "d"], "values": [1, 2, 3, 4]})
In [103]: df2.groupby(["cats", "B"]).mean()
```

```
Out[103]:
          values
cats B   
a c     1
d  2
b c     3
d  4
c c  NaN
d  NaN
```

Pivot tables:

```python
In [104]: raw_cat = pd.Categorical(["a", "a", "b", "b"], categories=["a", "b", "c"])
In [105]: df = pd.DataFrame({"A": raw_cat, "B": ["c", "d", "c", "d"], "values": [1, 2, 3, 4]})
In [106]: pd.pivot_table(df, values='values', index=['A', 'B'])
```

```
Out[106]:
        A B
a c  1
   d  2
b c  3
   d  4
c c NaN
   d NaN
Name: values, dtype: float64
```

## 22.7 Data munging

The optimized pandas data access methods `.loc`, `.iloc`, `.ix`, `.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.

### 22.7. Data munging

```python
In [107]:
```
22.7.1 Getting

If the slicing operation returns either a `DataFrame` or a column of type `Series`, the `category` dtype is preserved.

```python
In [107]: idx = pd.Index(["h","i","j","k","l","m","n",])
In [108]: cats = pd.Series(["a","b","b","b","c","c","c"], dtype="category", index=idx)
In [109]: values= [1,2,2,2,3,4,5]
In [110]: df = pd.DataFrame({"cats":cats,"values":values}, index=idx)

In [111]: df.iloc[2:4,:]
Out[111]:
   cats  values
  j  b    2
  k  b    2

In [112]: df.iloc[2:4,:].dtypes
Out[112]:
   cats   category
  values  int64
dtype: object

In [113]: df.loc["h":"j","cats"]
Out[113]:
   h  a
  i  b
  j  b
Name: cats, dtype: category
Categories (3, object): [a, b, c]

In [114]: df.ix["h":"j",0:1]
Out[114]:
   cats
  h  a
  i  b
  j  b

In [115]: df[df["cats"] == "b"]
Out[115]:
   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`:

```python
# get the complete "h" row as a Series
In [116]: df.loc["h", :]
Out[116]:
   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”.

662 Chapter 22. Categorical Data
In [117]: df.iat[0,0]
Out[117]: 'a'

In [118]: df["cats"].cat.categories = ["x","y","z"]

In [119]: df.at["h","cats"] # returns a string
Out[119]: 'x'

Note: This is a difference 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 pass in a list with a single value:

In [120]: df.loc["h","cats"]
Out[120]:
    h    x
Name: cats, dtype: category
Categories (3, object): [x, y, z]

22.7.2 Setting

Setting values in a categorical column (or Series) works as long as the value is included in the categories:

In [121]: idx = pd.Index(["h","i","j","k","l","m","n"])

In [122]: cats = pd.Categorical(["a","a","a","a","a","a","a"], categories=["a","b"])

In [123]: values = [1,1,1,1,1,1,1]

In [124]: df = pd.DataFrame{"cats":cats,"values":values}, index=idx)

In [125]: df.iloc[2:4,:] = ["b",2],["b",2]

In [126]: df
Out[126]:
    cats  values
     h     a    1
     i     a    1
     j     b    2
     k     b    2
     l     a    1
     m     a    1
     n     a    1

In [127]: try:
......:   df.iloc[2:4,:] = ["c",3],["c",3]
......: except ValueError as e:
......:   print("ValueError: " + str(e))
......:
ValueError: cannot setitem on a Categorical with a new category, set the categories first

Setting values by assigning categorical data will also check that the categories match:

In [128]: df.loc["j":"k","cats"] = pd.Categorical(["a","a"], categories=["a","b"])

In [129]: df
Out[129]:
    cats  values
     j     a    1
     k     a    1

22.7. Data munging
In [130]: 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:

In [131]: df = pd.DataFrame({"a":[1,1,1,1,1], "b":["a","a","a","a","a"]})
In [132]: df.loc[1:2,"a"] = pd.Categorical(["b","b"], categories=["a","b"])
In [133]: df.loc[2:3,"b"] = pd.Categorical(["b","b"], categories=["a","b"])

In [134]: df
Out[134]:
   a  b
0  1  a
1  b  a
2  b  b
3  1  b
4  1  a

In [135]: df.dtypes
Out[135]:
a object
b object
dtype: object

### 22.7.3 Merging

You can concat two *DataFrames* containing categorical data together, but the categories of these categoricals need to be the same:

In [136]: cat = pd.Series(["a","b"], dtype="category")
In [137]: vals = [1,2]
In [138]: df = pd.DataFrame({"cats":cat, "vals":vals})
In [139]: res = pd.concat([df,df])

In [140]: res
Out[140]:
   cats  vals
0      a      1
1      b      2
0      a      1
1 b 2

In [141]: res.dtypes
Out[141]:
cats category
vals   int64
dtype: object

In this case the categories are not the same and so an error is raised:

In [142]: df_different = df.copy()
In [143]: df_different["cats"].cat.categories = ["c","d"]
In [144]: try:  
......:   pd.concat([df,df_different])
......: except ValueError as e:
......:   print("ValueError: " + str(e))
......:  
ValueError: incompatible categories in categorical concat

The same applies to df.append(df_different).

### 22.8 Getting Data In/Out

New in version 0.15.2.

Writing data (Series, Frames) to a HDF store that contains a category dtype was implemented in 0.15.2. See [here](#) for an example and caveats.

Writing data to and reading data from Stata format files was implemented in 0.15.2. 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 [145]: s = pd.Series(pd.Categorical(["a", 'b', 'b', 'a', 'a', 'd']))

    # rename the categories
In [146]: s.cat.categories = ["very good", "good", "bad"]

    # reorder the categories and add missing categories
In [147]: s = s.cat.set_categories(["very bad", "bad", "medium", "good", "very good"])

In [148]: df = pd.DataFrame({"cats":s, "vals":[1,2,3,4,5,6]})

In [149]: csv = StringIO()

    # write to CSV
In [150]: df.to_csv(csv)

    # read back from CSV
In [151]: df2 = pd.read_csv(StringIO(csv.getvalue()))

In [152]: df2.dtypes
Out[152]:
Unnamed: 0    int64
cats          object
vals    int64
dtype: object

In [153]: df2["cats"]
Out[153]:
0  very good
1    good
2    good
3  very good
4  very good
5     bad
Name: cats, dtype: object

# Redo the category
In [154]: df2["cats"] = df2["cats"].astype("category")

In [155]: df2["cats"].cat.set_categories(["very bad", "bad", "medium", "good", "very good"],
          inplace=True)

In [156]: df2.dtypes
Out[156]:
Unnamed: 0    int64
cats          category
vals    int64
dtype: object

In [157]: df2["cats"]
Out[157]:
0  very good
1    good
2    good
3  very good
4  very good
5     bad
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.

## 22.9 Missing Data

pandas primarily uses the value \texttt{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 \texttt{categories}, only in the \texttt{values}. Instead, it is understood that NaN is different, and is always a possibility. When working with the Categorical’s \texttt{codes}, missing values will always have a code of -1.

In [158]: s = pd.Series(["a", "b", np.nan, "a"], dtype="category")

# only two categories
In [159]: s
Out[159]:
0    a
1    b
2 NaN
3 a
dtype: category
Categories (2, object): [a, b]

**In [160]:** s.cat.codes
**Out[160]:**
0 0
1 1
2 -1
3 0
dtype: int8

Methods for working with missing data, e.g. *isnull()*,, *fillna()*,, *dropna()*,, all work normally:

**In [161]:** s = pd.Series(["a", "b", np.nan], dtype="category")

**In [162]:** s
**Out[162]:**
0 a
1 b
2 NaN
dtype: category
Categories (2, object): [a, b]

**In [163]:** pd.isnull(s)
**Out[163]:**
0 False
1 False
2 True
dtype: bool

**In [164]:** s.fillna("a")
**Out[164]:**
0 a
1 b
2 a
dtype: category
Categories (2, object): [a, b]

### 22.10 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*. 

22.10. Differences to R’s *factor* 667
22.11 Gotchas

22.11.1 Memory Usage

The memory usage of a `Categorical` is proportional to the number of categories times the length of the data. In contrast, an `object` dtype is a constant times the length of the data.

```python
In [165]: s = pd.Series(['foo', 'bar'] * 1000)

# object dtype
In [166]: s.nbytes
Out[166]: 8000

# category dtype
In [167]: s.astype('category').nbytes
Out[167]: 2008
```

**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.

```python
In [168]: s = pd.Series(['foo%04d' % i for i in range(2000)])

# object dtype
In [169]: s.nbytes
Out[169]: 8000

# category dtype
In [170]: s.astype('category').nbytes
Out[170]: 12000
```

22.11.2 Old style constructor usage

In earlier versions than pandas 0.15, a `Categorical` could be constructed by passing in precomputed `codes` (called then `labels`) instead of values with categories. The `codes` were interpreted as pointers to the categories with -1 as `NaN`. This type of constructor usage is replaced by the special constructor `Categorical.from_codes()`.

Unfortunately, in some special cases, using code which assumes the old style constructor usage will work with the current pandas version, resulting in subtle bugs:

```python
>>> cat = pd.Categorical([1, 2], [1, 2, 3])
>>> # old version
>>> cat.get_values()
array([2, 3], dtype=int64)

# new version
>>> cat.get_values()
array([1, 2], dtype=int64)
```

**Warning:** If you used `Categoricals` with older versions of pandas, please audit your code before upgrading and change your code to use the `from_codes()` constructor.
22.11.3 **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:

```python
In [171]: try:
    ....:     np.dtype("category")
    ....: except TypeError as e:
    ....:     print("TypeError: " + str(e))
    ....:
TypeError: data type "category" not understood
```

```python
In [172]: dtype = pd.Categorical(["a"]).dtype
```

```python
In [173]: try:
    ....:     np.dtype(dtype)
    ....: except TypeError as e:
    ....:     print("TypeError: " + str(e))
    ....:
TypeError: data type not understood
```

Dtype comparisons work:

```python
In [174]: dtype == np.str_
Out[174]: False
```

```python
In [175]: np.str_ == dtype
Out[175]: False
```

To check if a Series contains Categorical data, with pandas 0.16 or later, use `hasattr(s, 'cat')`

```python
In [176]: hasattr(pd.Series(['a'], dtype='category'), 'cat')
Out[176]: True
```

```python
In [177]: hasattr(pd.Series(['a']), 'cat')
Out[177]: False
```

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 [178]: s = pd.Series(pd.Categorical([1,2,3,4]))
```

```python
In [179]: 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/pydata/pandas!

22.11.4 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.
In [180]: df = pd.DataFrame({'a':[1,2,3,4],
                      'b':['a','b','c','d'],
                      'cats':pd.Categorical([1,2,3,2]))

In [181]: df.apply(lambda row: type(row['cats']), axis=1)
Out[181]:
0 <type 'long'>
1 <type 'long'>
2 <type 'long'>
3 <type 'long'>
dtype: object

In [182]: df.apply(lambda col: col.dtype, axis=0)
Out[182]:
a object
b object
cats object
dtype: object

**22.11.5 Categorical Index**

New in version 0.16.1.

A new CategoricalIndex index type is introduced in version 0.16.1. See the advanced indexing docs for a more detailed explanation.

Setting the index, will create a CategoricalIndex

In [183]: cats = pd.Categorical([1,2,3,4], categories=[4,2,3,1])

In [184]: strings = ['a','b','c','d']

In [185]: values = [4,2,3,1]

In [186]: df = pd.DataFrame({'strings':strings, 'values':values}, index=cats)

In [187]: df.index
Out[187]: CategoricalIndex([1, 2, 3, 4], categories=[4, 2, 3, 1], ordered=False, dtype='category')

# This now sorts by the categories order
In [188]: df.sort_index()
Out[188]:
   strings  values
4       d     1
2       b     2
3       c     3
1       a     4

In previous versions (<0.16.1) there is no index of type category, so setting the index to categorical column will convert the categorical data to a “normal” dtype first and therefore remove any custom ordering of the categories.

**22.11.6 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 [189]: cat = pd.Categorical([1,2,3,10], categories=[1,2,3,4,10])

In [190]: s = pd.Series(cat, name="cat")

In [191]: cat
Out[191]:
[1, 2, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]

In [192]: s.iloc[0:2] = 10

In [193]: cat
Out[193]:
[10, 10, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]

In [194]: df = pd.DataFrame(s)

In [195]: df["cat"].cat.categories = [1,2,3,4,5]

In [196]: cat
Out[196]:
[5, 5, 3, 5]
Categories (5, int64): [1, 2, 3, 4, 5]

Use copy=True to prevent such a behaviour or simply don’t reuse Categoricals:

In [197]: cat = pd.Categorical([1,2,3,10], categories=[1,2,3,4,10])

In [198]: s = pd.Series(cat, name="cat", copy=True)

In [199]: cat
Out[199]:
[1, 2, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]

In [200]: s.iloc[0:2] = 10

In [201]: cat
Out[201]:
[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 behaviour, while using a string array (e.g. np.array(['a','b','c','a'])) will not.
CHAPTER TWENTYTHREE

PLOTTING

We use the standard convention for referencing the matplotlib API:

```
In [1]: import matplotlib.pyplot as plt
```

The plots in this document are made using matplotlib’s ggplot style (new in version 1.4):

```
import matplotlib
matplotlib.style.use('ggplot')
```

If your version of matplotlib is 1.3 or lower, you can set `display.mpl_style` to ‘default’ with `pd.options.display.mpl_style = 'default'` to produce more appealing plots. When set, matplotlib’s `rcParams` are changed (globally!) to nicer-looking settings.

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.

### 23.1 Basic Plotting: `plot`

See the *cookbook* for some advanced strategies

The `plot` method on Series and DataFrame is just a simple wrapper around `plt.plot()`:

```
In [2]: ts = pd.Series(np.random.randn(1000), index=pd.date_range('1/1/2000', periods=1000))
In [3]: ts = ts.cumsum()
In [4]: ts.plot()
```

```
Out[4]: <matplotlib.axes._subplots.AxesSubplot at 0x9e433bec>
```
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:

In [5]: df = pd.DataFrame(np.random.randn(1000, 4), index=ts.index, columns=list('ABCD'))

In [6]: df = df.cumsum()

In [7]: plt.figure(); df.plot();
You can plot one column versus another using the \texttt{x} and \texttt{y} keywords in \texttt{plot()}: 

\texttt{In [8]: df3 = pd.DataFrame(np.random.randn(1000, 2), columns=['B', 'C']).cumsum()}

\texttt{In [9]: df3['A'] = pd.Series(list(range(len(df))))}

\texttt{In [10]: df3.plot(x='A', y='B')}

\texttt{Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x9e1aeb6c>}

23.1. Basic Plotting: \texttt{plot}
23.2 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()`. These 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

Note: For more formatting and styling options, see below.
New in version 0.17.

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:

```
In [11]: df = pd.DataFrame()

In [12]: df.plot.<TAB>
```

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.tools.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`.

### 23.2.1 Bar plots

For labeled, non-time series data, you may wish to produce a bar plot:

```
In [13]: plt.figure();

In [14]: df.ix[5].plot(kind='bar'); plt.axhline(0, color='k')
```

Out[14]: `<matplotlib.lines.Line2D at 0x9ed176ec>`
Calling a DataFrame’s `plot()` method with `kind='bar'` produces a multiple bar plot:

```python
In [15]: df2 = pd.DataFrame(np.random.rand(10, 4), columns=['a', 'b', 'c', 'd'])
In [16]: df2.plot(kind='bar');```
To produce a stacked bar plot, pass `stacked=True`:

```python
In [17]: df2.plot(kind='bar', stacked=True);
```
To get horizontal bar plots, pass `kind='barh'`:

```python
In [18]: df2.plot(kind='barh', stacked=True);
```
23.2.2 Histograms

New in version 0.15.0.

Histogram can be drawn specifying kind='hist'.

In [19]: df4 = pd.DataFrame({'a': np.random.randn(1000) + 1, 'b': np.random.randn(1000),
                        'c': np.random.randn(1000) - 1}, columns=['a', 'b', 'c'])

In [20]: plt.figure();

In [21]: df4.plot(kind='hist', alpha=0.5)
Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x9f0ec46c>
Histogram can be stacked by `stacked=True`. Bin size can be changed by `bins` keyword.

```python
In [22]: plt.figure();

In [23]: df4.plot(kind='hist', stacked=True, bins=20)
Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x9f3132cc>
You can pass other keywords supported by matplotlib hist. For example, horizontal and cumulative histogram can be drawn by orientation='horizontal' and cumulative='True'.

In [24]: plt.figure();

In [25]: df4['a'].plot(kind='hist', orientation='horizontal', cumulative=True)
Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0xa45ed04c>
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 [26]: plt.figure();

In [27]: df['A'].diff().hist()
Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x9ee5856c>
```
DataFrame.hist() plots the histograms of the columns on multiple subplots:

In [28]: plt.figure()
Out[28]: <matplotlib.figure.Figure at 0xb0706f2c>

In [29]: df.diff().hist(color='k', alpha=0.5, bins=50)
Out[29]:
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x9f2071cc>,
      <matplotlib.axes._subplots.AxesSubplot object at 0x9dba50ec>],
      [<matplotlib.axes._subplots.AxesSubplot object at 0x9ee34b4c>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x9e8c922c>]], dtype=object)
New in version 0.10.0.

The `by` keyword can be specified to plot grouped histograms:

In [30]: data = pd.Series(np.random.randn(1000))

In [31]: data.hist(by=np.random.randint(0, 4, 1000), figsize=(6, 4))

Out[31]:
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x9db440ec>,
   <matplotlib.axes._subplots.AxesSubplot object at 0x9de009ac>],
   [<matplotlib.axes._subplots.AxesSubplot object at 0x9e450b4c>,
   <matplotlib.axes._subplots.AxesSubplot object at 0x9e4e684c>]], dtype=object)
23.2.3 Box Plots

Boxplot can be drawn calling a `Series` and `DataFrame.plot` with `kind='box'`, or `DataFrame.boxplot` to visualize the distribution of values within each column.

New in version 0.15.0.

The `plot` method now supports `kind='box'` to draw boxplot.

For instance, here is a boxplot representing five trials of 10 observations of a uniform random variable on [0,1).

```python
In [32]: df = pd.DataFrame(np.random.rand(10, 5), columns=['A', 'B', 'C', 'D', 'E'])

In [33]: df.plot(kind='box')
Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0x9dd0802c>
```
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`.

```
In [34]: color = dict(boxes='DarkGreen', whiskers='DarkOrange',
        medians='DarkBlue', caps='Gray')

In [35]: df.plot(kind='box', color=color, sym='r+')
```
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 [36]: df.plot(kind='box', vert=False, positions=[1, 4, 5, 6, 8])
Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x9d742c4c>
```
See the `boxplot` method and the `matplotlib` boxplot documentation for more.
The existing interface `DataFrame.boxplot` to plot boxplot still can be used.

```python
In [37]: df = pd.DataFrame(np.random.rand(10,5))
In [38]: plt.figure();
In [39]: bp = df.boxplot()
```
You can create a stratified boxplot using the by keyword argument to create groupings. For instance,

```python
In [40]: df = pd.DataFrame(np.random.rand(10,2), columns=['Col1', 'Col2'] )

In [41]: df['X'] = pd.Series(['A','A','A','A','A','B','B','B','B','B'])

In [42]: plt.figure();

In [43]: bp = df.boxplot(by='X')
```
You can also pass a subset of columns to plot, as well as group by multiple columns:

```python
In [44]: df = pd.DataFrame(np.random.rand(10,3), columns=['Col1', 'Col2', 'Col3'])
In [45]: df['X'] = pd.Series(['A','A','A','A','A','B','B','B','B','B'])
In [46]: df['Y'] = pd.Series(['A','B','A','B','A','B','A','B','A','B'])
In [47]: plt.figure();
In [48]: bp = df.boxplot(column=['Col1','Col2'], by=['X','Y'])
```
Basically, plot functions return `matplotlib Axes` as a return value. In `boxplot`, the return type can be changed by argument `return_type`, and whether the subplots is enabled (`subplots=True` in `plot` or `by` is specified in `boxplot`).

When `subplots=False`/`by` is `None`:

- If `return_type` is `'dict'`, a dictionary containing the `matplotlib Lines` is returned. The keys are “boxes”, “caps”.
  
  This is the default of `boxplot` in historical reason. Note that `plot(kind='box')` returns Axes as default as the same as other plots.

- If `return_type` is `'axes'`, a `matplotlib Axes` containing the boxplot is returned.

- If `return_type` is `'both'`, a namedtuple containing the `matplotlib Axes` and `matplotlib Lines` is returned.

When `subplots=True`/`by` is some column of the DataFrame:

- A dict of `return_type` is returned, where the keys are the columns of the DataFrame. The plot has a facet for each column of the DataFrame, with a separate box for each value of `by`.

Finally, when calling `boxplot` on a `Groupby` object, a dict of `return_type` is returned, where the keys are the same as the `Groupby` object. The plot has a facet for each key, with each facet containing a box for each column of the DataFrame.
In [49]: np.random.seed(1234)

In [50]: df_box = pd.DataFrame(np.random.randn(50, 2))

In [51]: df_box['g'] = np.random.choice(['A', 'B'], size=50)

In [52]: df_box.loc[df_box['g'] == 'B', 1] += 3

In [53]: bp = df_box.boxplot(by='g')

Boxplot grouped by g

Compare to:

In [54]: bp = df_box.groupby('g').boxplot()
23.2.4 Area Plot

New in version 0.14.

You can create area plots with `Series.plot` and `DataFrame.plot` by passing `kind='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 [55]: df = pd.DataFrame(np.random.rand(10, 4), columns=['a', 'b', 'c', 'd'])
In [56]: df.plot(kind='area');
```
To produce an unstacked plot, pass `stacked=False`. Alpha value is set to 0.5 unless otherwise specified:

```
In [57]: df.plot(kind='area', stacked=False);
```
23.2.5 Scatter Plot

New in version 0.13.

You can create scatter plots with DataFrame.plot by passing kind='scatter'. Scatter plot requires numeric columns for x and y axis. These can be specified by x and y keywords each.

```
In [58]: df = pd.DataFrame(np.random.rand(50, 4), columns=['a', 'b', 'c', 'd'])
In [59]: df.plot(kind='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 [60]: ax = df.plot(kind='scatter', x='a', y='b',
             ....:           color='DarkBlue', label='Group 1');
             ....:
In [61]: df.plot(kind='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:

In [62]: df.plot(kind='scatter', x='a', y='b', c='c', s=50);
You can pass other keywords supported by matplotlib `scatter`. Below example shows a bubble chart using a dataframe column values as bubble size.

```
In [63]: df.plot(kind='scatter', x='a', y='b', s=df['c']*200);
```
23.2.6 Hexagonal Bin Plot

New in version 0.14.

You can create hexagonal bin plots with `DataFrame.plot()` and `kind='hexbin'`. Hexbin plots can be a useful alternative to scatter plots if your data are too dense to plot each point individually.

```python
In [64]: df = pd.DataFrame(np.random.randn(1000, 2), columns=['a', 'b'])
In [65]: df['b'] = df['b'] + np.arange(1000)
In [66]: df.plot(kind='hexbin', x='a', y='b', gridsize=25)
Out[66]: <matplotlib.axes._subplots.AxesSubplot at 0x9c6e2fcc>
```

See the `scatter` method and the `matplotlib scatter documentation` for more.
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 [67]: df = pd.DataFrame(np.random.randn(1000, 2), columns=['a', 'b'])
In [68]: df['b'] = df['b'] = df['b'] + np.arange(1000)
In [69]: df['z'] = np.random.uniform(0, 3, 1000)
In [70]: df.plot(kind='hexbin', x='a', y='b', C='z', reduce_C_function=np.max, 
    ....:     gridsize=25)
```

```
Out[70]: <matplotlib.axes._subplots.AxesSubplot at 0x9cbedccc>
```
See the `hexbin` method and the `matplotlib` hexbin documentation for more.

### 23.2.7 Pie plot

New in version 0.14.

You can create a pie plot with `DataFrame.plot()` or `Series.plot()` with `kind='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 [71]: series = pd.Series(3 * np.random.rand(4), index=['a', 'b', 'c', 'd'], name='series')

In [72]: series.plot(kind='pie', figsize=(6, 6))
```

Out[72]: `<matplotlib.axes._subplots.AxesSubplot at 0x9cd248cc>`

```
For pie plots it’s best to use square figures, one’s with an equal aspect ratio. 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.

In [73]: df = pd.DataFrame(3 * np.random.rand(4, 2), index=['a', 'b', 'c', 'd'], columns=['x', 'y'])

In [74]: df.plot(kind='pie', subplots=True, figsize=(8, 4))
Out[74]:
array([<matplotlib.axes._subplots.AxesSubplot object at 0x9cd0c4cc>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x9d67412c>], dtype=object)
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 [75]: series.plot(kind='pie', labels=['AA', 'BB', 'CC', 'DD'], colors=['r', 'g', 'b', 'c'],
               autopct='%.2f', fontsize=20, figsize=(6, 6))
```

Out[75]: `<matplotlib.axes._subplots.AxesSubplot at 0x9d27f80c>`
If you pass values whose sum total is less than 1.0, matplotlib draws a semicircle.

```
In [76]: series = pd.Series([0.1] * 4, index=['a', 'b', 'c', 'd'], name='series2')

In [77]: series.plot(kind='pie', figsize=(6, 6))
```

Out[77]: <matplotlib.axes._subplots.AxesSubplot at 0x9d1ca44c>
See the matplotlib pie documentation for more.

### 23.3 Plotting with Missing Data

Pandas tries to be pragmatic about plotting DataFrames 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.
23.4 Plotting Tools

These functions can be imported from pandas.tools.plotting and take a Series or DataFrame as an argument.

23.4.1 Scatter Matrix Plot

New in version 0.7.3.

You can create a scatter plot matrix using the scatter_matrix method in pandas.tools.plotting:

```
In [78]: from pandas.tools.plotting import scatter_matrix

In [79]: df = pd.DataFrame(np.random.randn(1000, 4), columns=['a', 'b', 'c', 'd'])

In [80]: scatter_matrix(df, alpha=0.2, figsize=(6, 6), diagonal='kde')
```

Out[80]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x9d4f276c>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x9d229cec>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x9d39f2ac>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x9cf9b78c>]],
      dtype=object)
```
23.4.2 Density Plot

New in version 0.8.0.

You can create density plots using the Series/DataFrame.plot and setting kind='kde':

In [81]: ser = pd.Series(np.random.randn(1000))

In [82]: ser.plot(kind='kde')
Out[82]: <matplotlib.axes._subplots.AxesSubplot at 0x9dfbbdac>
23.4.3 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. 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.

In [83]: from pandas.tools.plotting import andrews_curves
   
In [84]: data = pd.read_csv('data/iris.data')
   
In [85]: plt.figure()
Out[85]: <matplotlib.figure.Figure at 0x9e633acc>
   
In [86]: andrews_curves(data, 'Name')
Out[86]: <matplotlib.axes._subplots.AxesSubplot at 0xea8890c>
23.4.4 Parallel Coordinates

Parallel coordinates is a plotting technique for plotting multivariate data. It 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.

In [87]: from pandas.tools.plotting import parallel_coordinates

In [88]: data = pd.read_csv('data/iris.data')

In [89]: plt.figure()
Out[89]: <matplotlib.figure.Figure at 0x9e07b96c>

In [90]: parallel_coordinates(data, 'Name')
Out[90]: <matplotlib.axes._subplots.AxesSubplot at 0x9e416fac>
23.4.5 Lag Plot

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.

```
In [91]: from pandas.tools.plotting import lag_plot

In [92]: plt.figure()
Out[92]: <matplotlib.figure.Figure at 0xb083614c>

In [93]: data = pd.Series(0.1 * np.random.rand(1000) +
                      0.9 * np.sin(np.linspace(-99 * np.pi, 99 * np.pi, num=1000)))

In [94]: lag_plot(data)
Out[94]: <matplotlib.axes._subplots.AxesSubplot at 0xb08b1d2c>
```
23.4.6 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.

```
In [95]: from pandas.tools.plotting import autocorrelation_plot

In [96]: plt.figure()
Out[96]: <matplotlib.figure.Figure at 0xb08c0f8c>

In [97]: data = pd.Series(0.7 * np.random.rand(1000) +
                        0.3 * np.sin(np.linspace(-9 * np.pi, 9 * np.pi, num=1000)))
   ....:
In [98]: autocorrelation_plot(data)
Out[98]: <matplotlib.axes._subplots.AxesSubplot at 0xb098778c>
```
### 23.4.7 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 [99]: from pandas.tools.plotting import bootstrap_plot

In [100]: data = pd.Series(np.random.rand(1000))

In [101]: bootstrap_plot(data, size=50, samples=500, color='grey')
Out[101]: <matplotlib.figure.Figure at 0xb0897c8c>
23.4.8 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.

Note: The “Iris” dataset is available here.

In [102]: from pandas.tools.plotting import radviz

In [103]: data = pd.read_csv('data/iris.data')

In [104]: plt.figure()
Out[104]: <matplotlib.figure.Figure at 0x9ce79e8c>

In [105]: radviz(data, 'Name')
Out[105]: <matplotlib.axes._subplots.AxesSubplot at 0x9ce6ec2c>
23.5 Plot Formatting

Most plotting methods have a set of keyword arguments that control the layout and formatting of the returned plot:

```
In [106]: plt.figure(); 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.

### 23.5.1 Controlling the Legend

You may set the `legend` argument to `False` to hide the legend, which is shown by default.

```python
In [107]: df = pd.DataFrame(np.random.randn(1000, 4), index=ts.index, columns=list('ABCD'))

In [108]: df = df.cumsum()

In [109]: df.plot(legend=False)
Out[109]: <matplotlib.axes._subplots.AxesSubplot at 0xb083620c>
```
23.5.2 Scales

You may pass `logy` to get a log-scale Y axis.

```python
In [110]: ts = pd.Series(np.random.randn(1000), index=pd.date_range('1/1/2000', periods=1000))

In [111]: ts = np.exp(ts.cumsum())

In [112]: ts.plot(logy=True)
Out[112]: <matplotlib.axes._subplots.AxesSubplot at 0x9e4871ac>
```
See also the `logx` and `loglog` keyword arguments.

### 23.5.3 Plotting on a Secondary Y-axis

To plot data on a secondary y-axis, use the `secondary_y` keyword:

```python
In [113]: df.A.plot()
Out[113]: <matplotlib.axes._subplots.AxesSubplot at 0x9e40918c>
```

```python
In [114]: df.B.plot(secondary_y=True, style='g')
Out[114]: <matplotlib.axes._subplots.AxesSubplot at 0x9d4d5aac>
```
To plot some columns in a DataFrame, give the column names to the `secondary_y` keyword:

```
In [115]: plt.figure()
Out[115]: <matplotlib.figure.Figure at 0x9e95e40c>

In [116]: ax = df.plot(secondary_y=['A', 'B'])

In [117]: ax.set_ylabel('CD scale')
Out[117]: <matplotlib.text.Text at 0x9f09e1cc>

In [118]: ax.right_ax.set_ylabel('AB scale')
Out[118]: <matplotlib.text.Text at 0x9edf2f2cc>
```
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:

```python
In [119]: plt.figure()
Out[119]: <matplotlib.figure.Figure at 0x9cda83cc>

In [120]: df.plot(secondary_y=['A', 'B'], mark_right=False)
Out[120]: <matplotlib.axes._subplots.AxesSubplot at 0x9cd82a0c>
```
23.5.4 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 labelling is performed:

```
In [121]: plt.figure()
Out[121]: <matplotlib.figure.Figure at 0x9e95e8ac>

In [122]: df.A.plot()
Out[122]: <matplotlib.axes._subplots.AxesSubplot at 0x9f04a32c>
```
Using the `x_compat` parameter, you can suppress this behavior:

In [123]: plt.figure()
Out[123]: <matplotlib.figure.Figure at 0x9f205d8c>

In [124]: df.A.plot(x_compat=True)
Out[124]: <matplotlib.axes._subplots.AxesSubplot at 0x9f20556c>
If you have more than one plot that needs to be suppressed, the `use` method in `pandas.plot_params` can be used in a `with` statement:

```python
In [125]: plt.figure()
Out[125]: <matplotlib.figure.Figure at 0x9da6ceac>

In [126]: with pd.plot_params.use('x_compat', True):
   
   df.A.plot(color='r')
   df.B.plot(color='g')
   df.C.plot(color='b')
   
```
23.5.5 Subplots

Each Series in a DataFrame can be plotted on a different axis with the `subplots` keyword:

```
In [127]: df.plot(subplots=True, figsize=(6, 6));
```
### 23.5.6 Using Layout and Targetting Multiple Axes

The layout of subplots can be specified by `layout` keyword. It can accept `(rows, columns)`. The `layout` keyword can be used in `hist` and `boxplot` also. If input is invalid, `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.

```python
In [128]: df.plot(subplots=True, layout=(2, 3), figsize=(6, 6), sharex=False);
```
The above example is identical to using

```
In [129]: 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).

Also, you can pass multiple axes created beforehand as list-like via `ax` keyword. This allows to use more complicated layout. The passed axes must be the same number as the subplots being drawn.

When multiple axes are passed via `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 [130]: fig, axes = plt.subplots(4, 4, figsize=(6, 6));

In [131]: plt.subplots_adjust(wspace=0.5, hspace=0.5);

In [132]: target1 = [axes[0][0], axes[1][1], axes[2][2], axes[3][3]]

In [133]: target2 = [axes[3][0], axes[2][1], axes[1][2], axes[0][3]]

In [134]: df.plot(subplots=True, ax=target1, legend=False, sharex=False, sharey=False);

In [135]: (-df).plot(subplots=True, ax=target2, legend=False, sharex=False, sharey=False);
```
Another option is passing an `ax` argument to `Series.plot()` to plot on a particular axis:

```python
In [136]: fig, axes = plt.subplots(nrows=2, ncols=2)
In [137]: df['A'].plot(ax=axes[0,0]); axes[0,0].set_title('A');
In [138]: df['B'].plot(ax=axes[0,1]); axes[0,1].set_title('B');
In [139]: df['C'].plot(ax=axes[1,0]); axes[1,0].set_title('C');
In [140]: df['D'].plot(ax=axes[1,1]); axes[1,1].set_title('D');
```
23.5.7 Plotting With Error Bars

New in version 0.14.

Plotting with error bars is now supported in the `DataFrame.plot()` and `Series.plot()` functions.

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 a `M` length `Series`, a `Mx2` array should be provided indicating lower and upper (or left and right) errors. For a `MxN` `DataFrame`, asymmetrical errors should be in a `Mx2xN` array.

Here is an example of one way to easily plot group means with standard deviations from the raw data.
# Generate the data
In [141]: ix3 = pd.MultiIndex.from_arrays([['a', 'a', 'a', 'b', 'b', 'b'], ['foo', 'foo', 'bar', 'foo', 'foo', 'bar'], names=['letter', 'word'])

In [142]: df3 = pd.DataFrame({'data1': [3, 2, 4, 3, 2, 4], 'data2': [6, 5, 7, 5, 4, 5]}, index=ix3)

# Group by index labels and take the means and standard deviations for each group
In [143]: gp3 = df3.groupby(level=('letter', 'word'))

In [144]: means = gp3.mean()

In [145]: errors = gp3.std()

In [146]: means
Out[146]:
   data1  data2
letter word
a   bar   3.5   6.0
     foo   2.5   5.5
b   bar   2.5   5.5
     foo   3.0   4.5

In [147]: errors
Out[147]:
   data1  data2
letter word
a   bar 0.707107 1.414214
     foo 0.707107 0.707107
b   bar 0.707107 0.707107
     foo 1.414214 0.707107

# Plot
In [148]: fig, ax = plt.subplots()

In [149]: means.plot(yerr=errors, ax=ax, kind='bar')
Out[149]: <matplotlib.axes._subplots.AxesSubplot at 0x9ad6050c>
23.5.8 Plotting Tables

New in version 0.14.

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 [150]: fig, ax = plt.subplots(1, 1)

In [151]: df = pd.DataFrame(np.random.rand(5, 3), columns=['a', 'b', 'c'])

In [152]: ax.get_xaxis().set_visible(False) # Hide Ticks

In [153]: df.plot(table=True, ax=ax)
Out[153]: <matplotlib.axes._subplots.AxesSubplot at 0x9959708c>
Also, you can pass different DataFrame or Series for table keyword. The data will be drawn as displayed in print method (not transposed automatically). If required, it should be transposed manually as below example.

In [154]: fig, ax = plt.subplots(1, 1)

In [155]: ax.get_xaxis().set_visible(False)  # Hide Ticks

In [156]: df.plot(table=np.round(df.T, 2), ax=ax)

Out[156]: <matplotlib.axes._subplots.AxesSubplot at 0x9aec176c>
Finally, there is a helper function `pandas.tools.plotting.table` to create a table from `DataFrame` and `Series`, and add it to an `matplotlib.Axes`. This function can accept keywords which `matplotlib` table has.

In [157]: from pandas.tools.plotting import table

In [158]: fig, ax = plt.subplots(1, 1)

In [159]: table(ax, np.round(df.describe(), 2),
       ....:     loc='upper right', colWidths=[0.2, 0.2, 0.2])
       ....:
Out[159]: <matplotlib.table.Table at 0x968bda6c>

In [160]: df.plot(ax=ax, ylim=(0, 2), legend=None)
Out[160]: <matplotlib.axes._subplots.AxesSubplot at 0x9d7ef38c>
Note: You can get table instances on the axes using `axes.tables` property for further decorations. See the matplotlib table documentation for more.

23.5.9 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 simply pass ‘cubehelix’ to `colormap=

```
In [161]: df = pd.DataFrame(np.random.randn(1000, 10), index=ts.index)
In [162]: df = df.cumsum()
In [163]: plt.figure()
Out[163]: <matplotlib.figure.Figure at 0x9689b7ec>
```
In [164]: df.plot(colormap='cubehelix')
Out[164]: <matplotlib.axes._subplots.AxesSubplot at 0x9689f62c>

or we can pass the colormap itself

In [165]: from matplotlib import cm

In [166]: plt.figure()
Out[166]: <matplotlib.figure.Figure at 0x967a2c8c>

In [167]: df.plot(colormap=cm.cubehelix)
Out[167]: <matplotlib.axes._subplots.AxesSubplot at 0x9679758c>

23.5. Plot Formatting
Colormaps can also be used other plot types, like bar charts:

```
In [168]: dd = pd.DataFrame(np.random.randn(10, 10)).applymap(abs)

In [169]: dd = dd.cumsum()

In [170]: plt.figure()
Out[170]: <matplotlib.figure.Figure at 0x96507f4c>

In [171]: dd.plot(kind='bar', colormap='Greens')
Out[171]: <matplotlib.axes._subplots.AxesSubplot at 0x964eccc>
```
Parallel coordinates charts:

In [172]: plt.figure()
Out[172]: <matplotlib.figure.Figure at 0x963f104c>

In [173]: parallel_coordinates(data, 'Name', colormap='gist_rainbow')
Out[173]: <matplotlib.axes._subplots.AxesSubplot at 0x9607eecc>
Andrews curves charts:

```
In [174]: plt.figure()
Out[174]: <matplotlib.figure.Figure at 0x95c94e6c>

In [175]: andrews_curves(data, 'Name', colormap='winter')
Out[175]: <matplotlib.axes._subplots.AxesSubplot at 0x95c9474c>
```
23.6 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.

**Note:** The speed up for large data sets only applies to pandas 0.14.0 and later.

```python
In [176]: price = pd.Series(np.random.randn(150).cumsum(),
       index=pd.date_range('2000-1-1', periods=150, freq='B'))

In [177]: ma = pd.rolling_mean(price, 20)

In [178]: mstd = pd.rolling_std(price, 20)

In [179]: plt.figure()
```
23.7 Trellis plotting interface

**Warning:** 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. The docs below include some example on how to convert your existing code to `seaborn`.

**Note:** The tips data set can be downloaded here. Once you download it execute...
tips_data = pd.read_csv('tips.csv')

from the directory where you downloaded the file.

We import the rplot API:

In [183]: import pandas.tools.rplot as rplot

### 23.7.1 Examples

RPlot was an API for producing Trellis plots. These plots allow you to arrange data in a rectangular grid by values of certain attributes. In the example below, data from the tips data set is arranged by the attributes 'sex' and 'smoker'. Since both of those attributes can take on one of two values, the resulting grid has two columns and two rows. A histogram is displayed for each cell of the grid.

In [184]: plt.figure()
Out[184]: <matplotlib.figure.Figure at 0x9590982c>

In [185]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')

In [186]: plot.add(rplot.TrellisGrid(['sex', 'smoker']))

In [187]: plot.add(rplot.GeomHistogram())

In [188]: plot.render(plt.gcf())
Out[188]: <matplotlib.figure.Figure at 0x9590982c>
A similar plot can be made with seaborn using the FacetGrid object, resulting in the following image:

```python
import seaborn as sns
g = sns.FacetGrid(tips_data, row="sex", col="smoker")
g.map(plt.hist, "total_bill")
```
Example below is the same as previous except the plot is set to kernel density estimation. A seaborn example is included beneath.

```python
In [189]: plt.figure()
Out[189]: <matplotlib.figure.Figure at 0x955cf62c>

In [190]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')

In [191]: plot.add(rplot.TrellisGrid(['sex', 'smoker']))

In [192]: plot.add(rplot.GeomDensity())

In [193]: plot.render(plt.gcf())
Out[193]: <matplotlib.figure.Figure at 0x955cf62c>
```
```python
g = sns.FacetGrid(tips_data, row="sex", col="smoker")
g.map(sns.kdeplot, "total_bill")
```
The plot below shows that it is possible to have two or more plots for the same data displayed on the same Trellis grid cell.

```python
In [194]: plt.figure()
Out[194]: <matplotlib.figure.Figure at 0x952166ac>

In [195]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')

In [196]: plot.add(rplot.TrellisGrid(['sex', 'smoker']))

In [197]: plot.add(rplot.GeomScatter())

In [198]: plot.add(rplot.GeomPolyFit(degree=2))

In [199]: plot.render(plt.gcf())
Out[199]: <matplotlib.figure.Figure at 0x952166ac>
```
A seaborn equivalent for a simple scatter plot:

```python
g = sns.FacetGrid(tips_data, row="sex", col="smoker")
g.map(plt.scatter, "total_bill", "tip")
```
and with a regression line, using the dedicated `seaborn regplot` function:

```python
import seaborn as sns

g = sns.FacetGrid(tips_data, row='sex', col='smoker', margin_titles=True)
g.map(sns.regplot, 'total_bill', 'tip', order=2)
```

---

**23.7. Trellis plotting interface**
Below is a similar plot but with 2D kernel density estimation plot superimposed, followed by a `seaborn` equivalent:

```
In [200]: plt.figure()
Out[200]: <matplotlib.figure.Figure at 0x94ebebec>

In [201]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')

In [202]: plot.add(rplot.TrellisGrid(["sex", "smoker"]))

In [203]: plot.add(rplot.GeomScatter())

In [204]: plot.add(rplot.GeomDensity2D())

In [205]: plot.render(plt.gcf())
Out[205]: <matplotlib.figure.Figure at 0x94ebebec>
```
```python
g = sns.FacetGrid(tips_data, row="sex", col="smoker")
g.map(plt.scatter, "total_bill", "tip")
g.map(sns.kdeplot, "total_bill", "tip")
```
It is possible to only use one attribute for grouping data. The example above only uses ‘sex’ attribute. If the second grouping attribute is not specified, the plots will be arranged in a column.

In [206]: plt.figure()
Out[206]: <matplotlib.figure.Figure at 0x94b528ac>

In [207]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')

In [208]: plot.add(rplot.TrellisGrid(['sex', '.']))

In [209]: plot.add(rplot.GeomHistogram())

In [210]: plot.render(plt.gcf())
Out[210]: <matplotlib.figure.Figure at 0x94b528ac>
If the first grouping attribute is not specified the plots will be arranged in a row.

```python
In [211]: plt.figure()
Out[211]: <matplotlib.figure.Figure at 0x94b9ddac>

In [212]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')

In [213]: plot.add(rplot.TrellisGrid(['.', 'smoker']))

In [214]: plot.add(rplot.GeomHistogram())

In [215]: plot.render(plt.gcf())
Out[215]: <matplotlib.figure.Figure at 0x94b9ddac>
```
In seaborn, this can also be done by only specifying one of the `row` and `col` arguments.

In the example below the colour and shape of the scatter plot graphical objects is mapped to ‘day’ and ‘size’ attributes respectively. You use scale objects to specify these mappings. The list of scale classes is given below with initialization arguments for quick reference.

```python
In [216]: plt.figure()
Out[216]: <matplotlib.figure.Figure at 0x94ee56ac>

In [217]: plot = rplot.RPlot(tips_data, x='tip', y='total_bill')

In [218]: plot.add(rplot.TrellisGrid(["sex", 'smoker']))

In [219]: plot.add(rplot.GeomPoint(size=80.0, colour=rplot.ScaleRandomColour('day'), shape=rplot.ScaleShape('size'), alpha=1.0))

In [220]: plot.render(plt.gcf())
Out[220]: <matplotlib.figure.Figure at 0x94ee56ac>
```
This can also be done in **seaborn**, at least for 3 variables:

```python
import seaborn as sns
import pandas as pd
from matplotlib.pyplot import plt

# Load the tips dataset
tips_data = pd.read_csv('tips.csv')

# Create a FacetGrid object with the data
# row and col arguments specify the conditioning variables
# hue argument specifies the color of the points

g = sns.FacetGrid(tips_data, row="sex", col="smoker", hue="day")

g.map(plt.scatter, "tip", "total_bill")

g.add_legend()
```

---

**23.7. Trellis plotting interface** 753
IO TOOLS (TEXT, CSV, HDF5, ...)  

The pandas I/O API is 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_msgpack` (experimental)
- `read_html`
- `read_gbq` (experimental)
- `read_stata`
- `read_sas`
- `read_clipboard`
- `read_pickle`

The corresponding `writer` functions are object methods that are accessed like `df.to_csv()`

- `to_csv`
- `to_excel`
- `to_hdf`
- `to_sql`
- `to_json`
- `to_msgpack` (experimental)
- `to_html`
- `to_gbq` (experimental)
- `to_stata`
- `to_clipboard`
- `to_pickle`
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 according to your Python version, i.e. from `StringIO` import `StringIO` for Python 2 and from `io` import `StringIO` for Python 3.

## 24.1 CSV & Text files

The two workhorse functions for reading text files (a.k.a. flat files) are `read_csv()` and `read_table()`. They both use the same parsing code to intelligently convert tabular data into a DataFrame object. See the cookbook for some advanced strategies

They can take a number of arguments:

- **filepath_or_buffer**: Either a string path to a file, URL (including http, ftp, and S3 locations), or any object with a read method (such as an open file or `StringIO`).
- **sep or delimiter**: A delimiter / separator to split fields on. With `sep=None`, `read_csv` will try to infer the delimiter automatically in some cases by “sniffing”. The separator may be specified as a regular expression; for instance you may use `'|\s*'` to indicate a pipe plus arbitrary whitespace.
- **delim_whitespace**: Parse whitespace-delimited (spaces or tabs) file (much faster than using a regular expression)
- **compression**: decompress ‘gzip’ and ‘bz2’ formats on the fly. Set to ‘infer’ (the default) to guess a format based on the file extension.
- **dialect**: string or `csv.Dialect` instance to expose more ways to specify the file format
- **dtype**: A data type name or a dict of column name to data type. If not specified, data types will be inferred. (Unsupported with engine='python')
- **header**: row number(s) to use as the column names, and the start of the data. Defaults to 0 if no names passed, otherwise `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 are skipped). Note that this parameter ignores commented lines and empty lines if `skip_blank_lines=True` (the default), so header=0 denotes the first line of data rather than the first line of the file.
- **skip_blank_lines**: whether to skip over blank lines rather than interpreting them as NaN values
- **skiprows**: A collection of numbers for rows in the file to skip. Can also be an integer to skip the first n rows
- **index_col**: column number, column name, or list of column numbers/names, to use as the index (row labels) of the resulting DataFrame. By default, it will number the rows without using any column, unless there is one more data column than there are headers, in which case the first column is taken as the index.
- **names**: List of column names to use as column names. To replace header existing in file, explicitly pass `header=0`.
- **na_values**: optional string or list of strings to recognize as NaN (missing values), either in addition to or in lieu of the default set.
- **true_values**: list of strings to recognize as True
- **false_values**: list of strings to recognize as False
- **keep_default_na**: whether to include the default set of missing values in addition to the ones specified in `na_values`
• **parse_dates**: if True then index will be parsed as dates (False by default). You can specify more complicated options to parse a subset of columns or a combination of columns into a single date column (list of ints or names, list of lists, or dict) [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column [[1, 3]] -> combine columns 1 and 3 and parse as a single date column {'foo': [1, 3]} -> parse columns 1, 3 as date and call result ‘foo’

• **keep_date_col**: if True, then date component columns passed into `parse_dates` will be retained in the output (False by default).

• **date_parser**: function to use to parse strings into datetime objects. If `parse_dates` is True, it defaults to the very robust `dateutil.parser`. Specifying this implicitly sets `parse_dates` as True. You can also use functions from community supported date converters from `date_converters.py`

• **dayfirst**: if True then uses the DD/MM international/European date format (This is False by default)

• **thousands**: specifies the thousands separator. If not None, this character will be stripped from numeric dtypes. However, if it is the first character in a field, that column will be imported as a string. In the PythonParser, if not None, then parser will try to look for it in the output and parse relevant data to numeric dtypes. Because it has to essentially scan through the data again, this causes a significant performance hit so only use if necessary.

• **lineterminator**: string (length 1), default None, Character to break file into lines. Only valid with C parser

• **quotechar**: string. 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. Controls whether quotes should be recognized. Values are taken from csv:`QUOTE_*` values. Acceptable values are 0, 1, 2, and 3 for `QUOTE_MINIMAL`, `QUOTE_ALL`, `QUOTE_NONNUMERIC` and `QUOTE_NONE`, respectively.

• **skipinitialspace**: boolean, default False, Skip spaces after delimiter

• **escapechar**: string, to specify how to escape quoted data

• **comment**: 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, fully commented lines are ignored by the parameter `header` but not by `skiprows`. For example, if comment=‘#’, parsing ‘#empty1,2,3na,b,c’ with `header=0` will result in ‘1,2,3’ being treated as the header.

• **nrows**: Number of rows to read out of the file. Useful to only read a small portion of a large file

• **iterator**: If True, return a `TextFileReader` to enable reading a file into memory piece by piece

• **chunksize**: An number of rows to be used to “chunk” a file into pieces. Will cause an `TextFileReader` object to be returned. More on this below in the section on iterating and chunking

• **skip_footer**: number of lines to skip at bottom of file (default 0) (Unsupported with engine='c')

• **converters**: a dictionary of functions for converting values in certain columns, where keys are either integers or column labels

• **encoding**: a string representing the encoding to use for decoding unicode data, e.g. ‘utf-8’ or ‘latin-1’. Full list of Python standard encodings

• **verbose**: show number of NA values inserted in non-numeric columns

• **squeeze**: if True then output with only one column is turned into Series

• **error_bad_lines**: if False then any lines causing an error will be skipped bad lines

• **usecols**: a subset of columns to return, results in much faster parsing time and lower memory usage.

• **mangle_dupe_cols**: boolean, default True, then duplicate columns will be specified as ‘X.0’...’X.N’, rather than ‘X’...’X’
• **tupleize_cols**: boolean, default False, if False, convert a list of tuples to a multi-index of columns, otherwise, leave the column index as a list of tuples

• **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.

Consider a typical CSV file containing, in this case, some time series data:

```python
In [1]: print(open('foo.csv').read())
date,A,B,C
20090101,a,1,2
20090102,b,3,4
20090103,c,4,5
```

The default for `read_csv` is to create a DataFrame with simple numbered rows:

```python
In [2]: pd.read_csv('foo.csv')
Out[2]:
    date  A  B  C
0 20090101 a 1  2
1 20090102 b 3  4
2 20090103 c 4  5
```

In the case of indexed data, you can pass the column number or column name you wish to use as the index:

```python
In [3]: pd.read_csv('foo.csv', index_col=0)
Out[3]:
    A  B  C
date
20090101 a 1 2
20090102 b 3 4
20090103 c 4 5
```

```python
In [4]: pd.read_csv('foo.csv', index_col='date')
Out[4]:
    A  B  C
date
20090101 a 1 2
20090102 b 3 4
20090103 c 4 5
```

You can also use a list of columns to create a hierarchical index:

```python
In [5]: pd.read_csv('foo.csv', index_col=[0, 'A'])
Out[5]:
    B  C
date
20090101 a 1 2
20090102 b 3 4
20090103 c 4 5
```

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:

```python
In [6]: 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 [7]: dia = csv.excel()

In [8]: dia.quoting = csv.QUOTE_NONE

In [9]: pd.read_csv(StringIO(data), dialect=dia)
Out[9]:
   label1  label2  label3
index1   a       c       e
index2   b       d       f
```

All of the dialect options can be specified separately by keyword arguments:

```
In [10]: data = 'a,b,c~1,2,3~4,5,6'

In [11]: pd.read_csv(StringIO(data), lineterminator='~')
Out[11]:
   a  b  c
0  1  2  3
1  4  5  6
```

Another common dialect option is `skipinitialspace`, to skip any whitespace after a delimiter:

```
In [12]: data = 'a, b, c

1, 2, 3

4, 5, 6'

In [13]: print(data)
a, b, c
1, 2, 3
4, 5, 6

In [14]: pd.read_csv(StringIO(data), skipinitialspace=True)
Out[14]:
   a  b  c
0  1  2  3
1  4  5  6
```

The parsers make every attempt to “do the right thing” and not be very fragile. Type inference is a pretty big deal. So if a column can be coerced to integer dtype without altering the contents, it will do so. Any non-numeric columns will come through as object dtype as with the rest of pandas objects.

### 24.1.1 Specifying column data types

Starting with v0.10, you can indicate the data type for the whole DataFrame or individual columns:

```
In [15]: data = 'a,b,c\n
1,2,3\n
4,5,6\n
7,8,9'

In [16]: print(data)
a, b, c
1, 2, 3
4, 5, 6
7, 8, 9

In [17]: df = pd.read_csv(StringIO(data), dtype=object)

In [18]: df
```
Out[18]:
    a  b  c
0  1  2  3
1  4  5  6
2  7  8  9

In [19]: df['a'][0]
Out[19]: '1'

In [20]: df = pd.read_csv(StringIO(data), dtype={'b': object, 'c': np.float64})

In [21]: df.dtypes
Out[21]:
    a   int64
    b   object
    c   float64
dtype: object

Note: The dtype option is currently only supported by the C engine. Specifying dtype with engine other than 'c' raises a ValueError.

24.1.2 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:

In [22]: data = 'a,b,c

1,2,3
4,5,6
7,8,9'

In [23]: print(data)
a,b,c
1,2,3
4,5,6
7,8,9

In [24]: pd.read_csv(StringIO(data))
Out[24]:
    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):

In [25]: print(data)
a,b,c
1,2,3
4,5,6
7,8,9

In [26]: pd.read_csv(StringIO(data), names=['foo', 'bar', 'baz'], header=0)
Out[26]:
foo  bar  baz
0  1  2  3
1  4  5  6
In [27]: pd.read_csv(StringIO(data), names=['foo', 'bar', 'baz'], header=None)
Out[27]:
   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:

In [28]: data = 'skip this skip it
   
   a,b,c
   
   1,2,3
   
   4,5,6
   
   7,8,9'

In [29]: pd.read_csv(StringIO(data), header=1)
Out[29]:
   a  b  c
0  1  2  3
1  4  5  6
2  7  8  9

Filtering columns (usecols)

The usecols argument allows you to select any subset of the columns in a file, either using the column names or position numbers:

In [30]: data = 'a,b,c,d
   
   1,2,3,foo
   
   4,5,6,bar
   
   7,8,9,baz'

In [31]: pd.read_csv(StringIO(data))
Out[31]:
   a  b  c  d
0  1  2  3  foo
1  4  5  6  bar
2  7  8  9  baz

In [32]: pd.read_csv(StringIO(data), usecols=['b', 'd'])
Out[32]:
   b  d
0  2  foo
1  5  bar
2  8  baz

In [33]: pd.read_csv(StringIO(data), usecols=[0, 2, 3])
Out[33]:
   a  c  d
0  1  3  foo
1  4  6  bar
2  7  9  baz

24.1.3 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. Both of these are API changes introduced in version 0.15.
In [34]: data = 'a,b,c
   \n# commented line
1,2,3
4,5,6'

In [35]: print(data)
a,b,c
1,2,3
4,5,6
   # commented line

In [36]: pd.read_csv(StringIO(data), comment='#')
Out[36]:
   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 [37]: data = 'a,b,c
   
1,2,3

4,5,6'

In [38]: pd.read_csv(StringIO(data), skip_blank_lines=False)
Out[38]:
   a  b  c
0  NaN NaN NaN
1  1  2  3
2  NaN NaN NaN
3  NaN NaN NaN
4  4  5  6
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 [39]: data = '#comment
a,b,c
A,B,C
1,2,3'

In [40]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[40]:
   A  B  C
0  1  2  3

In [41]: data = 'A,B,C
#comment
a,b,c
1,2,3'

In [42]: pd.read_csv(StringIO(data), comment='#', skiprows=2)
Out[42]:
   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 [43]: data = '# empty
# second empty line
# third empty line
X,Y,Z
1,2,3
A,B,C
1,2.,4.
5.,NaN,10.0'

In [44]: print(data)
# empty
# second empty line
# third empty line
X,Y,Z
1,2,3
A,B,C
1,2.,4.
5.,NaN,10.0

In [45]: pd.read_csv(StringIO(data), comment='#', skiprows=4, header=1)
Out[45]:
   A  B  C
0  1  2  4
1  5  NaN 10
```

Comments

Sometimes comments or meta data may be included in a file:

```
In [46]: 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 [47]: df = pd.read_csv('tmp.csv')

In [48]: df
Out[48]:
```

24.1. CSV & Text files 763
We can suppress the comments using the `comment` keyword:

```
In [49]: df = pd.read_csv('tmp.csv', comment='#')
In [50]: df
Out[50]:
   ID   level category
0  0 Patient1  123000     x # really unpleasant
1  1 Patient2  23000       y # wouldn't take his medicine
2  2 Patient3  1234018    z # awesome
```

### 24.1.4 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 [51]: data = b'word,length
Träumen,7
Grüße,5'.decode('utf8').encode('latin-1')
In [52]: df = pd.read_csv(BytesIO(data), encoding='latin-1')
In [53]: df
Out[53]:
   word   length
0  Träumen      7
1   Grüße       5

In [54]: df['word'][1]
Out[54]: u'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

### 24.1.5 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 [55]: data = 'a,b,c
4,apple,bat,5.7
8,orange,cow,10'
In [56]: pd.read_csv(StringIO(data))
Out[56]:
   a   b   c
0  4 apple bath 5.7
1  8  orange cow 10.0

In [57]: data = 'index,a,b,c
4,apple,bat,5.7
8,orange,cow,10'
In [58]: pd.read_csv(StringIO(data), index_col=0)
Out[58]:
   index
0  a   b   c
```

764 Chapter 24. IO Tools (Text, CSV, HDF5, ...
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`:

```python
In [59]: data = 'a,b,c
4,apple,bat,
8,orange,cow,'

In [60]: print(data)
a,b,c
4,apple,bat,
8,orange,cow,

In [61]: pd.read_csv(StringIO(data))
Out[61]:
   a   b   c
0  4    NaN
1  8    NaN

In [62]: pd.read_csv(StringIO(data), index_col=False)
Out[62]:
   a   b   c
0  4 apple bat
1  8 orange cow
```

### 24.1.6 Date Handling

#### Specifying Date Columns

To better facilitate working with datetime data, `read_csv()` and `read_table()` use the keyword arguments `parse_dates` and `date_parser` to allow users to specify a variety of columns and date/time formats to turn the input text data into `datetime` objects.

The simplest case is to just pass in `parse_dates=True`:

```python
# Use a column as an index, and parse it as dates.
In [63]: df = pd.read_csv('foo.csv', index_col=0, parse_dates=True)

In [64]: df
Out[64]:
     A  B  C
date
2009-01-01 a 1 2
2009-01-02 b 3 4
2009-01-03 c 4 5

# These are python datetime objects
In [65]: df.index
Out[65]: DatetimeIndex(['2009-01-01', '2009-01-02', '2009-01-03'], dtype='datetime64[ns]', name='date', freq=None)
```

It is often the case that we may want to store date and time data separately, or store various date fields separately. the `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 `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:
pandas: powerful Python data analysis toolkit, Release 0.17.0

In [66]: 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 [67]: df = pd.read_csv('tmp.csv', header=None, parse_dates=[[1, 2], [1, 3]])

In [68]: df
Out[68]:
       1_2   1_3   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

By default the parser removes the component date columns, but you can choose to retain them via the
keep_date_col keyword:

In [69]: df = pd.read_csv('tmp.csv', header=None, parse_dates=[[1, 2], [1, 3]],
   ....: keep_date_col=True)
   ....:

In [70]: df
Out[70]:
     nominal actual       0       1       2
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

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 [71]: date_spec = {'nominal': [1, 2], 'actual': [1, 3]}

In [72]: df = pd.read_csv('tmp.csv', header=None, parse_dates=date_spec)

In [73]: df
Out[73]:
     nominal actual       0       4
0 1999-01-27 19:00:00 1999-01-27 18:56:00 KORD 0.81
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:

```
In [74]: date_spec = {'nominal': [1, 2], 'actual': [1, 3]}

In [75]: df = pd.read_csv('tmp.csv', header=None, parse_dates=date_spec,
                      index_col=0)  # index is the nominal column

In [76]: df
```
```
Out[76]:
          actual  0  4
nominal
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: `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.

Note: When passing a dict as the `parse_dates` argument, the order of the columns prepended is not guaranteed, because `dict` objects do not impose an ordering on their keys. On Python 2.7+ you may use `collections.OrderedDict` instead of a regular `dict` if this matters to you. Because of this, when using a dict for ‘parse_dates’ in conjunction with the `index_col` argument, it’s best to specify `index_col` as a column label rather then as an index on the resulting frame.

**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:

```
In [77]: import pandas.io.date_converters as conv

In [78]: df = pd.read_csv('tmp.csv', header=None, parse_dates=date_spec,
                      date_parser=conv.parse_date_time)

In [79]: df
```
```
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
```
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.,
   
   ```python
   date_parser(['2013', '2013'], ['1', '2'])
   ```
   
2. If #1 fails, `date_parser` is called with all the columns concatenated row-wise into a single array (e.g.,
   
   ```python
   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()`:
   ```python
   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` con-
tains 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.

### 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”

`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.

```python
# Try to infer the format for the index column
In [80]: df = pd.read_csv('foo.csv', index_col=0, parse_dates=True,
    ....:              infer_datetime_format=True)
    ....:
```

---

768 Chapter 24. IO Tools (Text, CSV, HDF5, ...
In [81]: df
Out[81]:
   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 [82]: print(open('tmp.csv').read())
date,value,cat
1/6/2000,5,a
2/6/2000,10,b
3/6/2000,15,c

In [83]: pd.read_csv('tmp.csv', parse_dates=[0])
Out[83]:
   date  value  cat
0 2000-01-06    5  a
1 2000-02-06   10  b
2 2000-03-06   15  c

In [84]: pd.read_csv('tmp.csv', dayfirst=True, parse_dates=[0])
Out[84]:
   date  value  cat
0 2000-06-01    5  a
1 2000-06-02   10  b
2 2000-06-03   15  c

24.1.7 **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:

In [85]: val = '0.3066101993807095471566981359501369297504425048828125'

In [86]: data = 'a,b,c\n1,2,\n'.format(val)

In [87]: abs(pd.read_csv(StringIO(data), engine='c', float_precision=None)['c'][0] - float(val))
Out[87]: 0.0

In [88]: abs(pd.read_csv(StringIO(data), engine='c', float_precision='high')['c'][0] - float(val))
Out[88]: 5.5511151231257827e-17

In [89]: abs(pd.read_csv(StringIO(data), engine='c', float_precision='round_trip')['c'][0] - float(val))
Out[89]: 0.0
24.1.8 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:

```
In [90]: print(open('tmp.csv').read())
ID|level|category
Patient1|123,000|x
Patient2|23,000|y
Patient3|1,234,018|z
```

```
In [91]: df = pd.read_csv('tmp.csv', sep='|')
In [92]: df
Out[92]:
     ID     level category
0  Patient1    123,000     x
1   Patient2     23,000     y
2  Patient3    1,234,018     z
```

The thousands keyword allows integers to be parsed correctly:

```
In [94]: print(open('tmp.csv').read())
ID|level|category
Patient1|123,000|x
Patient2|23,000|y
Patient3|1,234,018|z
```

```
In [95]: df = pd.read_csv('tmp.csv', sep='|', thousands=',')
In [96]: df
Out[96]:
     ID     level category
0  Patient1    123000     x
1   Patient2    23000     y
2  Patient3    1234018     z
```

24.1.9 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', 'NA', '#NA', 'NULL', 'NaN', '-NaN', 'nan', '-nan']. Although a 0-length string '' is not included in the default NaN values list, it is still treated as a missing value.
read_csv(path, na_values=[5])

the default values, in addition to 5, 5.0 when interpreted as numbers are recognized as NaN

read_csv(path, keep_default_na=False, na_values=[])

only an empty field will be NaN

read_csv(path, keep_default_na=False, na_values=["NA", "0"],)

only NA and 0 as strings are NaN

read_csv(path, na_values=["Nope"],)

the default values, in addition to the string "Nope" are recognized as NaN

### 24.1.10 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.

### 24.1.11 Returning Series

Using the squeeze keyword, the parser will return output with a single column as a Series:

In [98]: print(open('tmp.csv').read())

<table>
<thead>
<tr>
<th>level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patient1,123000</td>
</tr>
<tr>
<td>Patient2,23000</td>
</tr>
<tr>
<td>Patient3,1234018</td>
</tr>
</tbody>
</table>

In [99]: output = pd.read_csv('tmp.csv', squeeze=True)

In [100]: output

Out[100]:

<table>
<thead>
<tr>
<th>level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patient1</td>
</tr>
<tr>
<td>Patient2</td>
</tr>
<tr>
<td>Patient3</td>
</tr>
</tbody>
</table>

Name: level, dtype: int64

In [101]: type(output)

Out[101]: pandas.core.series.Series

### 24.1.12 Boolean values

The common values True, False, TRUE, and FALSE are all recognized as boolean. Sometime you would want to recognize some other values as being boolean. To do this use the true_values and false_values options:

In [102]: data= ’a,b,c\n1,Yes,2\n3,No,4’

In [103]: print(data)
a,b,c
1,Yes,2
3,No,4
In [104]: pd.read_csv(StringIO(data))
Out[104]:
   a  b  c
0  1  Yes  2
1  3    No  4

In [105]: pd.read_csv(StringIO(data), true_values=['Yes'], false_values=['No'])
Out[105]:
   a  b  c
0  1   True  2
1  3   False  4

24.1.13 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 will cause an error by default:

In [27]: data = 'a,b,c
1,2,3
4,5,6,7
8,9,10'

In [28]: pd.read_csv(StringIO(data))
---------------------------------------------------------------------------
  CParserError Traceback (most recent call last)
  CParserError: Error tokenizing data.  C error: Expected 3 fields in line 3, saw 4

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

24.1.14 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:

In [106]: data = 'a,b\n"hello, \"Bob\", nice to see you",5'

In [107]: print(data)
a,b
"hello, \"Bob\", nice to see you",5

In [108]: pd.read_csv(StringIO(data), escapechar='\\')
Out[108]:
   a  b
0 hello, "Bob", nice to see you 5

24.1.15 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:
• 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 behaviour, if not specified, is to infer.

• widths: A list of field widths which can be used instead of ‘colspecs’ if the intervals are contiguous.

Consider a typical fixed-width data file:

```
In [109]: 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:

```
#Column specifications are a list of half-intervals
In [110]: colspecs = [(0, 6), (8, 20), (21, 33), (34, 43)]

In [111]: df = pd.read_fwf('bar.csv', colspecs=colspecs, header=None, index_col=0)

In [112]: df
Out[112]:
       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:

```
#Widths are a list of integers
In [113]: widths = [6, 14, 13, 10]

In [114]: df = pd.read_fwf('bar.csv', widths=widths, header=None)

In [115]: df
Out[115]:
       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.

New in version 0.13.0.

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).

```
In [116]: df = pd.read_fwf('bar.csv', header=None, index_col=0)
```
In [117]: df
Out [117]:
   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

24.1.16 Indexes

Files with an “implicit” index column

Consider a file with one less entry in the header than the number of data columns:

In [118]: 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:

In [119]: pd.read_csv('foo.csv')
Out [119]:
    A  B  C
20090101 a 1 2
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:

In [120]: df = pd.read_csv('foo.csv', parse_dates=True)
In [121]: df.index
Out [121]: 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:

In [122]: 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

774 Chapter 24. IO Tools (Text, CSV, HDF5, ...)
The `index_col` argument to `read_csv` and `read_table` can take a list of column numbers to turn multiple columns into a MultiIndex for the index of the returned object:

In [123]: df = pd.read_csv("data/mindex_ex.csv", index_col=[0,1])

In [124]: df
Out[124]:
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
   H 5.40 2.70
   I 6.40 1.20

In [125]: df.ix[1978]
Out[125]:
   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 order to have the pre-0.13 behavior of tupleizing columns, specify `tupleize_cols=True`.

In [126]: from pandas.util.testing import makeCustomDataframe as mkdf

In [127]: df = mkdf(5,3,r_idx_nlevels=2,c_idx_nlevels=4)

In [128]: df.to_csv('mi.csv')

In [129]: print(open('mi.csv').read())
C0,,C_l1_g0,C_l1_g1,C_l1_g2
C1,,C_l1_g0,C_l1_g1,C_l1_g2
C2,,C_l1_g0,C_l1_g1,C_l1_g2
C3,,C_l1_g0,C_l1_g1,C_l1_g2
R0,R1,,,
In [130]: pd.read_csv('mi.csv',header=[0,1,2,3],index_col=[0,1])
Out[130]:
   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

Starting in 0.13.0, read_csv will be able to interpret a more common format of multi-columns indices.

In [131]: print(open('mi2.csv').read())

one,1,2,3,4,5,6
two,7,8,9,10,11,12

In [132]: pd.read_csv('mi2.csv',header=[0,1],index_col=0)
Out[132]:
   a  b  c
 one 1  2  3
  two 7  8  9

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.

24.1.17 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 [133]: print(open('tmp2.sv').read())

0:0.469112299907:0.282863344329:1.59005850317:1.3563237102
1:1.21211202502:0.173214649053:0.119208711297:1.04423596628
2:0.861848963348:2.10456921889:0.494929274069:1.07180380704
3:0.721555162244:0.706771113363:1.03957498511:0.271859885543
4:0.424972329789:0.567020349794:0.276232019278:1.08740069129
5:0.673689708088:0.113648409689:1.47842655244:0.524987667115
6:0.40470521868:0.57704598592:1.71500201611:1.03926848351
7:0.370646858236:1.15789225064:1.34431181273:0.844885141425
8:1.07576978372:0.19094997528:1.64356307036:1.46938795954
9:0.357020564133:0.67460010373:1.77690371697:0.968913812447
In [134]: pd.read_csv('tmp2.sv', sep=None, engine='python')
Out[134]:
    Unnamed: 0  0  1  2  3
0  0.469112 -0.282863 -1.509059 -1.135632
1  1.212112 -0.173215  0.119209 -1.044236
2  2.0861849 -2.104569 -0.494929  1.071804
3  3.721555  -0.706771 -1.039575  0.271860
4  4.0424972  0.567020  0.276232 -1.087401
5  5.673690  0.113648 -1.478427  0.524988
6  6.040705  0.577046 -1.715002 -1.039268
7  7.370647 -1.157892 -1.344312  0.844885
8  8.075770 -0.109050  1.643563 -1.469388
9  9.357021 -0.674600 -1.776904 -0.968914

24.1.18 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:

In [135]: print(open('tmp.sv').read())

|0|1|2|3|
0|0.469112299907| -0.28286344329| -1.50905850317| -1.13563237102|
1|1.21211202502| -0.173214649053|  0.119208711297| -1.04423596628|
2| -0.86184893348| -2.10456921889| -0.49492740691|  1.07180380704|
3| 0.72155162244| -0.70677113363| -1.03957498511|  0.271859885543|
4| -0.424972329789|  0.567020349794|  0.276232019278| -1.08740069129|
5| -0.673690708088|  0.11364809689| -1.47842655244|  0.524987667115|
6| 0.40470521868|  0.57704598592| -1.71500201611| -1.03926848351|
7| -0.370646858236| -1.15789225064| -1.34431181273|  0.844885141425|
8| 1.07576978372| -0.10904997528|  1.64356307036| -1.46938795954|
9| 0.357020564133| -0.67460010373| -1.77690371697| -0.968913812447

In [136]: table = pd.read_table('tmp.sv', sep='|')

In [137]: table
Out[137]:
    Unnamed: 0  0  1  2  3
0  0.469112 -0.282863 -1.509059 -1.135632
1  1.212112 -0.173215  0.119209 -1.044236
2  2.0861849 -2.104569 -0.494929  1.071804
3  3.721555  -0.706771 -1.039575  0.271860
4  4.0424972  0.567020  0.276232 -1.087401
5  5.673690  0.113648 -1.478427  0.524988
6  6.040705  0.577046 -1.715002 -1.039268
7  7.370647 -1.157892 -1.344312  0.844885
8  8.075770 -0.109050  1.643563 -1.469388
9  9.357021 -0.674600 -1.776904 -0.968914

By specifying a chunksize to read_csv or read_table, the return value will be an iterable object of type TextFileReader:

In [138]: reader = pd.read_table('tmp.sv', sep='|', chunksize=4)

In [139]: reader
Out[139]: <pandas.io.parsers.TextFileReader at 0xb05ef4ac>
In [140]: for chunk in reader:
.....:    print(chunk)
.....:

    Unnamed: 0 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
    Unnamed: 0 0 1 2 3
0   4 -0.424972 0.567020 0.276232 -1.087401
1   5 -0.673690 0.113648 -1.478427 0.524988
2   6 0.404705 0.577046 -1.715002 -1.039268
3   7 -0.370647 -1.157892 -1.344312 0.844885
    Unnamed: 0 0 1 2 3
0   8 1.075770 -0.10905 1.643563 -1.469388
1   9 0.357021 -0.67460 -1.776904 -0.968914

Specifying iterator=True will also return the TextFileReader object:

In [141]: reader = pd.read_table('tmp.sv', sep='|', iterator=True)

In [142]: reader.get_chunk(5)

Out[142]:
    Unnamed: 0 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

24.1.19 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)
- skip_footer
- 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'.

24.1.20 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 StringIO
- 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
• `cols`: 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 ‘\n’)
• `quoting`: Set quoting rules as in csv module (default csv.QUOTE_MINIMAL)
• `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
• `tupleize_cols`: If False (default), write as a list of tuples, otherwise write in an expanded line format suitable for `read_csv`
• `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.
- `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.
24.2 JSON

Read and write JSON format files and strings.

24.2.1 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}

The format of the JSON string

<table>
<thead>
<tr>
<th>Format</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>split</td>
<td>dict like {index -&gt; [index], columns -&gt; [columns], data -&gt; [values]}</td>
</tr>
<tr>
<td>records</td>
<td>list like {{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.

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.

In [143]: dfj = DataFrame(randn(5, 2), columns=list('AB'))

In [144]: json = dfj.to_json()

In [145]: json
Out[145]: '{"A":{"0":-1.2945235903,"1":0.2766617129,"2":-0.0139597524,"3":-0.923060654,"4":0.8957173022},"B":{"0":0.4137381054,"1":-0.472034511,"2":-0.3625429925,"3":-0.0061535699,"4":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:
In [146]: dfjo = DataFrame(dict(A=range(1, 4), B=range(4, 7), C=range(7, 10)),
......: columns=list('ABC'), index=list('xyz'))
......:

In [147]: dfjo
Out[147]:
   A  B  C
x 1  4  7
y 2  5  8
z 3  6  9

In [148]: sjo = Series(dict(x=15, y=16, z=17), name='D')

In [149]: sjo
Out[149]:
   x  
  
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:

In [150]: dfjo.to_json(orient="columns")
Out[150]: '{"A":{"x":1,"y":4,"z":7},"B":{"x":4,"y":5,"z":6},"C":{"x":7,"y":8,"z":9}}'

Index oriented (the default for Series) similar to column oriented but the index labels are now primary:

In [151]: dfjo.to_json(orient="index")

In [152]: sjo.to_json(orient="index")
Out[152]: '{"x":15,"y":16,"z":17}''

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:

In [153]: dfjo.to_json(orient="records")
Out[153]: '[[1,4,7],[2,5,8],[3,6,9]]'

In [154]: sjo.to_json(orient="records")
Out[154]: '[15,16,17]''

Value oriented is a bare-bones option which serializes to nested JSON arrays of values only, column and index labels are not included:

In [155]: dfjo.to_json(orient="values")
Out[155]: '[[1,4,7],[2,5,8],[3,6,9]]'

Split oriented serializes to a JSON object containing separate entries for values, index and columns. Name is also included for Series:

In [156]: dfjo.to_json(orient="split")
Out[156]: '{"columns":["A","B","C"],"index":null,"data":null}''

In [157]: sjo.to_json(orient="split")
Out[157]: '{"name":"D","index":null,"data":null}''

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

```
In [158]: dfd = DataFrame(randn(5, 2), columns=list('AB'))
In [159]: dfd['date'] = Timestamp('20130101')
In [160]: dfd = dfd.sort_index(1, ascending=False)
In [161]: json = dfd.to_json(date_format='iso')
In [162]: json
Out[162]: '{"date":{"0":"2013-01-01T00:00:00.000000Z","1":"2013-01-01T00:00:00.000000Z","2":...}'
```

Writing in ISO date format, with microseconds

```
In [163]: json = dfd.to_json(date_format='iso', date_unit='us')
In [164]: json
Out[164]: '{"date":{"0":"2013-01-01T00:00:00.000000Z","1":"2013-01-01T00:00:00.000000Z","2":...}'
```

Epoch timestamps, in seconds

```
In [165]: json = dfd.to_json(date_format='epoch', date_unit='s')
In [166]: json
Out[166]: '{"date":{"0":1356998400,"1":1356998400,"2":1356998400,"3":1356998400,"4":1356998400},"B"...}'
```

Writing to a file, with a date index and a date column

```
In [167]: dfj2 = dfj.copy()
In [168]: dfj2['date'] = Timestamp('20130101')
In [169]: dfj2['ints'] = list(range(5))
In [170]: dfj2['bools'] = True
In [171]: dfj2.index = date_range('20130101', periods=5)
In [172]: dfj2.to_json('test.json')
In [173]: open('test.json').read()
Out[173]: '{"A":{"0":"1356998400000":-1.2945235903,"1357084800000":0.2766617129,"1357171200000":-0.01395...}
```

Fallback Behavior

If the JSON serializer cannot handle the container contents directly it will fallback in the following manner:

- if a `toDict` method is defined by the unrecognised object then that will be called and its returned `dict` will be JSON serialized.
- if a `default_handler` has been passed to `to_json` that will be called to convert the object.
• otherwise an attempt is made to convert the object to a `dict` by parsing its contents. However if the object is complex this will often fail with an `OverflowError`.

Your best bet when encountering `OverflowError` during serialization is to specify a `default_handler`. For example timedelta can cause problems:

```
In [141]: from datetime import timedelta
In [142]: dftd = DataFrame([timedelta(23), timedelta(seconds=5), 42])
In [143]: dftd.to_json()
```

```
---------------------------------------------------------------------------
OverflowError                                 Traceback (most recent call last)
OverflowError: Maximum recursion level reached
```

which can be dealt with by specifying a simple `default_handler`:

```
In [174]: dftd.to_json(default_handler=str)
Out[174]: '{"0":{"0":1987200000,"1":5000,"2":42}}'
```

```
In [175]: def my_handler(obj):
      ....:     return obj.total_seconds()
      ....:
```

### 24.2.2 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}`

The format of the JSON string

<table>
<thead>
<tr>
<th><code>split</code></th>
<th>dict like <code>{index -&gt; [index], columns -&gt; [columns], data -&gt; [values]}</code></th>
</tr>
</thead>
<tbody>
<tr>
<td><code>records</code></td>
<td>list like <code>[{column -&gt; value}, ..., {column -&gt; value}]</code></td>
</tr>
<tr>
<td><code>index</code></td>
<td>dict like <code>{index -&gt; {column -&gt; value}}</code></td>
</tr>
<tr>
<td><code>columns</code></td>
<td>dict like <code>{column -&gt; {index -&gt; value}}</code></td>
</tr>
<tr>
<td><code>values</code></td>
<td>just the values array</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

24.2. JSON
• **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.

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 [176]: pd.read_json(json)
Out[176]:
   A     B    date
0 -1.206412  2.565646  2013-01-01
1  1.431256  1.340309  2013-01-01
2 -1.170299 -0.226169  2013-01-01
3  0.410835  0.813850  2013-01-01
4  0.132003 -0.827317  2013-01-01
```

Reading from a file:
In [177]: `pd.read_json('test.json')`
Out[177]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>bools</th>
<th>date</th>
<th>ints</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>2013-01-01</td>
<td>-1.294524</td>
<td>0.413738</td>
<td>True</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>2013-01-02</td>
<td>0.276662</td>
<td>-0.472035</td>
<td>True</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>2013-01-03</td>
<td>-0.013960</td>
<td>-0.362543</td>
<td>True</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>2013-01-04</td>
<td>-0.006154</td>
<td>-0.923061</td>
<td>True</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>2013-01-05</td>
<td>0.895717</td>
<td>0.805244</td>
<td>True</td>
<td>4</td>
</tr>
</tbody>
</table>

Don’t convert any data (but still convert axes and dates):

In [178]: `pd.read_json('test.json', dtype=object).dtypes`
Out[178]:

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>object</td>
</tr>
<tr>
<td>B</td>
<td>object</td>
</tr>
<tr>
<td>bools</td>
<td>object</td>
</tr>
<tr>
<td>date</td>
<td>object</td>
</tr>
<tr>
<td>ints</td>
<td>object</td>
</tr>
</tbody>
</table>

dtype: object

Specify dtypes for conversion:

In [179]: `pd.read_json('test.json', dtype={'A' : 'float32', 'bools' : 'int8'}).dtypes`
Out[179]:

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>float32</td>
</tr>
<tr>
<td>B</td>
<td>float64</td>
</tr>
<tr>
<td>bools</td>
<td>int8</td>
</tr>
<tr>
<td>date</td>
<td>datetime64[ns]</td>
</tr>
<tr>
<td>ints</td>
<td>int64</td>
</tr>
</tbody>
</table>

dtype: object

Preserve string indices:

In [180]: `si = DataFrame(np.zeros((4, 4)), columns=list(range(4)), index=[str(i) for i in range(4)])`

In [181]: `si`
Out[181]:

<table>
<thead>
<tr>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

In [182]: `si.index`
Out[182]: Index([u'0', u'1', u'2', u'3'], dtype='object')

In [183]: `si.columns`
Out[183]: Int64Index([0, 1, 2, 3], dtype='int64')

In [184]: `json = si.to_json()`

In [185]: `sij = pd.read_json(json, convert_axes=False)`

In [186]: `sij`
In [187]: sij.index
Out[187]: Index(['0', '1', '2', '3'], dtype='object')

In [188]: sij.columns
Out[188]: Index(['0', '1', '2', '3'], dtype='object')

Dates written in nanoseconds need to be read back in nanoseconds:

In [189]: json = dfj2.to_json(date_unit='ns')

# Try to parse timestamps as milliseconds -> Won't Work
In [190]: dfju = pd.read_json(json, date_unit='ms')

In [191]: dfju
Out[191]:
   A         B     bools  date         ints
0 1.356998e+18 -1.294524  0.413738    True 2013-01-01 0
1 1.357085e+18  0.276662 -0.472035    True 2013-01-01 1
2 1.357171e+18 -0.013960 -0.362543    True 2013-01-01 2
3 1.357258e+18 -0.006154 -0.923061    True 2013-01-01 3
4 1.357344e+18  0.895717  0.805244    True 2013-01-01 4

# Let pandas detect the correct precision
In [192]: dfju = pd.read_json(json)

In [193]: dfju
Out[193]:
   A         B     bools  date         ints
0 2013-01-01 -1.294524  0.413738    True 2013-01-01 0
1 2013-01-02  0.276662 -0.472035    True 2013-01-01 1
2 2013-01-03 -0.013960 -0.362543    True 2013-01-01 2
3 2013-01-04 -0.006154 -0.923061    True 2013-01-01 3
4 2013-01-05  0.895717  0.805244    True 2013-01-01 4

# Or specify that all timestamps are in nanoseconds
In [194]: dfju = pd.read_json(json, date_unit='ns')

In [195]: dfju
Out[195]:
   A         B     bools  date         ints
0 2013-01-01 -1.294524  0.413738    True 2013-01-01 0
1 2013-01-02  0.276662 -0.472035    True 2013-01-01 1
2 2013-01-03 -0.013960 -0.362543    True 2013-01-01 2
3 2013-01-04 -0.006154 -0.923061    True 2013-01-01 3
4 2013-01-05  0.895717  0.805244    True 2013-01-01 4

The Numpy Parameter

Note: 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:

```python
In [196]: randfloats = np.random.uniform(-100, 1000, 10000)
In [197]: randfloats.shape = (1000, 10)
In [198]: dffloats = DataFrame(randfloats, columns=list('ABCDEFGHIJ'))
In [199]: jsonfloats = dffloats.to_json()
In [200]: timeit read_json(jsonfloats)
100 loops, best of 3: 12.7 ms per loop
In [201]: timeit read_json(jsonfloats, numpy=True)
100 loops, best of 3: 7.08 ms per loop
```

The speedup is less noticeable for smaller datasets:

```python
In [202]: jsonfloats = dffloats.head(100).to_json()
In [203]: timeit read_json(jsonfloats)
100 loops, best of 3: 5.08 ms per loop
In [204]: timeit read_json(jsonfloats, numpy=True)
100 loops, best of 3: 3.96 ms per loop
```

**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.

### 24.2.3 Normalization

New in version 0.13.0.

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 [205]: from pandas.io.json import json_normalize
In [206]: data = [{
            'state': 'Florida',
            'shortname': 'FL',
            'info': {
                'governor': 'Rick Scott'
            },
            'counties': [
                {'name': 'Dade', 'population': 12345},
                {'name': 'Broward', 'population': 40000},
                {'name': 'Palm Beach', 'population': 60000}
            ],
            'state': 'Ohio',
            'shortname': 'OH',
            'info': {}
        }
```

24.2. JSON
In [207]: json_normalize(data, 'counties', ['state', 'shortname', ['info', 'governor']])
Out[207]:
       name  population  info.governor  state  shortname
   0     Dade      12345          Rick Scott   Florida   FL
   1   Broward       40000            Rick Scott   Florida   FL
   2  Palm Beach      60000            Rick Scott   Florida   FL
   3   Summit         1234        John Kasich   Ohio     OH
   4  Cuyahoga        1337        John Kasich   Ohio     OH

24.3 HTML

24.3.1 Reading HTML Content

From version 0.12.0, the `read_html()` function can accept an HTML string/file/URL and will parse HTML tables into list of pandas DataFrames. Let’s look at a few examples.

**Warning:** We highly encourage you to read the HTML parsing gotchas regarding the issues surrounding the BeautifulSoup4/html5lib/lxml parsers.

Read a URL with no options

In [208]: url = 'http://www.fdic.gov/bank/individual/failed/banklist.html'

In [209]: dfs = read_html(url)

In [210]: dfs
Out[210]:
   Bank Name City ST CERT
0  Hometown National Bank Longview WA 35156
1  The Bank of Georgia Peachtree City GA 35259
2  Premier Bank Denver CO 34112
3  Edgebrook Bank Chicago IL 37772
4  Doral BankEn Espanol San Juan PR 32102
5  Capitol City Bank & Trust Company Atlanta GA 33938
6  Highland Community Bank Chicago IL 20290
   ... ... ... 
535  Hamilton Bank, NAEn Espanol Miami FL 24382
536  Sinclair National Bank Gravette AR 34248
537  Superior Bank, FSB Hinsdale IL 32646
538  Malta National Bank Malta OH 6629
539  First Alliance Bank & Trust Co. Manchester NH 34264
540  National State Bank of Metropolis Metropolis IL 3815
541  Bank of Honolulu Honolulu HI 21029
Acquiring Institution       Closing Date \
0  Twin City Bank            October 2, 2015
1  Fidelity Bank            October 2, 2015
2  United Fidelity Bank, fsb July 10, 2015
3  Republic Bank of Chicago May 8, 2015
4  Banco Popular de Puerto Rico February 27, 2015
5  First-Citizens Bank & Trust Company February 13, 2015
6  United Fidelity Bank, fsb January 23, 2015
.. ... ... ...
159 Israel Discount Bank of New York January 11, 2002
160 Delta Trust & Bank        September 7, 2001
161 Superior Federal, FSB     July 27, 2001
162 North Valley Bank         May 3, 2001
163 Southern New Hampshire Bank & Trust February 2, 2001
164 Banterra Bank of Marion  December 14, 2000
165 Bank of the Orient        October 13, 2000

Updated Date Loss Share Type Agreement Terminated Termination Date
0  October 7, 2015  NaN  NaN  NaN 
1  October 7, 2015  NaN  NaN  NaN 
2  July 28, 2015    none NaN  NaN 
3  July 23, 2015    none NaN  NaN 
4  May 13, 2015     none NaN  NaN 
5  April 21, 2015   none NaN  NaN 
6  April 21, 2015   none NaN  NaN 
.. ... ... ... ...
534 September 21, 2015 none NaN  NaN 
535 February 10, 2004 none NaN  NaN 
536 August 19, 2014   none NaN  NaN 
537 November 18, 2002 none NaN  NaN 
538 February 18, 2003 none NaN  NaN 
539 March 17, 2005    none NaN  NaN 
540 March 17, 2005    none NaN  NaN 
541 ... ... ... ... ...
542 rows x 10 columns]

Note: The data from the above URL changes every Monday so the resulting data above and the data below may be slightly different.

Read in the content of the file from the above URL and pass it to read_html as a string

In [211]: with open(file_path, 'r') as f: 
   ....:     dfs = read_html(f.read()) 
   ....:

In [212]: dfs
Out[212]:

[ Bank Name       City     ST     CERT  
0               Banks of Wisconsin d/b/a Bank of Kenosha Kenosha WI  35386 
1               Central Arizona Bank Scottsdale AZ  34527 
2               Sunrise Bank Valdosta GA  58185 
3               Pisgah Community Bank Asheville NC  58701 
4               Douglas County Bank Douglasville GA  21649 
5               Parkway Bank Lenoir NC  57158 
6               Chipola Community Bank Marianna FL  58034 
..               ... ... ... ...
499             Hamilton Bank, NAEn Espanol Miami FL  24382 
500             Sinclair National Bank Gravette AR  34248 

[542 rows x 10 columns]
<table>
<thead>
<tr>
<th>Acquiring Institution</th>
<th>Closing Date</th>
<th>Updated Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>Western State Bank</td>
<td>May 14, 2013</td>
<td>May 20, 2013</td>
</tr>
<tr>
<td>Synovus Bank</td>
<td>May 10, 2013</td>
<td>May 21, 2013</td>
</tr>
<tr>
<td>Capital Bank, N.A.</td>
<td>May 10, 2013</td>
<td>May 14, 2013</td>
</tr>
<tr>
<td>Hamilton State Bank</td>
<td>April 26, 2013</td>
<td>May 16, 2013</td>
</tr>
<tr>
<td>CertusBank, National Association</td>
<td>April 26, 2013</td>
<td>May 17, 2013</td>
</tr>
<tr>
<td>First Federal Bank of Florida</td>
<td>April 19, 2013</td>
<td>May 16, 2013</td>
</tr>
</tbody>
</table>

You can even pass in an instance of `StringIO` if you so desire

```
In [213]: with open(file_path, 'r') as f:
    ......:   sio = StringIO(f.read())
    ......:

In [214]: dfs = read_html(sio)
```

```
In [215]: dfs
```

```
<table>
<thead>
<tr>
<th>Bank Name</th>
<th>City</th>
<th>ST</th>
<th>CERT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Banks of Wisconsin d/b/a Bank of Kenosha</td>
<td>Kenosha WI</td>
<td>35386</td>
<td></td>
</tr>
<tr>
<td>Central Arizona Bank</td>
<td>Scottsdale AZ</td>
<td>34527</td>
<td></td>
</tr>
<tr>
<td>Sunrise Bank</td>
<td>Valdosta GA</td>
<td>58185</td>
<td></td>
</tr>
<tr>
<td>Pisgah Community Bank</td>
<td>Asheville NC</td>
<td>58701</td>
<td></td>
</tr>
<tr>
<td>Douglas County Bank</td>
<td>Douglasville GA</td>
<td>21649</td>
<td></td>
</tr>
<tr>
<td>Parkway Bank</td>
<td>Lenoir NC</td>
<td>57158</td>
<td></td>
</tr>
<tr>
<td>Chipola Community Bank</td>
<td>Marianna FL</td>
<td>58034</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Acquiring Institution</th>
<th>Closing Date</th>
<th>Updated Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>Western State Bank</td>
<td>May 14, 2013</td>
<td>May 20, 2013</td>
</tr>
<tr>
<td>Synovus Bank</td>
<td>May 10, 2013</td>
<td>May 21, 2013</td>
</tr>
<tr>
<td>Capital Bank, N.A.</td>
<td>May 10, 2013</td>
<td>May 14, 2013</td>
</tr>
<tr>
<td>Hamilton State Bank</td>
<td>April 26, 2013</td>
<td>May 16, 2013</td>
</tr>
</tbody>
</table>
5 CertusBank, National Association April 26, 2013 May 17, 2013
6 First Federal Bank of Florida April 19, 2013 May 16, 2013

[506 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

match = 'Metcalf Bank'
df_list = read_html(url, match=match)

Specify a header row (by default <th> elements are used to form the column index); if specified, the header row is taken from the data minus the parsed header elements (<th> elements).

dfs = read_html(url, header=0)

Specify an index column
dfs = read_html(url, index_col=0)

Specify a number of rows to skip
dfs = read_html(url, skiprows=0)

Specify a number of rows to skip using a list (xrange (Python 2 only) works as well)
dfs = read_html(url, skiprows=range(2))

Don’t infer numeric and date types
dfs = read_html(url, infer_types=False)

Specify an HTML attribute
df1 = read_html(url, attrs={'id': 'table'})
df2 = read_html(url, attrs={'class': 'sortable'})
print(np.array_equal(df1[0], df2[0]))  # Should be True

Use some combination of the above
dfs = read_html(url, match='Metcalf Bank', index_col=0)

Read in pandas to_html output (with some loss of floating point precision)
df = DataFrame(randn(2, 2))
s = df.to_html(float_format='{0:.40g}'.format)
dfin = 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)

```python
dfs = read_html(url, 'Metcalf Bank', index_col=0, flavor=['lxml'])
```

or

```python
dfs = 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.*

```python
dfs = read_html(url, 'Metcalf Bank', index_col=0, flavor=['lxml', 'bs4'])
```

### 24.3.2 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 [216]:** `df = DataFrame(randn(2, 2))`

**In [217]:** `df`

```
Out[217]:
0  1
0 -0.184744 0.496971
1 -0.856240 1.857977
```

**In [218]:** `print(df.to_html())`  # raw html

```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 [219]: 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> 

HTML: 

`float_format` takes a Python callable to control the precision of floating point values

In [220]: print(df.to_html(float_format='{0:.10f}'.format))
<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>-0.1847438576</td> 
<td>0.4969711327</td> 
</tr> 
<tr> 
<th>1</th> 
<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

In [221]: print(df.to_html(bold_rows=False))
<table border="1" class="dataframe">
<thead>
<tr style="text-align: right;"> 
<th></th> 
<th>0</th>  
<th>1</th> 
</tr> 
</thead>
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.

```
In [222]: print(df.to_html(classes=['awesome_table_class', 'even_more_awesome_class']))
```

```
<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>
```

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 [223]: df = DataFrame({'a': list('&<>'), 'b': randn(3)})
```

```
Escaped:
```

```
In [224]: print(df.to_html(escape=False))
```

```
<table border="1" class="dataframe">
<thead>
<tr style="text-align: right;">
<th></th>
<th>a</th>
<th>b</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>
```
Not escaped:

In [225]: print(df.to_html(escape=False))

Note: Some browsers may not show a difference in the rendering of the previous two HTML tables.

24.4 Excel files

The read_excel() method can read Excel 2003 (.xls) and Excel 2007+ (.xlsx) files using the xlrd Python module. 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.
24.4.1 Reading Excel Files

In the most basic use-case, read_excel takes a path to an Excel file, and the sheetname indicating which sheet to parse.

```
# Returns a DataFrame
read_excel('path_to_file.xls', sheetname='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 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.

```python
# using the ExcelFile class
data = {}
with pd.ExcelFile('path_to_file.xls') as xls:
    data['Sheet1'] = read_excel(xls, 'Sheet1', index_col=None, na_values=['NA'])
    data['Sheet2'] = read_excel(xls, 'Sheet2', index_col=None, na_values=['NA'])
```

```python
# equivalent using the read_excel function
data = read_excel('path_to_file.xls', ['Sheet1', 'Sheet2'], index_col=None, na_values=['NA'])
```

New in version 0.12.

ExcelFile has been moved to the top level namespace.

New in version 0.17.

read_excel can take an ExcelFile object as input

**Specifying Sheets**

**Note:** The second argument is sheetname, not to be confused with ExcelFile.sheet_names
Note: An ExcelFile’s attribute sheet_names provides access to a list of sheets.

- The arguments sheetname allows specifying the sheet or sheets to read.
- The default value for sheetname 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.

# Returns a DataFrame
```
read_excel('path_to_file.xls', 'Sheet1', index_col=None, na_values=['NA'])
```

Using the sheet index:
```
# Returns a DataFrame
read_excel('path_to_file.xls', 0, index_col=None, na_values=['NA'])
```

Using all default values:
```
# Returns a DataFrame
read_excel('path_to_file.xls')
```

Using None to get all sheets:
```
# Returns a dictionary of DataFrames
read_excel('path_to_file.xls', sheetname=None)
```

Using a list to get multiple sheets:
```
# Returns the 1st and 4th sheet, as a dictionary of DataFrames.
read_excel('path_to_file.xls', sheetname=['Sheet1',3])
```

New in version 0.16.

read_excel can read more than one sheet, by setting sheetname to either a list of sheet names, a list of sheet positions, or None to read all sheets.

New in version 0.13.

Sheets can be specified by sheet index or sheet name, using an integer or string, respectively.

**Reading a MultiIndex**

New in version 0.17.

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:
```
In [226]: df = pd.DataFrame({'a':[1,2,3,4], 'b':[5,6,7,8]},
                      index=pd.MultiIndex.from_product([['a','b'],['c','d']]))
```

```
In [227]: df.to_excel('path_to_file.xlsx')
```
In [228]: df = pd.read_excel('path_to_file.xlsx', index_col=[0,1])

In [229]: df
Out[229]:
   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.

In [230]: df.index = df.index.set_names(['lvl1', 'lvl2'])

In [231]: df.to_excel('path_to_file.xlsx')

In [232]: df = pd.read_excel('path_to_file.xlsx', index_col=[0,1])

In [233]: df
Out[233]:
   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

In [234]: df.columns = pd.MultiIndex.from_product([['a'],['b', 'd']], names=['c1', 'c2'])

In [235]: df.to_excel('path_to_file.xlsx')

In [236]: df = pd.read_excel('path_to_file.xlsx', index_col=[0,1], header=[0,1])

In [237]: df
Out[237]:
   c1  a
   c2  b  d
   lvl1 lvl2
   a  c  1  5
d  2  6
   b  c  3  7
d  4  8

**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.

### 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 `parse_cols` keyword to allow you to specify a subset of columns to parse.

If `parse_cols` is an integer, then it is assumed to indicate the last column to be parsed.
If `parse_cols` is a list of integers, then it is assumed to be the file column indices to be parsed.

```python
read_excel('path_to_file.xls', 'Sheet1', parse_cols=[0, 2, 3])
```

## 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
read_excel('path_to_file.xls', 'Sheet1', converters={'MyBools': bool})
```

This options 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
cfun = lambda x: int(x) if x else -1
read_excel('path_to_file.xls', 'Sheet1', converters={'MyInts': cfun})
```

### 24.4.2 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. One difference from 0.12.0 is that the `index_label` will be placed in the second row instead of the first. You can get the previous behaviour by setting the `merge_cells` option in `to_excel()` to `False`:

```python
df.to_excel('path_to_file.xlsx', index_label='label', merge_cells=False)
```

The Panel class also has a `to_excel` instance method, which writes each DataFrame in the Panel to a separate sheet. In order to write separate DataFrames to separate sheets in a single Excel file, one can pass an `ExcelWriter`.

```python
with 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

New in version 0.17.
Pandas supports writing Excel files to buffer-like objects such as StringIO or BytesIO using ExcelWriter.

New in version 0.17.
Added support for Openpyxl >= 2.2

```python
# Safe import for either Python 2.x or 3.x
try:
    from io import BytesIO
except ImportError:
    from cStringIO import StringIO as BytesIO

bio = BytesIO()

# By setting the 'engine' in the ExcelWriter constructor.
writer = 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.

24.4.3 Excel writer engines

New in version 0.13.
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 and openpyxl for .xlsm files and xlwt for .xls files. If you have multiple engines installed, you can set the default engine through setting the config options io.excel.xlsx.writer and io.excel.xls.writer. pandas will fall back on openpyxl for .xlsx 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: This includes stable support for Openpyxl from 1.6.1. However, it is advised to use version 2.2 and higher, especially when working with styles.
- xlsxwriter
- xlwt
By setting the 'engine' in the DataFrame and Panel 'to_excel()' methods.

df.to_excel('path_to_file.xlsx', sheet_name='Sheet1', engine='xlsxwriter')

By setting the 'engine' in the ExcelWriter constructor.

writer = ExcelWriter('path_to_file.xlsx', engine='xlsxwriter')

Or via pandas configuration.

from pandas import options
options.io.excel.xlsx.writer = 'xlsxwriter'

df.to_excel('path_to_file.xlsx', sheet_name='Sheet1')

## 24.5 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_table 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:

```python
clipdf = pd.read_clipboard()
```

```
In [238]: clipdf
Out[238]:
   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.

```
In [239]: df=pd.DataFrame(randn(5,3))
```

```
In [240]: df
Out[240]:
     0     1     2
0 -0.288267 -0.084905  0.004772
1  1.382989  0.343635 -1.253994
2 -0.124925  0.212244  0.496654
3  0.525417  1.238640 -1.210543
4 -1.175743 -0.172372 -0.734129

In [241]: df.to_clipboard()

In [242]: pd.read_clipboard()
Out[242]:
     0     1     2
0 -0.288267 -0.084905  0.004772
1  1.382989  0.343635 -1.253994
```
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 gtk or PyQt4 modules) on Linux to use these methods.

24.6 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 [243]: df
Out[243]:
          0         1         2
0 -0.288267 -0.084905  0.004772
1  1.382989  0.343635 -1.253994
2 -0.124925  0.212244  0.496654
3  0.525417  1.238640 -1.210543
4 -1.175743 -0.172372 -0.734129
```

```python
In [244]: 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 [245]: read_pickle('foo.pkl')
Out[245]:
          0         1         2
0 -0.288267 -0.084905  0.004772
1  1.382989  0.343635 -1.253994
2 -0.124925  0.212244  0.496654
3  0.525417  1.238640 -1.210543
4 -1.175743 -0.172372 -0.734129
```

**Warning:** Loading pickled data received from untrusted sources can be unsafe. See: [http://docs.python.org/2.7/library/pickle.html](http://docs.python.org/2.7/library/pickle.html)

**Warning:** Several internal refactorings, 0.13 (*Series Refactoring*), and 0.15 (*Index Refactoring*), preserve compatibility with pickles created prior to these versions. However, these must be read with `pd.read_pickle`, rather than the default python `pickle.load`. See this question for a detailed explanation.

Note: These methods were previously `pd.save` and `pd.load`, prior to 0.12.0, and are now deprecated.

24.7 msgpack (experimental)

New in version 0.13.0.

Starting in 0.13.0, pandas is supporting the `msgpack` format for object serialization. This is a lightweight portable binary format, similar to binary JSON, that is highly space efficient, and provides good performance both on the
writing (serialization), and reading (deserialization).

**Warning:** This is a very new feature of pandas. We intend to provide certain optimizations in the io of the msgpack data. Since this is marked as an EXPERIMENTAL LIBRARY, the storage format may not be stable until a future release.

```python
In [246]: df = DataFrame(np.random.rand(5,2),columns=list('AB'))

In [247]: df.to_msgpack('foo.msg')

In [248]: pd.read_msgpack('foo.msg')
Out[248]:
   A   B
0 0.154336 0.710999
1 0.398096 0.765220
2 0.586749 0.293052
3 0.290293 0.710783
4 0.988593 0.062106

In [249]: s = Series(np.random.rand(5),index=date_range('20130101',periods=5))

You can pass a list of objects and you will receive them back on deserialization.

In [250]: pd.to_msgpack('foo.msg', df, 'foo', np.array([1,2,3]), s)

In [251]: pd.read_msgpack('foo.msg')
Out[251]:
   A         B
0 0.154336 0.710999
1 0.398096 0.765220
2 0.586749 0.293052
3 0.290293 0.710783
4 0.988593 0.062106

foo
[1 2 3]
2013-01-01 0.690810
2013-01-02 0.235907
2013-01-03 0.712756
2013-01-04 0.119599
2013-01-05 0.023493
Freq: D, dtype: float64
```

You can pass `iterator=True` to iterate over the unpacked results

```python
In [252]: for o in pd.read_msgpack('foo.msg', iterator=True):
   print o
   ......:        print o
   ......:  A         B
0 0.154336 0.710999
1 0.398096 0.765220
2 0.586749 0.293052
3 0.290293 0.710783
4 0.988593 0.062106
foo
[1 2 3]
2013-01-01 0.690810
2013-01-02 0.235907
2013-01-03 0.712756
2013-01-04 0.119599
2013-01-05 0.023493
Freq: D, dtype: float64
```
You can pass `append=True` to the writer to append to an existing pack.

```python
In [253]: df.to_msgpack('foo.msg', append=True)
```

```python
In [254]: pd.read_msgpack('foo.msg')
Out[254]:

```  

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.154336</td>
<td>0.710999</td>
</tr>
<tr>
<td>1</td>
<td>0.398096</td>
<td>0.765220</td>
</tr>
<tr>
<td>2</td>
<td>0.586749</td>
<td>0.293052</td>
</tr>
<tr>
<td>3</td>
<td>0.290293</td>
<td>0.710783</td>
</tr>
<tr>
<td>4</td>
<td>0.988593</td>
<td>0.062106</td>
</tr>
</tbody>
</table>

```

Unlike other io methods, `to_msgpack` is available on both a per-object basis, `df.to_msgpack()` and using the top-level `pd.to_msgpack(...)` where you can pack arbitrary collections of python lists, dicts, scalars, while intermixing pandas objects.

```python
In [255]: pd.to_msgpack('foo2.msg', { 'dict' : [ { 'df' : df }, { 'string' : 'foo' }, { 'scalar' : 1. }, { 's' : s } ] })
```

```python
In [256]: pd.read_msgpack('foo2.msg')
Out[256]:

```  

```
```

#### 24.7.1 Read/Write API

```
```

Furthermore you can concatenate the strings to produce a list of the original objects.

```python
In [258]: pd.read_msgpack(df.to_msgpack() + s.to_msgpack())
```

```python
Out [258]:
```

```
```

```
```
HBDFStore 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:** As of version 0.15.0, pandas requires PyTables >= 3.0.0. Stores written with prior versions of pandas / PyTables >= 2.3 are fully compatible (this was the previous minimum PyTables required version).

**Warning:** There is a PyTables indexing bug which may appear when querying stores using an index. If you see a subset of results being returned, upgrade to PyTables >= 3.2. Stores created previously will need to be rewritten using the updated version.

**Warning:** As of version 0.17.0, HDFStore will not drop rows that have all missing values by default. Previously, if all values (except the index) were missing, HDFStore would not write those rows to disk.

```
In [259]: store = HDFStore('store.h5')

In [260]: print(store)
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
Empty

``` Objects can be written to the file just like adding key-value pairs to a dict:

```
In [261]: np.random.seed(1234)

In [262]: index = date_range('1/1/2000', periods=8)

In [263]: s = Series(randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [264]: df = DataFrame(randn(8, 3), index=index,
....:
       columns=['A', 'B', 'C'])

In [265]: wp = Panel(randn(2, 5, 4), items=['Item1', 'Item2'],
....:
       major_axis=date_range('1/1/2000', periods=5),
....:
       minor_axis=['A', 'B', 'C', 'D'])

# store.put('s', s) is an equivalent method
In [266]: store['s'] = s
```
In [267]: store['df'] = df

In [268]: store['wp'] = wp

# the type of stored data
In [269]: store.root.wp._v_attr.pandas_type
Out[269]: 'wide'

In [270]: store
Out[270]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df frame (shape->[8,3])
/s series (shape->[5])
/wp wide (shape->[2,5,4])

In a current or later Python session, you can retrieve stored objects:

# store.get('df') is an equivalent method
In [271]: store['df']
Out[271]:
     A     B     C
2000-01-01 0.887163 0.859588 -0.636524
2000-01-02 0.015696 -2.242685  1.150036
2000-01-03 0.991946  0.953324 -2.021255
2000-01-04 -0.334077  0.002118  0.405453
2000-01-05  0.289092  1.321158 -1.546906
2000-01-06 -0.202646 -0.655969  0.193421
2000-01-07  0.553439  1.318152 -0.469305
2000-01-08  0.675554 -1.817027 -0.183109

# dotted (attribute) access provides get as well
In [272]: store.df
Out[272]:
     A     B     C
2000-01-01 0.887163 0.859588 -0.636524
2000-01-02 0.015696 -2.242685  1.150036
2000-01-03 0.991946  0.953324 -2.021255
2000-01-04 -0.334077  0.002118  0.405453
2000-01-05  0.289092  1.321158 -1.546906
2000-01-06 -0.202646 -0.655969  0.193421
2000-01-07  0.553439  1.318152 -0.469305
2000-01-08  0.675554 -1.817027 -0.183109

Deletion of the object specified by the key

# store.remove('wp') is an equivalent method
In [273]: del store['wp']

In [274]: store
Out[274]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df frame (shape->[8,3])
/s series (shape->[5])

Closing a Store, Context Manager
In [275]: store.close()

In [276]: store
Out[276]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
File is CLOSED

In [277]: store.is_open
Out[277]: False

# Working with, and automatically closing the store with the context
# manager
In [278]: with HDFStore('store.h5') as store:
    ....:     store.keys()
    ....:

24.8.1 Read/Write API

HDFStore supports an top-level API using read_hdf for reading and to_hdf for writing, similar to how read_csv and to_csv work. (new in 0.11.0)

In [279]: df_tl = DataFrame(dict(A=list(range(5)), B=list(range(5))))

In [280]: df_tl.to_hdf('store_tl.h5','table',append=True)

In [281]: read_hdf('store_tl.h5', 'table', where = ['index>2'])
Out[281]:
   A  B
0  3  3
1  4  4

As of version 0.17.0, HDFStore will no longer drop rows that are all missing by default. This behavior can be enabled by setting dropna=True.

In [282]: df_with_missing = pd.DataFrame({'col1':[0, np.nan, 2],
                                      'col2':[1, np.nan, np.nan]})

In [283]: df_with_missing.to_hdf('file.h5', 'df_with_missing',
                                      format = 'table', mode='w')

In [284]: pd.read_hdf('file.h5', 'df_with_missing')
Out[284]:
   col1  col2
0   0   1
1  NaN  NaN
2   2  NaN

24.8. HDF5 (PyTables)
In [286]: df_with_missing.to_hdf('file.h5', 'df_with_missing',
   format = 'table', mode='w', dropna=True)
   
In [287]: pd.read_hdf('file.h5', 'df_with_missing')
Out[287]:
   col1  col2
0     0     1
2     2  NaN

This is also true for the major axis of a Panel:

In [288]: matrix = [[[np.nan, np.nan, np.nan],[1, np.nan, np.nan]],
   [[np.nan, np.nan, np.nan], [np.nan, 5, 6]],
   [[np.nan, np.nan, np.nan], [np.nan, 3, np.nan]]
   
In [289]: panel_with_major_axis_all_missing = Panel(matrix,
   items=['Item1', 'Item2', 'Item3'],
   major_axis=[1,2],
   minor_axis=['A', 'B', 'C'])
   
In [290]: panel_with_major_axis_all_missing
Out[290]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 2 (major_axis) x 3 (minor_axis)
Items axis: Item1 to Item3
Major_axis axis: 1 to 2
Minor_axis axis: A to C

In [291]: panel_with_major_axis_all_missing.to_hdf('file.h5', 'panel',
   dropna = True,
   format='table',
   mode='w')
   
In [292]: reloaded = read_hdf('file.h5', 'panel')

In [293]: reloaded
Out[293]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 1 (major_axis) x 3 (minor_axis)
Items axis: Item1 to Item3
Major_axis axis: 2 to 2
Minor_axis axis: A to C

24.8.2 Fixed Format

Note: This was prior to 0.13.0 the Storer 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 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.

```python
DataFrame(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.
this store must be selected in its entirety
```

### 24.8.3 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 & query type operations are supported. This format is specified by format='table' or format='t' to `append` or `put` or `to_hdf` New in version 0.13.

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 [294]: store = HDFStore('store.h5')
In [295]: df1 = df[0:4]
In [296]: df2 = df[4:]
# append data (creates a table automatically)
In [297]: store.append('df', df1)
In [298]: store.append('df', df2)
In [299]: store
Out[299]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df frame_table (typ->appendable,nrows->8,ncols->3,indexers->[index])

# select the entire object
In [300]: store.select('df')
Out[300]:
<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>B</td>
<td>C</td>
</tr>
<tr>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>2000-01-01</td>
<td>0.887163</td>
<td>0.859588</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>0.015696</td>
<td>-2.242685</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>0.991946</td>
<td>0.953324</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>-0.334077</td>
<td>0.002118</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>0.289092</td>
<td>1.321158</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>-0.202646</td>
<td>-0.655969</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>0.553439</td>
<td>1.318152</td>
</tr>
<tr>
<td>2000-01-08</td>
<td>0.675554</td>
<td>-1.817027</td>
</tr>
</tbody>
</table>

# the type of stored data
In [301]: store.root.df._v_attrs.pandas_type
Out[301]: 'frame_table'
```

Note: You can also create a table by passing format='table' or format='t' to a `put` operation.
24.8.4 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 [302]: `store.put('foo/bar/bah', df)`
In [303]: `store.append('food/orange', df)`
In [304]: `store.append('food/apple', df)`

In [305]: `store`  
Out[305]: `<class 'pandas.io.pytables.HDFStore'>`  
File path: store.h5  
/df frame_table {typ->appendable, nrows->8, ncols->3, indexers->[index]}  
/foo/bar/bah frame {shape->[8, 3]}  
/food/apple frame_table {typ->appendable, nrows->8, ncols->3, indexers->[index]}  
/food/orange frame_table {typ->appendable, nrows->8, ncols->3, indexers->[index]}

# a list of keys are returned  
In [306]: `store.keys()`  
Out[306]: `['/df', '/food/apple', '/food/orange', '/foo/bar/bah']`

# remove all nodes under this level  
In [307]: `store.remove('food')`

In [308]: `store`  
Out[308]: `<class 'pandas.io.pytables.HDFStore'>`  
File path: store.h5  
/df frame_table {typ->appendable, nrows->8, ncols->3, indexers->[index]}  
/foo/bar/bah frame {shape->[8, 3]}

24.8.5 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 appends will truncate strings at this length.

Passing `min_itemsize={'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`.

In [309]: `df_mixed = DataFrame({  
...:     'A' : randn(8),  
...:     'B' : randn(8),  
...:     'C' : np.array(randn(8),dtype='float32'),  
...:     'string' : 'string',  
...:     'int' : 1,  
...:     'bool' : True,  
...:     'datetime64' : Timestamp('20010102')),  
...:     index=list(range(8))})`
In [310]: df_mixed.ix[3:5,['A', 'B', 'string', 'datetime64']] = np.nan

In [311]: store.append('df_mixed', df_mixed, min_itemsize = {'values': 50})

In [312]: df_mixed1 = store.select('df_mixed')

In [313]: df_mixed1
Out[313]:
   A   B   C   bool  datetime64  int   string
0  0.704721 -1.152659 -0.430096  True  2001-01-02   1   string
1 -0.785435  0.631979  0.767369  True  2001-01-02   1   string
2  0.462060  0.039513  0.984920  True  2001-01-02   1   string
3  NaN    NaN    0.270836  True  NaT       1      NaN
4  NaN    NaN  1.391986  True  NaT       1      NaN
5  NaN    NaN   0.079842  True  NaT       1      NaN
6 2.007843  0.152631  0.399965  True  2001-01-02   1   string
7 0.226963  0.164530 -1.027851  True  2001-01-02   1   string

In [314]: df_mixed1.get_dtype_counts()
Out[314]:
bool       1
datetime64[ns]  1
float32      1
float64      2
int64       1
object      1
dtype: int64

# we have provided a minimum string column size
In [315]: store.root.df_mixed.table
Out[315]:
/df_mixed/table (Table(8,)) ''
   description := {
      "index": Int64Col(shape=(), dflt=0, pos=0),
      "values_block_0": Float64Col(shape=(2,), dflt=0.0, pos=1),
      "values_block_1": Float32Col(shape=(1,), dflt=0.0, pos=2),
      "values_block_2": Int64Col(shape=(1,), dflt=0, pos=3),
      "values_block_3": Int64Col(shape=(1,), dflt=0, pos=4),
      "values_block_4": BoolCol(shape=(1,), dflt=False, pos=5),
      "values_block_5": StringCol(itemsize=50, shape=(1,), dflt='', pos=6)}
byteorder := 'little'
chunkshape := (689,)
autoindex := True
colindexes := {
   "index": Index(6, medium, shuffle, zlib(1)).is_csi=False}

Storing Multi-Index DataFrames

Storing multi-index dataframes as tables is very similar to storing/selecting from homogeneous index DataFrames.

In [316]: index = 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 [317]: df_mi = DataFrame(np.random.randn(10, 3), index=index, 
......:       columns=['A', 'B', 'C'])
......:

In [318]: df_mi
Out[318]:
foo bar
foo one -0.584718 0.816594 -0.081947
    two -0.344766 0.528288 -1.068989
    three -0.511881 0.291205  0.566534
bar one  0.503592 0.285296  0.484288
    two  1.363482 -0.781105 -0.468018
baz two  1.224574 -1.281108  0.875476
    three -1.710715 -0.450765  0.749164
qux one -0.203933 -0.182175  0.680656
    two -1.818499  0.047072  0.394844
    three -0.248432 -0.617707 -0.682884

In [319]: store.append('df_mi', df_mi)

In [320]: store.select('df_mi')
Out[320]:
foo bar
foo one -0.584718 0.816594 -0.081947
    two -0.344766 0.528288 -1.068989
    three -0.511881 0.291205  0.566534
bar one  0.503592 0.285296  0.484288
    two  1.363482 -0.781105 -0.468018
baz two  1.224574 -1.281108  0.875476
    three -1.710715 -0.450765  0.749164
qux one -0.203933 -0.182175  0.680656
    two -1.818499  0.047072  0.394844
    three -0.248432 -0.617707 -0.682884

# the levels are automatically included as data columns

In [321]: store.select('df_mi', 'foo=bar')
Out[321]:
foo bar
foo one -0.584718 0.816594 -0.081947
    two -0.344766 0.528288 -1.068989
    three -0.511881 0.291205  0.566534
bar one  0.503592 0.285296  0.484288
    two  1.363482 -0.781105 -0.468018
baz two  1.224574 -1.281108  0.875476
    three -1.710715 -0.450765  0.749164
qux one -0.203933 -0.182175  0.680656
    two -1.818499  0.047072  0.394844
    three -0.248432 -0.617707 -0.682884

24.8.6 Querying

Querying a Table

**Warning:** This query capabilities have changed substantially starting in 0.13.0. Queries from prior version are accepted (with a DeprecationWarning) printed if its not string-like.

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 a DataFrame
• **major_axis, minor_axis, and items** are supported indexers of the Panel
• if **data_columns** are specified, these can be used as additional indexers

Valid comparison operators are:
=, ==, !=, >, >=, <, <=

Valid boolean expressions are combined with:
• |: or
• &: and
• ( 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"'
• "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
string = "HolyMoly'
store.select('df', 'index == string')

instead of this
string = "HolyMoly'
store.select('df', 'index == %s' % 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
store.select('df', 'index == $r' % string)

which will quote string.

Here are some examples:

**In [322]:** dfq = DataFrame(randn(10,4),columns=list('ABCD'),index=date_range('20130101',periods=10))

**In [323]:** store.append('dfq',dfq,format='table',data_columns=True)

Use boolean expressions, with in-line function evaluation.

**In [324]:** store.select('dfq','index>Timestamp('20130104') & columns=['A', 'B'])

**Out[324]:**

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013-01-05</td>
<td>1.210384</td>
<td>0.797435</td>
</tr>
<tr>
<td>2013-01-06</td>
<td>-0.850346</td>
<td>1.176812</td>
</tr>
<tr>
<td>2013-01-07</td>
<td>0.984188</td>
<td>-0.121728</td>
</tr>
<tr>
<td>2013-01-08</td>
<td>0.796595</td>
<td>-0.474021</td>
</tr>
<tr>
<td>2013-01-09</td>
<td>-0.804834</td>
<td>-2.123620</td>
</tr>
<tr>
<td>2013-01-10</td>
<td>0.334198</td>
<td>0.536784</td>
</tr>
</tbody>
</table>

Use and inline column reference

**In [325]:** store.select('dfq','where="A>0 or C>0"')

**Out[325]:**

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013-01-01</td>
<td>0.436258</td>
<td>-1.703013</td>
<td>0.393711</td>
<td>-0.479324</td>
</tr>
<tr>
<td>2013-01-02</td>
<td>-0.299016</td>
<td>0.694103</td>
<td>0.678630</td>
<td>0.239556</td>
</tr>
<tr>
<td>2013-01-03</td>
<td>0.151227</td>
<td>0.816127</td>
<td>1.893534</td>
<td>0.639633</td>
</tr>
<tr>
<td>2013-01-04</td>
<td>-0.962029</td>
<td>-2.085266</td>
<td>1.930247</td>
<td>-1.735349</td>
</tr>
<tr>
<td>2013-01-05</td>
<td>1.210384</td>
<td>0.797435</td>
<td>-0.379811</td>
<td>0.702562</td>
</tr>
<tr>
<td>2013-01-07</td>
<td>0.984188</td>
<td>-0.121728</td>
<td>2.365769</td>
<td>0.496143</td>
</tr>
<tr>
<td>2013-01-08</td>
<td>0.796595</td>
<td>-0.474021</td>
<td>-0.056696</td>
<td>1.357797</td>
</tr>
<tr>
<td>2013-01-10</td>
<td>0.334198</td>
<td>0.536784</td>
<td>-0.743830</td>
<td>-0.320204</td>
</tr>
</tbody>
</table>

Works with a Panel as well.

**In [326]:** store.append('wp',wp)

**In [327]:** store

**Out[327]:**

<class 'pandas.io.pytables.HDFStore'>
File path: store.h5

/df          frame_table (typ->appendable,nrows->8,ncols->3,indexers->[index])
/df_mi       frame_table (typ->appendable_multi,nrows->10,ncols->5,indexers->[index],dc->)
/df_mixed    frame_table (typ->appendable,nrows->8,ncols->7,indexers->[index])
In [328]: store.select('wp', "major_axis>Timestamp('20000102') & minor_axis=['A', 'B']")
Out[328]:
<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

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 [329]: store.select('df', "columns=['A', 'B']")
Out[329]:
   A       B
2000-01-01 0.887163 0.859588
2000-01-02 0.015696 -2.242685
2000-01-03 0.991946 0.953324
2000-01-04 -0.334077 0.002118
2000-01-05 0.289092 1.321158
2000-01-06 -0.202646 -0.655969
2000-01-07 0.553439 1.318152
2000-01-08 0.289092 1.321158

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.

# this is effectively what the storage of a Panel looks like
In [330]: wp.to_frame()
Out[330]:
   Item1   Item2
major   minor
2000-01-01 A  1.058969  0.215269
   B -0.397840  0.841009
   C  0.337438 -1.445810
   D  1.047579 -1.401973
2000-01-02 A  1.045938 -0.100918
   B  0.863717 -0.548242
   C -0.122092 -0.144620
   ...   ...   ...
2000-01-04 B  0.036142  0.307969
   C -0.204978 -0.208499
   D  0.247792  1.033801
2000-01-05 A -0.897157 -2.400454
   B -0.136795  2.030604
   C  0.018289 -1.142631
   D  0.755414  0.211883

[20 rows x 2 columns]

# limiting the search
In [331]: store.select('wp',"major_axis>20000102 & minor_axis=['A','B']",
       ...:     start=0, stop=10)
       ...:     ....
Out[331]:
<class 'pandas.core.panel.Panel'>
Using timedelta64[ns]

New in version 0.13.

Beginning in 0.13.0, 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:

```
In [332]: from datetime import timedelta

In [333]: dftd = DataFrame(dict(A = Timestamp('20130101'), B = [ Timestamp('20130101') + timedelta(days=i,seconds=10) for i in range(10) ]))

In [334]: dftd['C'] = dftd['A']-dftd['B']

In [335]: dftd
```

```
Out[335]:
      A          B          C
0 2013-01-01 00:00:10 -1 days 00:23:59
1 2013-01-01 00:00:10 -2 days 00:23:59
2 2013-01-01 00:00:10 -3 days 00:23:59
3 2013-01-01 00:00:10 -4 days 00:23:59
4 2013-01-01 00:00:10 -5 days 00:23:59
5 2013-01-01 00:00:10 -6 days 00:23:59
6 2013-01-01 00:00:10 -7 days 00:23:59
7 2013-01-01 00:00:10 -8 days 00:23:59
8 2013-01-01 00:00:10 -9 days 00:23:59
9 2013-01-01 00:00:10 -10 days 00:23:59
```

```
In [336]: store.append('dftd',dftd,data_columns=True)

In [337]: store.select('dftd','C<'-'-3.5D')
```

```
Out[337]:
      A          B          C
4 2013-01-01 00:00:10 -5 days 00:23:59
5 2013-01-01 00:00:10 -6 days 00:23:59
6 2013-01-01 00:00:10 -7 days 00:23:59
7 2013-01-01 00:00:10 -8 days 00:23:59
8 2013-01-01 00:00:10 -9 days 00:23:59
9 2013-01-01 00:00:10 -10 days 00:23:59
```

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 automatically created (starting 0.10.1) on the indexables and any data columns you specify. This behavior can be turned off by passing `index=False` to `append`.

# we have automatically already created an index (in the first section)
In [338]: i = store.root.df.table.cols.index.index

In [339]: i.optlevel, i.kind
Out[339]: (6, 'medium')

# change an index by passing new parameters
In [340]: store.create_table_index('df', optlevel=9, kind='full')

In [341]: i = store.root.df.table.cols.index.index

In [342]: i.optlevel, i.kind
Out[342]: (9, 'full')

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.

In [343]: df_dc = df.copy()

In [344]: df_dc['string'] = 'foo'

In [345]: df_dc.ix[4:6,'string'] = np.nan

In [346]: df_dc.ix[7:9,'string'] = 'bar'

In [347]: df_dc['string2'] = 'cool'

In [348]: df_dc.ix[1:3,['B','C']] = 1.0

In [349]: df_dc
Out[349]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>string</th>
<th>string2</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01</td>
<td>0.887163</td>
<td>0.859588</td>
<td>-0.636524</td>
<td>foo</td>
<td>cool</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>0.015696</td>
<td>1.000000</td>
<td>1.000000</td>
<td>foo</td>
<td>cool</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>0.991946</td>
<td>1.000000</td>
<td>1.000000</td>
<td>foo</td>
<td>cool</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>-0.334077</td>
<td>0.002118</td>
<td>0.405453</td>
<td>foo</td>
<td>cool</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>0.289092</td>
<td>1.321158</td>
<td>-1.546906</td>
<td>NaN</td>
<td>cool</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>-0.202646</td>
<td>-0.655969</td>
<td>0.193421</td>
<td>NaN</td>
<td>cool</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>0.553439</td>
<td>1.318152</td>
<td>-0.469305</td>
<td>foo</td>
<td>cool</td>
</tr>
<tr>
<td>2000-01-08</td>
<td>0.675554</td>
<td>-1.817027</td>
<td>-0.183109</td>
<td>bar</td>
<td>cool</td>
</tr>
</tbody>
</table>

# on-disk operations
In [350]: store.append('df_dc', df_dc, data_columns = ['B', 'C', 'string', 'string2'])

In [351]: store.select('df_dc', [ Term('B>0') ])
Out[351]:

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>string</th>
<th>string2</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01</td>
<td>0.887163</td>
<td>0.859588</td>
<td>-0.636524</td>
<td>foo</td>
<td>cool</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>0.015696</td>
<td>1.000000</td>
<td>1.000000</td>
<td>foo</td>
<td>cool</td>
</tr>
</tbody>
</table>
2000-01-01 0.887163 0.859588 -0.636524 foo cool
2000-01-02 0.015696 1.000000 1.000000 foo cool
2000-01-03 0.991946 1.000000 1.000000 foo cool
2000-01-04 -0.334077 0.002118 0.405453 foo cool
2000-01-05 0.289092 1.321158 -1.546906 NaN cool
2000-01-07 0.553439 1.318152 -0.469305 foo cool

# getting creative
In [352]: store.select('df_dc', 'B > 0 & C > 0 & string == foo')
Out[352]:
A   B   C      string string2
2000-01-02 0.015696 1.000000 1.000000 foo cool
2000-01-03 0.991946 1.000000 1.000000 foo cool
2000-01-04 -0.334077 0.002118 0.405453 foo cool

# this is in-memory version of this type of selection
In [353]: df_dc[(df_dc.B > 0) & (df_dc.C > 0) & (df_dc.string == 'foo')]
Out[353]:
A   B   C      string string2
2000-01-02 0.015696 1.000000 1.000000 foo cool
2000-01-03 0.991946 1.000000 1.000000 foo cool
2000-01-04 -0.334077 0.002118 0.405453 foo cool

# we have automagically created this index and the B/C/string/string2
# columns are stored separately as 'PyTables' columns
In [354]: store.root.df_dc.table
Out[354]:
/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='', pos=4),
        "string2": StringCol(itemsize=4, shape=(), dflt='', pos=5)}
    byteorder := 'little'
    chunkshape := (1680,)
    autoindex := True
    colindexes := {
        "index": Index(6, medium, shuffle, zlib(1)).is_csi=False,
        "C": Index(6, medium, shuffle, zlib(1)).is_csi=False,
        "B": Index(6, medium, shuffle, zlib(1)).is_csi=False,
        "string2": Index(6, medium, shuffle, zlib(1)).is_csi=False,
        "string": 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**

Starting in 0.11.0, 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 [355]: for df in store.select('df', chunksize=3):
        ....:     print(df)
        ....:
pandas: powerful Python data analysis toolkit, Release 0.17.0

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-01</td>
<td>0.887163</td>
<td>0.859588</td>
<td>-0.636524</td>
</tr>
<tr>
<td>2000-01-02</td>
<td>0.015696</td>
<td>-2.242685</td>
<td>1.150036</td>
</tr>
<tr>
<td>2000-01-03</td>
<td>0.991946</td>
<td>0.953324</td>
<td>-2.021255</td>
</tr>
<tr>
<td>2000-01-04</td>
<td>-0.334077</td>
<td>0.002118</td>
<td>0.405453</td>
</tr>
<tr>
<td>2000-01-05</td>
<td>0.289092</td>
<td>1.321158</td>
<td>-1.546906</td>
</tr>
<tr>
<td>2000-01-06</td>
<td>-0.202646</td>
<td>-0.655969</td>
<td>0.193421</td>
</tr>
<tr>
<td>2000-01-07</td>
<td>0.553439</td>
<td>1.318152</td>
<td>-0.469305</td>
</tr>
<tr>
<td>2000-01-08</td>
<td>0.675554</td>
<td>-1.817027</td>
<td>-0.183109</td>
</tr>
</tbody>
</table>

**Note:** New in version 0.12.0.

You can also use the iterator with `read_hdf` which will open, then automatically close the store when finished iterating.

```python
for df in 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.

In [356]: dfeq = DataFrame({'number': np.arange(1,11)})

In [357]: dfeq
Out[357]:
number
0 1
1 2
2 3
3 4
4 5
5 6
6 7
7 8
8 9
9 10

In [358]: store.append('dfeq', dfeq, data_columns=['number'])

In [359]: def chunks(l, n):
       ...
       return [l[i:i+n] for i in range(0, len(l), n)]
       ...

In [360]: evens = [2,4,6,8,10]

In [361]: coordinates = store.select_as_coordinates('dfeq','number=evens')

In [362]: for c in chunks(coordinates, 2):
       ...
       print store.select('dfeq',where=c)
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.

```
In [363]: store.select_column('df_dc', 'index')
Out[363]:
0 2000-01-01
1 2000-01-02
2 2000-01-03
3 2000-01-04
4 2000-01-05
5 2000-01-06
6 2000-01-07
7 2000-01-08
Name: index, dtype: datetime64[ns]
```

```
In [364]: store.select_column('df_dc', 'string')
Out[364]:
0 foo
1 foo
2 foo
3 foo
4 NaN
5 NaN
6 foo
7 bar
Name: string, dtype: object
```

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.

```
In [365]: df_coord = DataFrame(np.random.randn(1000,2),index=date_range('20000101',periods=1000))
In [366]: store.append('df_coord',df_coord)
In [367]: c = store.select_as_coordinates('df_coord','index>20020101')
In [368]: c.summary()
Out[368]: u'Int64Index: 268 entries, 732 to 999'
In [369]: store.select('df_coord',where=c)
Out[369]:
          0       1
2002-01-02 -0.667994 -0.368175
```
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.

```
In [370]: df_mask = DataFrame(np.random.randn(1000,2),index=date_range('20000101',periods=1000))
In [371]: store.append('df_mask',df_mask)
In [372]: c = store.select_column('df_mask','index')
In [373]: where = c[DatetimeIndex(c).month==5].index
In [374]: store.select('df_mask',where=where)
Out[374]:
         0         1
2000-05-01 -0.098554 -0.280782
2000-05-02  0.739851  1.627182
2000-05-03  0.030132 -0.145601
2000-05-04  0.227530  1.048856
2000-05-05  1.773939  1.116887
2000-05-06  1.081251  1.509416
2000-05-07 -0.498694  0.913155
... ... ...
2002-05-25 -0.497252  0.348099
2002-05-26 -1.287350 -1.488122
2002-05-27 -0.726220  0.507747
2002-05-28  0.189871  0.980528
2002-05-29  0.555156  0.369371
2002-05-30 -0.637441 -3.434819
2002-05-31 -0.070283 -0.278044
[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.
In [375]: store.get_storer('df_dc').nrows  
Out[375]: 8

Multiple Table Queries

New in 0.10.1 are the methods append_to_multiple and select_as_multiple, that 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 entire 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.

In [376]: df_mt = DataFrame(randn(8, 6), index=date_range('1/1/2000', periods=8),  
columns=['A', 'B', 'C', 'D', 'E', 'F'])

In [377]: df_mt['foo'] = 'bar'

In [378]: df_mt.ix[1, ('A', 'B')] = np.nan

# you can also create the tables individually
In [379]: store.append_to_multiple({'df1_mt': ['A', 'B'], 'df2_mt': None },  
   df_mt, selector='df1_mt')

In [380]: store  
Out[380]: <class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df            frame_table (typ->appendable,nrows->8,ncols->7,indexers->[index])
/df1_mt        frame_table (typ->appendable,nrows->8,ncols->2,indices->[A,B])
/df2_mt        frame_table (typ->appendable,nrows->8,ncols->5,indices->[B,C])
/df_coord      frame_table (typ->appendable,nrows->8,ncols->2,indices->[index])
/df_dc         frame_table (typ->appendable,nrows->8,ncols->5,indices->[index])
/df_mask       frame_table (typ->appendable,nrows->8,ncols->5,indices->[index])
/df_mi         frame_table (typ->appendable_multi,nrows->10,ncols->5,indices->[index])
/df_mixed      frame_table (typ->appendable,nrows->8,ncols->7,indices->[index])
/df_eq         frame_table (typ->appendable,nrows->10,ncols->1,indices->[index],dc->[number])
/df_f         frame_table (typ->appendable,nrows->10,ncols->4,indices->[index],dc->[A,B,C,D])
/df_td         frame_table (typ->appendable,nrows->10,ncols->3,indices->[index],dc->[A,B,C])
/foo/bar/bah   frame (shape->[8,3])
/wp            wide_table (typ->appendable,nrows->20,ncols->2,indices->[major_axis,minor_axis])

# individual tables were created
In [381]: store.select('df1_mt')
Out[381]:
24.8.7 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. This is especially true in higher dimensional objects (Panel and Panel4D). 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.

# returns the number of rows deleted
In [384]: store.remove('wp', 'major_axis>20000102' )
Out[384]: 12

In [385]: store.select('wp')
Out[385]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 2 (major_axis) x 4 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-02 00:00:00
Minor_axis axis: A to D

**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 clean the file, use `ptrepack`

## 24.8.8 Notes & Caveats

### Compression

PyTables allows the stored data to be compressed. This applies to all kinds of stores, not just tables.

- Pass `complevel=int` for a compression level (1-9, with 0 being no compression, and the default)
- Pass `complib=lib` where lib is any of zlib, bzip2, lzo, blosc for whichever compression library you prefer.

HDFStore will use the file based compression scheme if no overriding `complib` or `complevel` options are provided. blosc offers very fast compression, and is my most used. Note that lzo and bzip2 may not be installed (by Python) by default.

Compression for all objects within the file

```python
store_compressed = HDFStore('store_compressed.h5', complevel=9, complib='blosc')
```

Or on-the-fly compression (this only applies to tables). You can turn off file compression for a specific table by passing `complevel=0`

```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.

```bash
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-threadsafe 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 its items (Panel) / columns (DataFrame) are fixed; only exactly the same columns can be appended

• 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.

### 24.8.9 DataTypes

The `HDFStore` will map an object dtype 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><code>floating</code>: float64, float32, float16</td>
<td>np.nan</td>
</tr>
<tr>
<td><code>integer</code>: int64, int32, int8, uint64, uint32, uint8</td>
<td></td>
</tr>
<tr>
<td><code>datetime64[ns]</code></td>
<td>NaT</td>
</tr>
<tr>
<td><code>timedelta64[ns]</code></td>
<td>NaT</td>
</tr>
<tr>
<td><code>categorical</code>: see the section below</td>
<td></td>
</tr>
<tr>
<td><code>object</code>: strings</td>
<td>np.nan</td>
</tr>
</tbody>
</table>

Unicode columns are not supported, and will fail.

#### Categorical Data

New in version 0.15.2.

Writing data to a `HDFStore` that contains a `category` dtype was implemented in 0.15.2. Queries work the same as if it was an object array. However, the `category` typed data is stored in a more efficient manner.

```python
In [386]: dfcat = DataFrame({ 'A' : Series(list('aabbcdba')).astype('category'), 'B' : np.random.randn(8) })
.....:

In [387]: dfcat
Out[387]:
   A   B
0  a  0.811031
1  a -0.356817
2  b  1.047085
3  b  0.664705
4  c -0.086919
5  d  0.416905
6  b -0.764381
7  a -0.287229

In [388]: dfcat.dtypes
Out[388]:
A  category
B  float64
```
**Warning:** The format of the Categorical is readable by prior versions of pandas (< 0.15.2), but will retrieve the data as an integer based column (e.g. the codes). However, the categories can be retrieved but require the user to select them manually using the explicit meta path. The data is stored like so:

```python
In [394]: cstore
Out[394]:
<class 'pandas.io.pytables.HDFStore'>
File path: cats.h5
/dfcat frame_table (typ->appendable,nrows->8,ncols->2,indexers->[index],dc->)
/dfcat/meta/A/meta series_table (typ->appendable,nrows->4,ncols->1,indexers->[index],dc->)

# to get the categories
In [395]: cstore.select('dfcat/meta/A/meta')
Out[395]:
0  a
1  b
2  c
3  d
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.

Starting in 0.11.0, 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 [396]: dfs = DataFrame(dict(A = 'foo', B = 'bar'),index=list(range(5)))

In [397]: dfs
Out[397]:
   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 [398]: store.append('dfs', dfs, min_itemsize = 30)

In [399]: store.get_storer('dfs').table
Out[399]:
/dfs/table (Table(5,)) ''
   description := {
       "index": Int64Col(shape=(), dflt=0, pos=0),
       "values_block_0": StringCol(itemsize=30, shape=(2,), dflt='', 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 size is calculated
In [400]: store.append('dfs2', dfs, min_itemsize = { 'A' : 30 })

In [401]: store.get_storer('dfs2').table
Out[401]:
/dfs2/table (Table(5,)) ''
   description := {
       "index": Int64Col(shape=(), dflt=0, pos=0),
       "values_block_0": StringCol(itemsize=3, shape=(1,), dflt='', pos=1),
       "A": StringCol(itemsize=30, shape=(), dflt='', pos=2)
       byteorder := 'little'
       chunkshape := (1598,)
       autoindex := True
       colindexes := {
           "A": Index(6, medium, shuffle, zlib(1)).is_csi=False,
           "index": 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 [402]: dfss = DataFrame(dict(A = ['foo','bar','nan']))
```

24.8. HDF5 (PyTables)
In [403]: dfss
Out[403]:
   A
0  foo
1  bar
2  nan

In [404]: store.append('dfss', dfss)
In [405]: store.select('dfss')
Out[405]:
   A
0  foo
1  bar
2  NaN

# here you need to specify a different nan rep
In [406]: store.append('dfss2', dfss, nan_rep='_nan_')
In [407]: store.select('dfss2')
Out[407]:
   A
0  foo
1  bar
2  nan

24.8.10 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 [408]: np.random.seed(1)
In [409]: 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 [410]: df_for_r.head()
Out[410]:
    class  first    second
0      0  0.417022  0.326645
1      0  0.720324  0.527058
2      1  0.000114  0.885942
3      1  0.302333  0.357270
4      1  0.146756  0.908535

In [411]: store_export = HDFStore('export.h5')
In [412]: store_export.append('df_for_r', df_for_r, data_columns=df_dc.columns)
In [413]: store_export
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`:

```r
# 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)
  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 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  0.417 0.327  0.417
2  0.720 0.527  0.720
3  0.000 0.886  0.000
4  0.302 0.357  0.302
5  0.147 0.908  0.147
6  0.092 0.623  0.092
```

**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.

---

### 24.8.11 Backwards Compatibility

0.10.1 of `HDFStore` can read tables created in a prior version of pandas, however query terms using the prior (undocumented) methodology are unsupported. `HDFStore` will issue a warning if you try to use a legacy-format file.
# a legacy store

```python
In [415]: legacy_store = HDFStore(legacy_file_path, 'r')
```

```python
In [416]: new_store = legacy_store.copy('store_new.h5')
```

```python
In [417]: new_store.close()
```

### 24.8.12 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 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 expected rows that PyTables will expected. 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.

### 24.8.13 Experimental

HDFStore supports Panel4D storage.
In [419]: p4d = Panel4D({ 'l1' : wp })

In [420]: p4d
Out[420]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 1 (labels) x 2 (items) x 5 (major_axis) x 4 (minor_axis)
Labels axis: l1 to l1
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

In [421]: store.append('p4d', p4d)

In [422]: store
Out[422]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df frame_table (typ->appendable,nrows->8,ncols->3,indexers->[index])
/df1_mt frame_table (typ->appendable,nrows->8,ncols->2,indexers->[index],dc->[A,B])
/df2_mt frame_table (typ->appendable,nrows->8,ncols->5,indexers->[index])
/df_coord frame_table (typ->appendable,nrows->1000,ncols->2,indexers->[index])
/df_dc frame_table (typ->appendable,nrows->8,ncols->5,indexers->[index],dc->[B,C,string,string2])
/df_mask frame_table (typ->appendable,nrows->1000,ncols->2,indexers->[index])
/df_mi frame_table (typ->appendable_multi,nrows->10,ncols->5,indexers->[index],dc->[A,B])
/df_mixed frame_table (typ->appendable,nrows->8,ncols->7,indexers->[index])
/dfq frame_table (typ->appendable,nrows->10,ncols->4,indexers->[index],dc->[A,B,C,D])
/dfs frame_table (typ->appendable,nrows->5,ncols->2,indexers->[index])
/dfs2 frame_table (typ->appendable,nrows->5,ncols->2,indexers->[index],dc->[A])
/dfs2 frame_table (typ->appendable,nrows->5,ncols->2,indexers->[index],dc->[A])
/dfs2 frame_table (typ->appendable,nrows->5,ncols->2,indexers->[index],dc->[A])
/df_mixed frame_table (typ->appendable,nrows->10,ncols->5,indexers->[index])
/foo/bar/bah frame (shape->[8,3])
/p4d frame_table (typ->appendable,nrows->40,ncols->1,indexers->[items,major_axis,minor_axis])
/wp frame_table (typ->appendable,nrows->8,ncols->2,indexers->[major_axis,minor_axis])

These, by default, index the three axes items, major_axis, minor_axis. On an AppendableTable it is possible to setup with the first append a different indexing scheme, depending on how you want to store your data. Pass the axes keyword with a list of dimensions (currently must by exactly 1 less than the total dimensions of the object). This cannot be changed after table creation.

In [423]: store.append('p4d2', p4d, axes=['labels', 'major_axis', 'minor_axis'])

In [424]: store
Out[424]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df frame_table (typ->appendable,nrows->8,ncols->3,indexers->[index])
/df1_mt frame_table (typ->appendable,nrows->8,ncols->2,indexers->[index],dc->[A,B])
/df2_mt frame_table (typ->appendable,nrows->8,ncols->5,indexers->[index])
/df_coord frame_table (typ->appendable,nrows->1000,ncols->2,indexers->[index])
/df_dc frame_table (typ->appendable,nrows->8,ncols->5,indexers->[index],dc->[B,C,string,string2])
/df_mask frame_table (typ->appendable,nrows->1000,ncols->2,indexers->[index])
/df_mi frame_table (typ->appendable,nrows->10,ncols->5,indexers->[index],dc->[A,B])
/df_mixed frame_table (typ->appendable,nrows->8,ncols->7,indexers->[index])
/dfq frame_table (typ->appendable,nrows->10,ncols->4,indexers->[index],dc->[A,B,C,D])
/dfs frame_table (typ->appendable,nrows->5,ncols->2,indexers->[index])
/dfs2 frame_table (typ->appendable,nrows->5,ncols->2,indexers->[index],dc->[A])
/dfs2 frame_table (typ->appendable,nrows->5,ncols->2,indexers->[index],dc->[A])
/dfs2 frame_table (typ->appendable,nrows->5,ncols->2,indexers->[index],dc->[A])
/df_mixed frame_table (typ->appendable,nrows->10,ncols->5,indexers->[index])
/foo/bar/bah frame (shape->[8,3])
/p4d frame_table (typ->appendable,nrows->40,ncols->1,indexers->[items,major_axis,minor_axis])
/wp frame_table (typ->appendable,nrows->8,ncols->2,indexers->[major_axis,minor_axis])
24.9 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.

New in version 0.14.0.

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:

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>read_sql_table</code></td>
<td>Read SQL database table into a DataFrame.</td>
</tr>
<tr>
<td><code>read_sql_query</code></td>
<td>Read SQL query into a DataFrame.</td>
</tr>
<tr>
<td><code>read_sql</code></td>
<td>Read SQL query or database table into a DataFrame.</td>
</tr>
<tr>
<td><code>DataFrame.to_sql</code></td>
<td>Write records stored in a DataFrame to a SQL database.</td>
</tr>
</tbody>
</table>

24.9.1 pandas.read_sql_table

`pandas.read_sql_table(table_name, con=None, schema=None, index_col=None, coerce_float=True, parse_dates=None, columns=None, chunksize=None)`

Read SQL database table into a DataFrame.

Given a table name and an SQLAlchemy connectable, returns a DataFrame. This function does not support DBAPI connections.

**Parameters**

- **table_name**: string
  - Name of SQL table in database
- **con**: SQLAlchemy connectable (or database string URI)
  - Sqlite DBAPI connection mode not supported
- **schema**: string, default None
  - SQL database schema
- **index_col**: string, default None
  - Index or columns (default None)
- **coerce_float**: boolean, default True
  - Convert floating point numbers to Python floats
- **parse_dates**: boolean, default None
  - Parse string values as dates
- **columns**: list, default None
  - All columns or a list of columns to read
- **chunksize**: int, default None
  - Number of rows per batch for query execution
Name of SQL schema in database to query (if database flavor supports this). If None, use default schema (default).

**index_col** : string, optional, default: None

Column to set as index

**coerce_float** : boolean, default True

Attempt to convert values to 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 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

**chunksize** : int, default None

If specified, return an iterator where chunksize is the number of rows to include in each chunk.

**Returns** DataFrame

See also:

**read_sql_query** Read SQL query into a DataFrame.

**read_sql**

**Notes**

Any datetime values with time zone information will be converted to UTC

### 24.9.2 pandas.read_sql_query

**pandas.read_sql_query** *(sql, con, index_col=None, coerce_float=True, params=None, parse_dates=None, chunksize=None)*

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** : string SQL query or SQLAlchemy Selectable (select or text object) to be executed.
- **con** : SQLAlchemy connectable(engine/connection) or database string URI or sqlite3 DBAPI2 connection Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.
**index_col** : string, optional, default: None

Column name to use as index for the returned DataFrame object.

**coerce_float** : boolean, default True

Attempt to convert values to 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 %\(\{\text{name}\}\)s so use params=\{'\text{name}': 'value'\}

**parse_dates** : list or dict, default: None

- List of column names to parse as dates
- Dict of {\text{\text{column}}_\text{name}: \text{\text{\text{format}}}_\text{\text{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 {\text{\text{column}}_\text{name}: \text{\text{\text{arg} \text{dict}}}}, where the arg dict corresponds to the keyword arguments of \text{\text{pandas.to_datetime()}} Especially useful with databases without native Datetime support, such as SQLite

**chunksize** : int, default None

If specified, return an iterator where \text{\text{chunksize}} is the number of rows to include in each chunk.

**Returns** DataFrame

**See also:**

- read_sql_table Read SQL database table into a DataFrame
- read_sql

**Notes**

Any datetime values with time zone information parsed via the \text{\text{parse_dates}} parameter will be converted to UTC

### 24.9.3 pandas.read_sql

pandas.read_sql(sql, con, index_col=None, coerce_float=True, params=None, parse_dates=None, columns=None, chunksize=None)

Read SQL query or database table into a DataFrame.

**Parameters**

- sql : string SQL query or SQLAlchemy Selectable (select or text object) to be executed, or database table name.
- con : SQLAlchemy connectable(engine/connection) or database string URI or DBAPI2 connection (fallback mode) Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.
- index_col : string, optional, default: None
column name to use as index for the returned DataFrame object.

coerce_float : boolean, default True

Attempt to convert values to 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

See also:

read_sql_table Read SQL database table into a DataFrame
read_sql_query Read SQL query into a DataFrame

Notes

This function is a convenience wrapper around read_sql_table and read_sql_query (and for backward compatibility) and will delegate to the specific function depending on the provided input (database table name or sql query). The delegated function might have more specific notes about their functionality not listed here.

24.9.4 pandas.DataFrame.to_sql

DataFrame.to_sql(name, con, flavor='sqlite', schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None)

Write records stored in a DataFrame to a SQL database.

Parameters name : string

Name of SQL table

con : SQLAlchemy engine or DBAPI2 connection (legacy mode)
Using SQLAlchemy makes it possible to use any DB supported by that library. If a
DBAPI2 object, only sqlite3 is supported.

**flavor**: `{'sqlite', 'mysql'}`, default `sqlite`

The flavor of SQL to use. Ignored when using SQLAlchemy engine. `mysql` is dep-
recated and will be removed in future versions, but it will be further supported through
SQLAlchemy engines.

**schema**: string, default None

Specify the schema (if database flavor supports this). If None, use default schema.

**if_exists**: `{'fail', 'replace', 'append'}`, default `fail`

- fail: If table exists, do nothing.
- replace: If table exists, drop it, recreate it, and insert data.
- append: If table exists, insert data. Create if does not exist.

**index**: boolean, default True

Write DataFrame index as a column.

**index_label**: string 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, default None

If not None, then rows will be written in batches of this size at a time. If None, all rows
will be written at once.

**dtype**: dict of column name to SQL type, default None

Optional specifying the datatype for columns. The SQL type should be a SQLAlchemy
type, or a string for sqlite3 fallback connection.

*Note*: The function `read_sql()` is a convenience wrapper around `read_sql_table()` and
`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 charac-
ters.

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

```
In [426]: from sqlalchemy import create_engine

# Create your engine.
In [427]: engine = create_engine('sqlite:////:memory:)
```

If you want to manage your own connections you can pass one of those instead:

```
with engine.connect() as conn, conn.begin():
    data = pd.read_sql_table('data', conn)
```
### 24.9.5 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>

In [428]: `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:

In [429]: `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:

In [430]: `from sqlalchemy.types import String`
In [431]: `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.

### 24.9.6 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 [432]: `pd.read_sql_table('data', engine)`
Out[432]:
```
   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
```

You can also specify the name of the column as the DataFrame index, and specify a subset of columns to be read.
In [433]: pd.read_sql_table('data', engine, index_col='id')
Out[433]:
    index    Date  Col_1  Col_2  Col_3
   id
26  0  2010-10-18    X  27.50   True
42  1  2010-10-19    Y -12.50  False
63  2  2010-10-20    Z  5.73   True

In [434]: pd.read_sql_table('data', engine, columns=['Col_1', 'Col_2'])
Out[434]:
   Col_1  Col_2
   0      X  27.50
   1      Y -12.50
   2      Z  5.73

And you can explicitly force columns to be parsed as dates:

In [435]: pd.read_sql_table('data', engine, parse_dates=['Date'])
Out[435]:
     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

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()

24.9.7 Schema support

New in version 0.15.0.

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:

    df.to_sql('table', engine, schema='other_schema')
    pd.read_sql_table('table', engine, schema='other_schema')

24.9.8 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.

In [436]: pd.read_sql_query('SELECT * FROM data', engine)
Out[436]:
    index id    Date  Col_1  Col_2  Col_3
   0     0   26  2010-10-18 00:00:00.000000    X  27.50   1
   1     1   42  2010-10-19 00:00:00.000000    Y -12.50  0
   2     2   63  2010-10-20 00:00:00.000000    Z  5.73   1

Of course, you can specify a more “complex” query.
In [437]: pd.read_sql_query("SELECT id, Col_1, Col_2 FROM data WHERE id = 42;", engine)
Out[437]:
<table>
<thead>
<tr>
<th>id</th>
<th>Col_1</th>
<th>Col_2</th>
</tr>
</thead>
<tbody>
<tr>
<td>42</td>
<td>Y</td>
<td>-12.5</td>
</tr>
</tbody>
</table>

The `read_sql_query()` function supports a `chunksize` argument. Specifying this will return an iterator through chunks of the query result:

In [438]: df = pd.DataFrame(np.random.randn(20, 3), columns=list('abc'))
In [439]: df.to_sql('data_chunks', engine, index=False)
In [440]: for chunk in pd.read_sql_query("SELECT * FROM data_chunks", engine, chunksize=5):
   .....:     print(chunk)
   .....:
<table>
<thead>
<tr>
<th>a</th>
<th>b</th>
<th>c</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.280665</td>
<td>-0.073113</td>
</tr>
<tr>
<td>1</td>
<td>0.369493</td>
<td>1.904659</td>
</tr>
<tr>
<td>2</td>
<td>0.659050</td>
<td>-1.627438</td>
</tr>
<tr>
<td>3</td>
<td>0.420282</td>
<td>0.810952</td>
</tr>
<tr>
<td>4</td>
<td>-0.400878</td>
<td>0.824006</td>
</tr>
<tr>
<td>a</td>
<td>b</td>
<td>c</td>
</tr>
<tr>
<td>----</td>
<td>------</td>
<td>------</td>
</tr>
<tr>
<td>0</td>
<td>1.954878</td>
<td>-1.331952</td>
</tr>
<tr>
<td>1</td>
<td>-1.650721</td>
<td>-0.890556</td>
</tr>
<tr>
<td>2</td>
<td>1.956079</td>
<td>-0.326499</td>
</tr>
<tr>
<td>3</td>
<td>1.114383</td>
<td>-0.586524</td>
</tr>
<tr>
<td>4</td>
<td>0.875839</td>
<td>0.623362</td>
</tr>
</tbody>
</table>

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])
```

### 24.9.9 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

24.9.10 Advanced SQLAlchemy queries

You can use SQLAlchemy constructs to describe your query.

Use `sqlalchemy.text()` to specify query parameters in a backend-neutral way

In [441]: import sqlalchemy as sa

In [442]: pd.read_sql(sa.text('SELECT * FROM data where Col_1=:col1'), engine, params={'col1': 'X'})

Out[442]:
    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

In [443]: metadata = sa.MetaData()

In [444]: 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 [445]: pd.read_sql(sa.select([data_table]).where(data_table.c.Col_3 == True), engine)

Out[445]:
    index  Date       Col_1  Col_2  Col_3
0       0 2010-10-18     X   27.50   True
1       2 2010-10-20     Z   5.73    True

You can combine SQLAlchemy expressions with parameters passed to `read_sql()` using `sqlalchemy.bindparam()`

In [446]: import datetime as dt

In [447]: expr = sa.select([data_table]).where(data_table.c.Date > sa.bindparam('date'))

In [448]: pd.read_sql(expr, engine, params={'date': dt.datetime(2010, 10, 18)})

Out[448]:
    index  Date       Col_1  Col_2  Col_3
24.10 Google BigQuery (Experimental)

New in version 0.13.0.

The pandas.io.gbq module provides a wrapper for Google’s BigQuery analytics web service to simplify retrieving results from BigQuery tables using SQL-like queries. Result sets are parsed into a pandas DataFrame with a shape and data types derived from the source table. Additionally, DataFrames can be inserted into new BigQuery tables or appended to existing tables.

**Warning:** To use this module, you will need a valid BigQuery account. Refer to the [BigQuery Documentation](https://developers.google.com/api-client-library/python/) for details on the service itself.

The key functions are:

- `read_gbq(query[, project_id, index_col, ...])` Load data from Google BigQuery.
- `to_gbq(dataframe, destination_table, project_id)` Write a DataFrame to a Google BigQuery table.

24.10.1 pandas.io.gbq.read_gbq

pandas.io.gbq.read_gbq(query, project_id=None, index_col=None, col_order=None, reauth=False, verbose=True)

Load data from Google BigQuery.

**THIS IS AN EXPERIMENTAL LIBRARY**

The main method a user calls to execute a Query in Google BigQuery and read results into a pandas DataFrame using the v2 Google API client for Python. Documentation for the API is available at [https://developers.google.com/api-client-library/python/](https://developers.google.com/api-client-library/python/). Authentication to the Google BigQuery service is via OAuth 2.0 using the product name ‘pandas GBQ’.

**Parameters**

- **query**: str
  SQL-Like Query to return data values
- **project_id**: str
  Google BigQuery Account project ID.
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 : boolean (default False)
   Force Google BigQuery to reauthenticate the user. This is useful if multiple accounts
   are used.

verbose : boolean (default True)
   Verbose output

Returns df: DataFrame
   DataFrame representing results of query

24.10.2 pandas.io.gbq.to_gbq

pandas.io.gbq.to_gbq(dataframe, destination_table, project_id, chunksize=10000, verbose=True,
reauth=False, if_exists='fail')

Write a DataFrame to a Google BigQuery table.

Parameters dataframe : DataFrame
   DataFrame to be written

destination_table : string
   Name of table to be written, in the form ‘dataset.tablename’

project_id : str
   Google BigQuery Account project ID.

chunksize : int (default 10000)
   Number of rows to be inserted in each chunk from the dataframe.

verbose : boolean (default True)
   Show percentage complete

reauth : boolean (default False)
   Force Google BigQuery to reauthenticate the user. This is useful if multiple accounts
   are used.

if_exists : {'fail', 'replace', 'append'}, default ‘fail’
   ‘fail’: If table exists, do nothing. ‘replace’: If table exists, drop it, recreate it, and insert
   data. ‘append’: If table exists, insert data. Create if does not exist.

24.10.3 Querying

Suppose you want to load all data from an existing BigQuery table : test_dataset.test_table into a DataFrame using
the read_gbq() function.
# Insert your BigQuery Project ID Here
# Can be found in the Google web console
projectid = "xxxxxxxx"

data_frame = pd.read_gbq('SELECT * FROM test_dataset.test_table', projectid)

You will then be authenticated to the specified BigQuery account via Google’s Oauth2 mechanism. In general, this is as simple as following the prompts in a browser window which will be opened for you. Should the browser not be available, or fail to launch, a code will be provided to complete the process manually. Additional information on the authentication mechanism can be found here.

You can define which column from BigQuery to use as an index in the destination DataFrame as well as a preferred column order as follows:

data_frame = pd.read_gbq('SELECT * FROM test_dataset.test_table',
    index_col='index_column_name',
    col_order=['col1', 'col2', 'col3'], projectid)

**Note:** You can find your project id in the BigQuery management console.

**Note:** You can toggle the verbose output via the `verbose` flag which defaults to `True`.

### 24.10.4 Writing DataFrames

Assume we want to write a DataFrame `df` into a BigQuery table using `to_gbq()`.

**In [449]:**

```python
df = pd.DataFrame({
    'my_string': list('abc'),
    'my_int64': list(range(1, 4)),
    'my_float64': np.arange(4.0, 7.0),
    'my_bool1': [True, False, True],
    'my_bool2': [False, True, False],
    'my_dates': pd.date_range('now', periods=3)
})
```

**Out[450]:**

```plaintext
my_bool1  my_bool2  my_dates  my_float64  my_int64  my_string
0      True   False 2015-10-09 20:22:39.878938 4  1  a
1    False      True 2015-10-10 20:22:39.878938 5  2  b
2      True   False 2015-10-11 20:22:39.878938 6  3  c
```

**In [451]:**

```python
df.to_gbq('my_dataset.my_table', projectid)
```

**Note:** The destination table and destination dataset will automatically be created if they do not already exist.
The `if_exists` argument can be used to dictate whether to 'fail', 'replace' or 'append' if the destination table already exists. The default value is 'fail'.

For example, assume that `if_exists` is set to 'fail'. The following snippet will raise a `TableCreationError` if the destination table already exists.

```python
df.to_gbq('my_dataset.my_table', projectid, if_exists='fail')
```

**Note:** If the `if_exists` argument is set to 'append', the destination dataframe will be written to the table using the defined table schema and column types. The dataframe must match the destination table in column order, structure, and data types. If the `if_exists` argument is set to 'replace', and the existing table has a different schema, a delay of 2 minutes will be forced to ensure that the new schema has propagated in the Google environment. See Google BigQuery issue 191.

Writing large DataFrames can result in errors due to size limitations being exceeded. This can be avoided by setting the `chunksize` argument when calling `to_gbq()`. For example, the following writes `df` to a BigQuery table in batches of 10000 rows at a time:

```python
df.to_gbq('my_dataset.my_table', projectid, chunksize=10000)
```

You can also see the progress of your post via the `verbose` flag which defaults to `True`. For example:

```python
In [8]: df.to_gbq('my_dataset.my_table', projectid, chunksize=10000, verbose=True)
```

```
Streaming Insert is 10% Complete
Streaming Insert is 20% Complete
Streaming Insert is 30% Complete
Streaming Insert is 40% Complete
Streaming Insert is 50% Complete
Streaming Insert is 60% Complete
Streaming Insert is 70% Complete
Streaming Insert is 80% Complete
Streaming Insert is 90% Complete
Streaming Insert is 100% Complete
```

**Note:** If an error occurs while streaming data to BigQuery, see Troubleshooting BigQuery Errors.

**Note:** The BigQuery SQL query language has some oddities, see the BigQuery Query Reference Documentation.

**Note:** While BigQuery uses SQL-like syntax, it has some important differences from traditional databases both in functionality, API limitations (size and quantity of queries or uploads), and how Google charges for use of the service. You should refer to Google BigQuery documentation often as the service seems to be changing and evolving. BigQuery is best for analyzing large sets of data quickly, but it is not a direct replacement for a transactional database.

### 24.10.5 Creating BigQuery Tables

**Warning:** As of 0.17, the function `generate_bq_schema()` has been deprecated and will be removed in a future version.

As of 0.15.2, the gbq module has a function `generate_bq_schema()` which will produce the dictionary representation schema of the specified pandas DataFrame.
In [10]: gbq.generate_bq_schema(df, default_type='STRING')

Out[10]: {'fields': [{'name': 'my_bool1', 'type': 'BOOLEAN'},
                  {'name': 'my_bool2', 'type': 'BOOLEAN'},
                  {'name': 'my_dates', 'type': 'TIMESTAMP'},
                  {'name': 'my_float64', 'type': 'FLOAT'},
                  {'name': 'my_int64', 'type': 'INTEGER'},
                  {'name': 'my_string', 'type': 'STRING'}]}

Note: If you delete and re-create a BigQuery table with the same name, but different table schema, you must wait 2
       minutes before streaming data into the table. As a workaround, consider creating the new table with a different name.
       Refer to Google BigQuery issue 191.

24.11 Stata Format

New in version 0.12.0.

24.11.1 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 [452]: df = DataFrame(randn(10, 2), columns=list('AB'))

In [453]: 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 (\urrent 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.

**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.
24.11.2 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.

```python
In [454]: pd.read_stata('stata.dta')
```
```
Out[454]:
   index  A     B
0      0  1.810535 -1.305727
1      1 -0.344987 -0.230840
2      2 -2.793085  1.937529
3      3  0.366332 -1.044589
4      4  2.051173  0.585662
5      5  0.429526 -0.606998
6      6  0.106223 -1.525680
7      7  0.795026 -0.374438
8      8  0.134048  1.202055
9      9  0.284748  0.262467
```

New in version 0.16.0.

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.

```python
In [455]: reader = pd.read_stata('stata.dta', chunksize=3)
```
```python
In [456]: 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()`.

```python
In [457]: reader = pd.read_stata('stata.dta', iterator=True)
```
```python
In [458]: chunk1 = reader.read(5)
```
```python
In [459]: 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

New in version 0.15.2.

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.

24.12 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.

24.12.1 netCDF

xray 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.

24.13 SAS Format

New in version 0.17.0.

The top-level function read_sas() currently can read (but not write) SAS xport (.XPT) format files. Pandas cannot currently handle SAS7BDAT files.

XPORT files only contain two value types: ASCII text and double precision numeric values. There is no automatic type conversion to integers, dates, or categoricals. By default the whole file is read and returned as a DataFrame.
Specify a chunksize or use iterator=True to obtain an XportReader object for incrementally reading the file. The XportReader object also has attributes that contain additional information about the file and its variables.

Read a SAS XPORT file:

```python
df = pd.read_sas('sas_xport.xpt')
```

Obtain an iterator and read an XPORT file 100,000 lines at a time:

```python
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.

## 24.14 Performance Considerations

This is an informal comparison of various IO methods, using pandas 0.13.1.

```python
In [1]: df = DataFrame(randn(1000000,2),columns=list('AB'))
In [2]: df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1000000 entries, 0 to 999999
Data columns (total 2 columns):
A       1000000 non-null float64
B       1000000 non-null float64
dtypes: float64(2)
memory usage: 22.9 MB
```

### Writing

```python
In [14]: %timeit test_sql_write(df)
1 loops, best of 3: 6.24 s per loop
In [15]: %timeit test_hdf_fixed_write(df)
1 loops, best of 3: 237 ms per loop
In [26]: %timeit test_hdf_fixed_write_compress(df)
1 loops, best of 3: 245 ms per loop
In [16]: %timeit test_hdf_table_write(df)
1 loops, best of 3: 901 ms per loop
In [27]: %timeit test_hdf_table_write_compress(df)
1 loops, best of 3: 952 ms per loop
In [17]: %timeit test_csv_write(df)
1 loops, best of 3: 3.44 s per loop
```

### Reading

```python
In [18]: %timeit test_sql_read()
1 loops, best of 3: 766 ms per loop
In [19]: %timeit test_hdf_fixed_read()
10 loops, best of 3: 19.1 ms per loop
```
In [28]: %timeit test_hdf_fixed_read_compress()
10 loops, best of 3: 36.3 ms per loop

In [20]: %timeit test_hdf_table_read()
10 loops, best of 3: 39 ms per loop

In [29]: %timeit test_hdf_table_read_compress()
10 loops, best of 3: 60.6 ms per loop

In [22]: %timeit test_csv_read()
1 loops, best of 3: 620 ms per loop

Space on disk (in bytes)

<table>
<thead>
<tr>
<th>File</th>
<th>Size (in bytes)</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>test.sql</td>
<td>25843712</td>
<td>Apr 8 14:11</td>
</tr>
<tr>
<td>test_fixed.hdf</td>
<td>24007368</td>
<td>Apr 8 14:11</td>
</tr>
<tr>
<td>test_fixed_compress.hdf</td>
<td>15580682</td>
<td>Apr 8 14:11</td>
</tr>
<tr>
<td>test_table.hdf</td>
<td>24458444</td>
<td>Apr 8 14:11</td>
</tr>
<tr>
<td>test_table_compress.hdf</td>
<td>16797283</td>
<td>Apr 8 14:11</td>
</tr>
<tr>
<td>test.csv</td>
<td>46152810</td>
<td>Apr 8 14:11</td>
</tr>
</tbody>
</table>

And here’s the code

```python
import sqlite3
import os
from pandas.io import sql
df = DataFrame(randn(1000000,2),columns=list('AB'))

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')

def test_hdf_fixed_read():
    pd.read_hdf('test_fixed.hdf','test')

def test_hdf_fixed_write_compress(df):
    df.to_hdf('test_fixed_compress.hdf','test',mode='w',complib='blosc')

def test_hdf_fixed_read_compress():
    pd.read_hdf('test_fixed_compress.hdf','test')

def test_hdf_table_write(df):
    df.to_hdf('test_table.hdf','test',mode='w',format='table')

def test_hdf_table_read():
    pd.read_hdf('test_table.hdf','test')
```

24.14. Performance Considerations
def test_hdf_table_write_compress(df):
    df.to_hdf('test_table_compress.hdf', 'test', mode='w', complib='blosc', format='table')

def test_hdf_table_read_compress():
    pd.read_hdf('test_table_compress.hdf', 'test')

def test_csv_write(df):
    df.to_csv('test.csv', mode='w')

def test_csv_read():
    pd.read_csv('test.csv', index_col=0)
Warning: In pandas 0.17.0, the sub-package `pandas.io.data` will be removed in favor of a separately installable `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 the same as in `pandas v0.16.1`. (GH8961)

You should replace the imports of the following:

```python
from pandas.io import data, wb
```

With:

```python
from pandas_datareader import data, wb
```

Functions from `pandas.io.data` and `pandas.io.ga` extract data from various Internet sources into a DataFrame. Currently the following sources are supported:

- **Yahoo! Finance**
- **Google Finance**
- **St.Louis FED (FRED)**
- **Kenneth French’s data library**
- **World Bank**
- **Google Analytics**

It should be noted, that various sources support different kinds of data, so not all sources implement the same methods and the data elements returned might also differ.

### 25.1 Yahoo! Finance

```python
In [1]: import pandas.io.data as web

In [2]: import datetime

In [3]: start = datetime.datetime(2010, 1, 1)

In [4]: end = datetime.datetime(2013, 1, 27)

In [5]: f = web.DataReader("F", 'yahoo', start, end)

In [6]: f.ix['2010-01-04']
```

```
Out[6]:
Open   10.170000
```
High   10.280000
Low    10.050000
Close  10.280000
Volume 60855800.000000
Adj Close  9.244219
Name: 2010-01-04 00:00:00, dtype: float64

25.2 Yahoo! Finance Options

*Experimental*

The Options class allows the download of options data from Yahoo! Finance.

The get_all_data method downloads and caches option data for all expiry months and provides a formatted DataFrame with a hierarchical index, so it is easy to get to the specific option you want.

In [7]: from pandas.io.data import Options

In [8]: aapl = Options('aapl', 'yahoo')

In [9]: data = aapl.get_all_data()

In [10]: data.iloc[0:5, 0:5]

Out[10]:

<table>
<thead>
<tr>
<th>Strike</th>
<th>Expiry</th>
<th>Type</th>
<th>Symbol</th>
<th>Last</th>
<th>Bid</th>
<th>Ask</th>
<th>Chg</th>
<th>PctChg</th>
</tr>
</thead>
<tbody>
<tr>
<td>34.29</td>
<td>2016-01-15</td>
<td>call</td>
<td>AAPL160115C00034290</td>
<td>76.65</td>
<td>77.10</td>
<td>77.65</td>
<td>0</td>
<td>0.00%</td>
</tr>
<tr>
<td>35.71</td>
<td>2016-01-15</td>
<td>call</td>
<td>AAPL160115C00035710</td>
<td>77.30</td>
<td>75.70</td>
<td>76.25</td>
<td>0</td>
<td>0.00%</td>
</tr>
<tr>
<td>37.14</td>
<td>2016-01-15</td>
<td>call</td>
<td>AAPL160115C00037140</td>
<td>71.50</td>
<td>79.00</td>
<td>79.50</td>
<td>0</td>
<td>0.00%</td>
</tr>
</tbody>
</table>

# Show the $100 strike puts at all expiry dates:

In [11]: data.loc[(100, slice(None), 'put'), :].iloc[0:5, 0:5]

Out[11]:

<table>
<thead>
<tr>
<th>Strike</th>
<th>Expiry</th>
<th>Type</th>
<th>Symbol</th>
<th>Last</th>
<th>Bid</th>
<th>Ask</th>
<th>Chg</th>
<th>PctChg</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>2015-10-16</td>
<td>put</td>
<td>AAPL151016P00100000</td>
<td>0.10</td>
<td>0.10</td>
<td>0.11</td>
<td>-0.12</td>
<td>-54.55%</td>
</tr>
<tr>
<td>100</td>
<td>2015-10-23</td>
<td>put</td>
<td>AAPL151023P00100000</td>
<td>0.31</td>
<td>0.29</td>
<td>0.31</td>
<td>-0.24</td>
<td>-43.64%</td>
</tr>
<tr>
<td>100</td>
<td>2015-10-30</td>
<td>put</td>
<td>AAPL151030P00100000</td>
<td>1.16</td>
<td>1.11</td>
<td>1.20</td>
<td>-0.38</td>
<td>-24.68%</td>
</tr>
<tr>
<td>100</td>
<td>2015-11-06</td>
<td>put</td>
<td>AAPL151106P00100000</td>
<td>1.36</td>
<td>1.34</td>
<td>1.44</td>
<td>-0.52</td>
<td>-27.66%</td>
</tr>
<tr>
<td>100</td>
<td>2015-11-13</td>
<td>put</td>
<td>AAPL151113P00100000</td>
<td>1.88</td>
<td>1.58</td>
<td>1.65</td>
<td>-0.28</td>
<td>-12.96%</td>
</tr>
</tbody>
</table>

# Show the volume traded of $100 strike puts at all expiry dates:

In [12]: data.loc[(100, slice(None), 'put'), 'Vol'].head()

Out[12]:

<table>
<thead>
<tr>
<th>Strike</th>
<th>Expiry</th>
<th>Type</th>
<th>Symbol</th>
<th>Vol</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>2015-10-16</td>
<td>put</td>
<td>AAPL151016P00100000</td>
<td>2642</td>
</tr>
<tr>
<td>100</td>
<td>2015-10-23</td>
<td>put</td>
<td>AAPL151023P00100000</td>
<td>538</td>
</tr>
<tr>
<td>100</td>
<td>2015-10-30</td>
<td>put</td>
<td>AAPL151030P00100000</td>
<td>321</td>
</tr>
<tr>
<td>100</td>
<td>2015-11-06</td>
<td>put</td>
<td>AAPL151106P00100000</td>
<td>10</td>
</tr>
<tr>
<td>100</td>
<td>2015-11-13</td>
<td>put</td>
<td>AAPL151113P00100000</td>
<td>2</td>
</tr>
</tbody>
</table>

If you don’t want to download all the data, more specific requests can be made.
In [13]: import datetime

In [14]: expiry = datetime.date(2016, 1, 1)

In [15]: data = aapl.get_call_data(expiry=expiry)

In [16]: data.iloc[0:5:, 0:5]
Out[16]:

<table>
<thead>
<tr>
<th>Strike</th>
<th>Expiry</th>
<th>Type</th>
<th>Symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td>34.29</td>
<td>2016-01-15</td>
<td>call</td>
<td>AAPL160115C00034290</td>
</tr>
<tr>
<td>35.71</td>
<td>2016-01-15</td>
<td>call</td>
<td>AAPL160115C00035710</td>
</tr>
<tr>
<td>37.14</td>
<td>2016-01-15</td>
<td>call</td>
<td>AAPL160115C00037140</td>
</tr>
<tr>
<td>38.57</td>
<td>2016-01-15</td>
<td>call</td>
<td>AAPL160115C00038570</td>
</tr>
<tr>
<td>40.00</td>
<td>2016-01-15</td>
<td>call</td>
<td>AAPL160115C00040000</td>
</tr>
</tbody>
</table>

Out[16]:

<table>
<thead>
<tr>
<th>Last</th>
<th>Bid</th>
<th>Ask</th>
<th>Chg</th>
<th>PctChg</th>
</tr>
</thead>
<tbody>
<tr>
<td>76.65</td>
<td>77.10</td>
<td></td>
<td>0</td>
<td>0.00%</td>
</tr>
<tr>
<td>77.30</td>
<td>75.70</td>
<td></td>
<td>0</td>
<td>0.00%</td>
</tr>
<tr>
<td>71.50</td>
<td>79.00</td>
<td></td>
<td>0</td>
<td>0.00%</td>
</tr>
<tr>
<td>86.45</td>
<td>72.85</td>
<td></td>
<td>0</td>
<td>0.00%</td>
</tr>
<tr>
<td>75.10</td>
<td>71.45</td>
<td></td>
<td>0</td>
<td>0.00%</td>
</tr>
</tbody>
</table>

Note that if you call `get_all_data` first, this second call will happen much faster, as the data is cached.

If a given expiry date is not available, data for the next available expiry will be returned (January 15, 2015 in the above example).

Available expiry dates can be accessed from the `expiry_dates` property.

In [17]: aapl.expiry_dates
Out[17]:

[datetime.date(2015, 10, 16),
 datetime.date(2015, 10, 23),
 datetime.date(2015, 10, 30),
 datetime.date(2015, 11, 6),
 datetime.date(2015, 11, 13),
 datetime.date(2015, 11, 20),
 datetime.date(2015, 12, 18),
 datetime.date(2016, 1, 15),
 datetime.date(2016, 4, 15),
 datetime.date(2016, 6, 17),
 datetime.date(2016, 7, 15),
 datetime.date(2017, 1, 20),
 datetime.date(2018, 1, 19)]

In [18]: data = aapl.get_call_data(expiry=aapl.expiry_dates[0])

In [19]: data.iloc[0:5:, 0:5]
Out[19]:

<table>
<thead>
<tr>
<th>Strike</th>
<th>Expiry</th>
<th>Type</th>
<th>Symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td>60</td>
<td>2015-10-16</td>
<td>call</td>
<td>AAPL151016C00066000</td>
</tr>
<tr>
<td>65</td>
<td>2015-10-16</td>
<td>call</td>
<td>AAPL151016C00065000</td>
</tr>
<tr>
<td>70</td>
<td>2015-10-16</td>
<td>call</td>
<td>AAPL151016C00070000</td>
</tr>
<tr>
<td>75</td>
<td>2015-10-16</td>
<td>call</td>
<td>AAPL151016C00075000</td>
</tr>
<tr>
<td>79</td>
<td>2015-10-16</td>
<td>call</td>
<td>AAPL151016C00079000</td>
</tr>
</tbody>
</table>

Out[19]:

<table>
<thead>
<tr>
<th>Last</th>
<th>Bid</th>
<th>Ask</th>
<th>Chg</th>
<th>PctChg</th>
</tr>
</thead>
<tbody>
<tr>
<td>51.00</td>
<td>51.45</td>
<td>51.85</td>
<td>2.29</td>
<td>4.70%</td>
</tr>
<tr>
<td>47.84</td>
<td>46.45</td>
<td>46.85</td>
<td>0.00</td>
<td>0.00%</td>
</tr>
<tr>
<td>38.68</td>
<td>41.45</td>
<td>41.90</td>
<td>0.00</td>
<td>0.00%</td>
</tr>
<tr>
<td>36.65</td>
<td>36.45</td>
<td>36.85</td>
<td>1.69</td>
<td>4.83%</td>
</tr>
<tr>
<td>30.80</td>
<td>32.45</td>
<td>32.85</td>
<td>0.00</td>
<td>0.00%</td>
</tr>
</tbody>
</table>

A list-like object containing dates can also be passed to the `expiry` parameter, returning options data for all expiry dates in the list.

In [20]: data = aapl.get_near_stock_price(expiry=aapl.expiry_dates[0:3])

In [21]: data.iloc[0:5:, 0:5]
Out[21]:

<table>
<thead>
<tr>
<th>Strike</th>
<th>Expiry</th>
<th>Type</th>
<th>Symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td>25</td>
<td>2015-10-16</td>
<td>call</td>
<td>AAPL151016C00079000</td>
</tr>
</tbody>
</table>

Out[21]:

<table>
<thead>
<tr>
<th>Last</th>
<th>Bid</th>
<th>Ask</th>
<th>Chg</th>
<th>PctChg</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The month and year parameters can be used to get all options data for a given month.

25.3 Google Finance

```python
In [22]: import pandas.io.data as web
In [23]: import datetime
In [24]: start = datetime.datetime(2010, 1, 1)
In [25]: end = datetime.datetime(2013, 1, 27)
In [26]: f = web.DataReader("F", 'google', start, end)
In [27]: f.ix['2010-01-04']
Out[27]:
Open   10.17  
High   10.28  
Low    10.05  
Close  10.28  
Volume 60855796.00
Name: 2010-01-04 00:00:00, dtype: float64
```

25.4 FRED

```python
In [28]: import pandas.io.data as web
In [29]: import datetime
In [30]: start = datetime.datetime(2010, 1, 1)
In [31]: end = datetime.datetime(2013, 1, 27)
In [32]: gdp=web.DataReader("GDP", "fred", start, end)
In [33]: gdp.ix['2013-01-01']
Out[33]:
GDP   16440.7
Name: 2013-01-01 00:00:00, dtype: float64
```

```python
# Multiple series:
In [34]: inflation = web.DataReader(["CPIAUCSL", "CPILFESL"], "fred", start, end)
In [35]: inflation.head()
Out[35]:
DATE     CPIAUCSL  CPILFESL
2010-01-01  217.488  220.633
```
25.5 Fama/French

Dataset names are listed at Fama/French Data Library.

In [36]: import pandas.io.data as web

In [37]: ip = web.DataReader("5_Industry_Portfolios", "famafrench")

In [38]: ip[4].ix[192607]
Out[38]:
   1   Cnsmr  5.43
   2  Manuf  2.73
   3  HiTec  1.83
   4  Hlth  1.77
   5  Other  2.16
Name: 192607, dtype: float64

25.6 World Bank

pandas users can easily access thousands of panel data series from the World Bank’s World Development Indicators by using the wb I/O functions.

25.6.1 Indicators

Either from exploring the World Bank site, or using the search function included, every world bank indicator is accessible.

For example, if you wanted to compare the Gross Domestic Products per capita in constant dollars in North America, you would use the search function:

In [1]: from pandas.io import wb

In [2]: wb.search('gdp.*capita.*const').iloc[:,:2]
Out[2]:
    id  name
  3242  GDPPCKD  GDP per Capita, constant US$, millions
  5143  NY.GDP.PCAP.KD  GDP per capita (constant 2005 US$)
  5145  NY.GDP.PCAP.KN  GDP per capita (constant LCU)
  5147  NY.GDP.PCAP.PP.KD  GDP per capita, PPP (constant 2005 international... 

Then you would use the download function to acquire the data from the World Bank’s servers:

In [3]: dat = wb.download(indicator='NY.GDP.PCAP.KD', country=['US', 'CA', 'MX'], start=2005, end=2008)

In [4]: print(dat)

NY.GDP.PCAP.KD
country  year
Canada  2008  36005.5004978584
The resulting dataset is a properly formatted DataFrame with a hierarchical index, so it is easy to apply .groupby transformations to it:

```python
In [6]: dat['NY.GDP.PCAP.KD'].groupby(level=0).mean()
Out[6]:
       country
    2005  2006  2007
Canada      35765.569188
Mexico       7965.245332
United States 43112.417952
```

Now imagine you want to compare GDP to the share of people with cellphone contracts around the world.

```python
In [7]: wb.search('cell.*%').iloc[:, :2]
Out[7]:
   id          name
3990  IT.CEL.SETS.FE.ZS Mobile cellular telephone users, female (% of popu...
3991  IT.CEL.SETS.MA.ZS Mobile cellular telephone users, male (% of popu...
4027  IT.MOB.COV.ZS Population coverage of mobile cellular telepho...
```

Notice that this second search was much faster than the first one because pandas now has a cached list of available data series.

```python
In [13]: ind = ['NY.GDP.PCAP.KD', 'IT.MOB.COV.ZS']
In [14]: dat = wb.download(indicator=ind, country='all', start=2011, end=2011).dropna()
In [15]: dat.columns = ['gdp', 'cellphone']
In [16]:
```

Finally, we use the statsmodels package to assess the relationship between our two variables using ordinary least squares regression. Unsurprisingly, populations in rich countries tend to use cellphones at a higher rate:

```python
In [17]:
In [18]:
In [19]:
In [20]:
```

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```
```
Date: Thu, 25 Jul 2013
Probability (F-statistic): 0.00105
Time: 15:24:42
Log-Likelihood: -139.16
Number of Observations: 33
AIC: 282.3
Df Residuals: 31
BIC: 285.3
Df Model: 1
===============================================================================
coefficient std error t P>|t| [95.0% Conf. Int.]
---------------------------------------------------------------------------------------------------
Intercept 16.5110 19.071 0.866 0.393 -22.384 55.406
np.log(gdp) 9.9333 2.747 3.616 0.001 4.331 15.535
==============================================================================
Omnibus: 36.054
Prob(Omnibus): 0.000
Jarque-Bera (JB): 119.133
Skew: -2.314
Prob(JB): 1.35e-26
Kurtosis: 11.077
Cond. No. 45.8
==============================================================================

25.6.2 Country Codes

New in version 0.15.1.

The country argument accepts a string or list of mixed two or three character ISO country codes, as well as dynamic World Bank exceptions to the ISO standards.

For a list of the the hard-coded country codes (used solely for error handling logic) see pandas.io.wb.country_codes.

25.6.3 Problematic Country Codes & Indicators

Note: The World Bank’s country list and indicators are dynamic. As of 0.15.1, wb.download() is more flexible. To achieve this, the warning and exception logic changed.

The world bank converts some country codes in their response, which makes error checking by pandas difficult. Retired indicators still persist in the search.

Given the new flexibility of 0.15.1, improved error handling by the user may be necessary for fringe cases.

To help identify issues:

There are at least 4 kinds of country codes:

1. Standard (2/3 digit ISO) - returns data, will warn and error properly.
2. Non-standard (WB Exceptions) - returns data, but will falsely warn.
3. Blank - silently missing from the response.
4. Bad - causes the entire response from WB to fail, always exception inducing.

There are at least 3 kinds of indicators:

1. Current - Returns data.
2. Retired - Appears in search results, yet won’t return data.
3. Bad - Will not return data.

Use the errors argument to control warnings and exceptions. Setting errors to ignore or warn, won’t stop failed responses. (ie, 100% bad indicators, or a single “bad” (#4 above) country code).
See docstrings for more info.

25.7 Google Analytics

The ga module provides a wrapper for Google Analytics API to simplify retrieving traffic data. Result sets are parsed into a pandas DataFrame with a shape and data types derived from the source table.

25.7.1 Configuring Access to Google Analytics

The first thing you need to do is to setup accesses to Google Analytics API. Follow the steps below:

1. **In the Google Developers Console**
   (a) enable the Analytics API
   (b) create a new project
   (c) create a new Client ID for an “Installed Application” (in the “APIs & auth / Credentials section” of the newly created project)
   (d) download it (JSON file)

2. **On your machine**
   (a) rename it to `client_secrets.json`
   (b) move it to the `pandas/io` module directory

The first time you use the `read_ga()` function, a browser window will open to ask you to authenticate to the Google API. Do proceed.

25.7.2 Using the Google Analytics API

The following will fetch users and pageviews (metrics) data per day of the week, for the first semester of 2014, from a particular property.

```python
import pandas.io.ga as ga
ga.read_ga(
    account_id = "2360420",
    profile_id = "19462946",
    property_id = "UA-2360420-5",
    metrics = ['users', 'pageviews'],
    dimensions = ['dayOfWeek'],
    start_date = "2014-01-01",
    end_date = "2014-08-01",
    index_col = 0,
    filters = "pagePath=~aboutus;ga:country==France",
)
```

The only mandatory arguments are metrics, dimensions and start_date. We strongly recommend that you always specify the account_id, profile_id and property_id to avoid accessing the wrong data bucket in Google Analytics.

The index_col argument indicates which dimension(s) has to be taken as index.

The filters argument indicates the filtering to apply to the query. In the above example, the page URL has to contain aboutus AND the visitors country has to be France.
Detailed information in the following:

- pandas & google analytics, by yhat
- Google Analytics integration in pandas, by Chang She
- Google Analytics Dimensions and Metrics Reference
26.1 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 sizeable speed-ups by offloading work to cython.

This tutorial assumes you have refactored as much as possible in python, for example 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.

26.1.1 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]:
      N    a       b    x
0  585  0.469112 -0.218470  x
1  841  0.282863 -0.061645  x
2  251 -1.509059  0.723780  x
3  972 -1.135632  0.551225  x
4  181  1.212112 -0.497767  x
5  458 -0.173215  0.837519  x
6  159  0.119209  1.103245  x
... ... ... ... 
993 190  0.131892  0.290162  x
994 931  0.342097  0.215341  x
995 374 -1.512743  0.874737  x
996 246  0.933753  1.120790  x
997 157 -0.308013  0.198768  x
998 977 -0.079915  1.757555  x
999 770 -1.010589 -1.115680  x
[1000 rows x 4 columns]
```
Here’s the function in pure python:

```python
In [3]: def f(x):
    ...:     return x * (x - 1)
    ...
```

```python
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):

```python
In [7]: %timeit df.apply(lambda x: integrate_f(x['a'], x['b'], x['N']), axis=1)
10 loops, best of 3: 174 ms per loop
```

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:

```python
In [5]: %prun -l 4 df.apply(lambda x: integrate_f(x['a'], x['b'], x['N']), axis=1)
```

862 Chapter 26. Enhancing Performance

By far the majority of time is spend inside either `integrate_f` or `f`, hence we’ll concentrate our efforts cythonizing these two functions.

**Note:** In python 2 replacing the `range` with its generator counterpart (`xrange`) would mean the `range` line would vanish. In python 3 `range` is already a generator.

### 26.1.2 Plain cython

First we’re going to need to import the cython magic function to ipython (for cython versions >=0.21 you can use `%load_ext Cython`):

```python
In [6]: %load_ext cythonmagic
```

Now, let’s simply copy our functions over to cython as is (the suffix is here to distinguish between function versions):

```python
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.

### 26.1.3 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)

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)
```

Ordered by: internal time
List reduced from 108 to 4 due to restriction <4>

<table>
<thead>
<tr>
<th>ncalls</th>
<th>ttime</th>
<th>percall</th>
<th>cumtime</th>
<th>percall</th>
<th>filename:lineno(function)</th>
</tr>
</thead>
<tbody>
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<td>6000</td>
<td>0.007</td>
<td>0.000</td>
<td>0.016</td>
<td>0.000</td>
<td>{pandas.lib.values_from_object}</td>
</tr>
<tr>
<td>3000</td>
<td>0.007</td>
<td>0.000</td>
<td>0.068</td>
<td>0.000</td>
<td>{pandas.lib.values_from_object}</td>
</tr>
<tr>
<td>3000</td>
<td>0.007</td>
<td>0.000</td>
<td>0.055</td>
<td>0.000</td>
<td>index.py:1703(get_value)</td>
</tr>
<tr>
<td>3000</td>
<td>0.007</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>series.py:549(<strong>getitem</strong>)</td>
</tr>
</tbody>
</table>

### 26.1.4 Using ndarray

It’s calling series... a lot! It’s creating a Series from each row, and getting from both the index and the series (three times for each row). Function calls are expensive in python, so maybe we could minimise these by cythonizing the apply part.

Note: We are now passing ndarrays into the cython function, fortunately cython plays very nicely with numpy.
pandas: powerful Python data analysis toolkit, Release 0.17.0

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
   ....:     for i in range(N):
   ....:         s += f_typed(a + i * dx)
   ....:     return s * dx
   ....: cpdef np.ndarray[double] apply_integrate_f(np.ndarray col_a, np.ndarray col_b, np.ndarray col_N):
   ....:     assert (col_a.dtype == np.float and col_b.dtype == np.float and col_N.dtype == np.int)
   ....:     cdef Py_ssize_t 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(len(col_a)):
   ....:         res[i] = integrate_f_typed(col_a[i], col_b[i], col_N[i])
   ....:     return res

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: In 0.13.0 since Series has internally been refactored to no longer sub-class ndarray but instead subclass NDFrame, you can not pass a Series directly as a ndarray typed parameter to a cython function. Instead pass the actual ndarray using the .values attribute of the Series.

Prior to 0.13.0

apply_integrate_f(df['a'], df['b'], df['N'])

Use .values to get the underlying ndarray

apply_integrate_f(df['a'].values, df['b'].values, df['N'].values)

Note: Loops like this would be extremely slow in python, but in Cython looping over numpy arrays is fast.

In [4]: %timeit apply_integrate_f(df['a'].values, df['b'].values, df['N'].values)
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:

In [11]: %prun -l 4 apply_integrate_f(df['a'].values, df['b'].values, df['N'].values)
187 function calls in 0.003 seconds

Ordered by: internal time
List reduced from 48 to 4 due to restriction <4>

<table>
<thead>
<tr>
<th>ncalls</th>
<th>tottime</th>
<th>percall</th>
<th>cumtime</th>
<th>percall</th>
<th>filename:lineno(function)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.003</td>
<td>0.003</td>
<td>0.003</td>
<td>0.003</td>
<td>_cython_magic_073e22cb442403aaff864a05d833c10b.apply_integrate_f_typed</td>
</tr>
<tr>
<td>3</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>internals.py:3123(iget)</td>
</tr>
<tr>
<td>6</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>generic.py:2248(<strong>setattr</strong>)</td>
</tr>
<tr>
<td>3</td>
<td>0.000</td>
<td>0.001</td>
<td>0.001</td>
<td>0.000</td>
<td>generic.py:1085(_get_item_cache)</td>
</tr>
</tbody>
</table>

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.

26.1.5 More advanced techniques

There is still hope for improvement. Here’s an example of using some more advanced cython techniques:

```
In [12]: %%cython
    ...: cimport cython
    ...: cimport 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)
        ...: cdef Py_ssize_t 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'].values, df['b'].values, df['N'].values)
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.

26.2 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 pycce 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.
26.2.1 Jit

Using numba to just-in-time compile your 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

@numba.jit
def compute_numba(df):
    result = apply_integrate_f_numba(df['a'].values, df['b'].values, df['N'].values)
    return pd.Series(result, index=df.index, name='result')
```

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.

In [4]: %timeit compute_numba(df)
1000 loops, best of 3: 798 us per loop

26.2.2 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)
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.values)
1000 loops, best of 3: 145 us per loop

26.2.3 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.

26.3 Expression Evaluation via eval() (Experimental)

New in version 0.13.

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().

26.3.1 Supported Syntax

These operations are supported by pandas.eval():
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- Arithmetic operations except for the left shift (<<) and right shift (>>) operators, e.g., \( df + 2 \times \pi / s \)

- **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**, \( \sin, \cos, \exp, \log, \expm1, \log1p, \sqrt, \sinh, \cosh, \tanh, \arcsin, \arccos, \arctan, \arccosh, \arcsinh, \arctanh, \text{abs} \) and \( \text{arctan2} \).

This Python syntax is **not** allowed:

- **Expressions**
  - Function calls other than math functions.
  - \( is/is\_not \) operations
  - if expressions
  - 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.

### 26.3.2 eval() Examples

```
pandas.eval() works well with expressions containing large arrays.
```

First let’s create a few decent-sized arrays to play with:

```
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():

```
In [15]: %timeit df1 + df2 + df3 + df4
10 loops, best of 3: 23.9 ms per loop

In [16]: %timeit pd.eval('df1 + df2 + df3 + df4')
100 loops, best of 3: 14.7 ms per loop
```

Now let’s do the same thing but with comparisons:
In [17]: %timeit (df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)
10 loops, best of 3: 72.8 ms per loop

In [18]: %timeit pd.eval('(df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)')
10 loops, best of 3: 25.6 ms per loop

eval() also works with unaligned pandas objects:

In [19]: s = pd.Series(np.random.randn(50))

In [20]: %timeit df1 + df2 + df3 + df4 + s
10 loops, best of 3: 83.1 ms per loop

In [21]: %timeit pd.eval('df1 + df2 + df3 + df4 + s')
10 loops, best of 3: 58.2 ms per loop

Note: Operations such as

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.

### 26.3.3 The DataFrame.eval method (Experimental)

New in version 0.13.

In addition to the top level pandas.eval() function you can also evaluate an expression in the “context” of a DataFrame.

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. Only a single assignment is permitted. The assignment target can be a new column name or an existing column name, and it must be a valid Python identifier.

In [24]: df = pd.DataFrame(dict(a=range(5), b=range(5, 10)))

In [25]: df.eval('c = a + b')
In [26]: df.eval('d = a + b + c')
In [27]: df.eval('a = 1')

In [28]: df
Out[28]:
   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 equivalent in standard Python would be

In [29]: df = pd.DataFrame(dict(a=range(5), b=range(5, 10)))
In [30]: df['c'] = df.a + df.b
In [31]: df['d'] = df.a + df.b + df.c
In [32]: df['a'] = 1
In [33]: df
Out[33]:
   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

26.3.4 Local Variables

In pandas version 0.14 the local variable API has changed. In pandas 0.13.x, you could refer to local variables the same way you would in standard Python. For example,

def = pd.DataFrame(np.random.randn(5, 2), columns=['a', 'b'])
newcol = np.random.randn(len(df))
df.eval('b + newcol')

UndefinedVariableError: name 'newcol' is not defined

As you can see from the exception generated, this syntax is no longer allowed. 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 [34]: df = pd.DataFrame(np.random.randn(5, 2), columns=list('ab'))
In [35]: newcol = np.random.randn(len(df))
In [36]: df.eval('b + @newcol')
Out[36]:
   0  -0.173926
   1   2.493083
   2  -0.881831
   3  -0.691045
   4   1.334703
dtype: float64
In [37]: df.query('b < @newcol')
Out[37]:
   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 [38]: a = np.random.randn()

In [39]: df.query('@a < a')
Out[39]:
   a    b
0 0.863987 -0.115998

In [40]: df.loc[a < df.a]  # same as the previous expression
Out[40]:
   a    b
0 0.863987 -0.115998

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,

In [41]: a, b = 1, 2
In [42]: pd.eval('@a + b')
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.

In [43]: pd.eval('a + b')
Out[43]: 3

26.3.5 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.

In [44]: expr = '(df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)'
In [45]: x = pd.eval(expr, parser='python')
In [46]: expr_no_parens = 'df1 > 0 & df2 > 0 & df3 > 0 & df4 > 0'
In [47]: y = pd.eval(expr_no_parens, parser='pandas')
In [48]: np.all(x == y)
Out[48]: True
The same expression can be “anded” together with the word `and` as well:

```python
In [49]: expr = '((df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0))'
In [50]: x = pd.eval(expr, parser='python')
In [51]: expr_with_ands = 'df1 > 0 and df2 > 0 and df3 > 0 and df4 > 0'
In [52]: y = pd.eval(expr_with_ands, parser='pandas')
In [53]: np.all(x == y)
Out[53]: True
```

The `and` and `or` operators here have the same precedence that they would in vanilla Python.

### 26.3.6 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.

```python
In [54]: %timeit df1 + df2 + df3 + df4
10 loops, best of 3: 23 ms per loop
In [55]: %timeit pd.eval('df1 + df2 + df3 + df4', engine='python')
10 loops, best of 3: 26 ms per loop
```

### 26.3.7 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().

26.3.8 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’d expressions. So, if you have an expression--for example
In [56]: df = pd.DataFrame({'strings': np.repeat(list('cba'), 3),
                          'nums': np.repeat(range(3), 3)})

In [57]: df
Out[57]:
   nums  strings
0     0     c
1     0     c
2     1     b
3     1     b
4     2     a
5     2     a
6     2     a
7     2     a
8     2     a

In [58]: df.query('strings == "a" and nums == 1')
Out[58]:
Empty DataFrame
Columns: [nums, strings]
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.
SPARSE DATA STRUCTURES

We have implemented “sparse” versions of Series, DataFrame, and Panel. These are not sparse in the typical “mostly 0”. You can view these objects as being “compressed” where any data matching a specific value (NaN/missing by default, though any value can be chosen) is omitted. A special SparseIndex object tracks where data has been “sparsified”. This will make much more sense in an example. All of the standard pandas data structures have a to_sparse method:

```python
In [1]: ts = pd.Series(randn(10))

In [2]: ts[2:-2] = np.nan

In [3]: sts = ts.to_sparse()

In [4]: sts
Out[4]:
   0   0.469112
   1  -0.282863
   2   NaN
   3   NaN
   4   NaN
   5   NaN
   6   NaN
   7   NaN
   8  -0.861849
   9  -2.104569
dtype: float64
BlockIndex
Block locations: array([0, 8])
Block lengths: array([2, 2])
```

The to_sparse method takes a kind argument (for the sparse index, see below) and a fill_value. So if we had a mostly zero Series, we could convert it to sparse with fill_value=0:

```python
In [5]: ts.fillna(0).to_sparse(fill_value=0)
Out[5]:
   0   0.469112
   1  -0.282863
   2   0.000000
   3   0.000000
   4   0.000000
   5   0.000000
   6   0.000000
   7   0.000000
   8  -0.861849
   9  -2.104569
dtype: float64
```
The sparse objects exist for memory efficiency reasons. Suppose you had a large, mostly NA DataFrame:

```
In [6]: df = pd.DataFrame(randn(10000, 4))
In [7]: df.ix[:9998] = np.nan
In [8]: sdf = df.to_sparse()
In [9]: sdf
```

```
Out[9]:
         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
5    NaN    NaN    NaN    NaN
...  ...  ...  ...  ...  ...
9993  NaN    NaN    NaN    NaN
9994  NaN    NaN    NaN    NaN
9995  NaN    NaN    NaN    NaN
9996  NaN    NaN    NaN    NaN
9997  NaN    NaN    NaN    NaN
9998  NaN    NaN    NaN    NaN
9999  0.280249 -1.648493 1.490865 -0.890819
```

```
[10000 rows x 4 columns]
```

```
In [10]: sdf.density
Out[10]: 0.0001
```

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. Functionally, their behavior should be nearly identical to their dense counterparts.

Any sparse object can be converted back to the standard dense form by calling `to_dense`:

```
In [11]: sts.to_dense()
Out[11]:
       0     1     2     3
0  0.469112  NaN  NaN  NaN
1 -0.282863  NaN  NaN  NaN
2     NaN  NaN  NaN  NaN
3     NaN  NaN  NaN  NaN
4     NaN  NaN  NaN  NaN
5     NaN  NaN  NaN  NaN
6     NaN  NaN  NaN  NaN
7     NaN  NaN  NaN  NaN
8  -0.861849  NaN  NaN  NaN
9  -2.104569  NaN  NaN  NaN
dtype: float64
```
27.1 SparseArray

SparseArray is the base layer for all of the sparse indexed data structures. It is a 1-dimensional ndarray-like object storing only values distinct from the fill_value:

In [12]: arr = np.random.randn(10)


In [14]: sparr = pd.SparseArray(arr)

In [15]: sparr
Out[15]:
[-1.95566352972, -1.6588664276, nan, nan, nan, 1.15893288864, 0.145297113733, nan, 0.606027190513, 1.33421134013]

Fill: nan
IntIndex
Indices: array([0, 1, 5, 6, 8, 9])

Like the indexed objects (SparseSeries, SparseDataFrame, SparsePanel), a SparseArray can be converted back to a regular ndarray by calling to_dense:

In [16]: sparr.to_dense()
Out[16]:
array([-1.9557, -1.6589, nan, nan, nan, 1.1589, 0.1453, nan, 0.606 , 1.3342])

27.2 SparseList

SparseList is a list-like data structure for managing a dynamic collection of SparseArrays. To create one, simply call the SparseList constructor with a fill_value (defaulting to NaN):

In [17]: spl = pd.SparseList()

In [18]: spl
Out[18]: <pandas.sparse.list.SparseList object at 0x9ec8aaac>

The two important methods are append and to_array. append can accept scalar values or any 1-dimensional sequence:

In [19]: spl.append(np.array([1., np.nan, np.nan, 2., 3.]))

In [20]: spl.append(5)

In [21]: spl.append(sparr)

In [22]: spl
Out[22]: <pandas.sparse.list.SparseList object at 0x9ec8aaac>
[1.0, nan, nan, 2.0, 3.0]
Fill: nan
IntIndex
Indices: array([0, 3, 4])

[5.0]
Fill: nan
IntIndex
As you can see, all of the contents are stored internally as a list of memory-efficient SparseArray objects. Once you’ve accumulated all of the data, you can call to_array to get a single SparseArray with all the data:

```
In [23]: spl.to_array()
Out[23]:
[1.0, nan, nan, 2.0, 3.0, 5.0, -1.95566352972, -1.6588664276, nan, nan, nan, 1.15893288864, 0.145297113733, nan, 0.606027190513, 1.33421134013]
```

27.3 SparseIndex objects

Two kinds of SparseIndex are implemented, block and integer. We recommend using block as it’s more memory efficient. The integer format keeps an array of all of the locations where the data are not equal to the fill value. The block format tracks only the locations and sizes of blocks of data.

27.4 Interaction with scipy.sparse

Experimental api to transform between sparse pandas and scipy.sparse structures.

A SparseSeries.to_coo() method is implemented for transforming a SparseSeries indexed by a MultiIndex to a scipy.sparse.coo_matrix.

The method requires a MultiIndex with two or more levels.

```
In [24]: s = pd.Series([3.0, np.nan, 1.0, 3.0, np.nan, np.nan])
In [25]: 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 [26]: s
Out[26]:
   A B C D
0  1  2  a  0  3
  1  b  0  1
  2  1  b  0  NaN
  1  3
  2  1  b  0  NaN
  1  NaN
dtype: float64
```
In the example below, we transform the `SparseSeries` 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 [29]: A, rows, columns = ss.to_coo(row_levels=['A', 'B'],
                column_levels=['C', 'D'],
                sort_labels=True)

In [30]: A
Out[30]:
<3x4 sparse matrix of type '<type 'numpy.float64'>'
with 3 stored elements in COOrdinate format>

In [31]: A.todense()
Out[31]:
matrix([[ 0.,  0.,  1.,  3.],
        [ 3.,  0.,  0.,  0.],
        [ 0.,  0.,  0.,  0.]])

In [32]: rows
Out[32]: [(1L, 1L), (1L, 2L), (2L, 1L)]

In [33]: columns
Out[33]: [('a', 0L), ('a', 1L), ('b', 0L), ('b', 1L)]

Specifying different row and column labels (and not sorting them) yields a different sparse matrix:

In [34]: A, rows, columns = ss.to_coo(row_levels=['A', 'B', 'C'],
                column_levels=['D'],
                sort_labels=False)

In [35]: A
Out[35]:
<3x2 sparse matrix of type '<type 'numpy.float64'>'
with 3 stored elements in COOrdinate format>

In [36]: A.todense()
Out[36]:
matrix([[ 3.,  0.],
        [ 1.,  3.],
        [ 0.,  0.]])
A convenience method `SparseSeries.from_coo()` is implemented for creating a `SparseSeries` from a `scipy.sparse.coo_matrix`.

```python
In [39]: from scipy import sparse

In [40]: A = sparse.coo_matrix(((3.0, 1.0, 2.0), ([1, 0, 0], [0, 2, 3])),
   ....:     shape=(3, 4))
   ....:

In [41]: A
Out[41]:
<3x4 sparse matrix of type '<type 'numpy.float64'>'
with 3 stored elements in COOrdinate format>

In [42]: A.todense()
Out[42]:
matrix([[ 0., 0., 1., 2.],
        [ 3., 0., 0., 0.],
        [ 0., 0., 0., 0.]])
```

The default behaviour (with `dense_index=False`) simply returns a `SparseSeries` containing only the non-null entries.

```python
In [43]: ss = pd.SparseSeries.from_coo(A)

In [44]: ss
Out[44]:
0 2 1
 3 2
1 0 3
dtype: float64
BlockIndex
Block locations: array([0])
Block lengths: array([3])
```

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.

```python
In [45]: ss_dense = pd.SparseSeries.from_coo(A, dense_index=True)

In [46]: ss_dense
Out[46]:
0 0 NaN
 1 NaN
 2 1
 3 2
1 0 3
 1 NaN
 2 NaN
 3 NaN
```
2 0  NaN
1  NaN
2  NaN
3  NaN
dtype: float64
BlockIndex
Block locations: array([2])
Block lengths: array([3])
28.1 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 a if or when using the boolean operations, and, or, or not. It is not clear what the result of

```python
>>> if pd.Series([False, True, False]):
    ...
```

should be. Should it be True because it’s not zero-length? 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().
```

If you see that, you need to explicitly choose what you want to do with it (e.g., use any(), all() or empty). or, 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")
```

or return if any value is True.

```python
>>> if pd.Series([False, True, False]).any():
    print("I am any")
```

To evaluate single-element pandas objects in a boolean context, use the method .bool():

```python
In [1]: pd.Series([True]).bool()
Out[1]: True
```

```python
In [2]: pd.Series([False]).bool()
Out[2]: False
```

```python
In [3]: pd.DataFrame([[True]]).bool()
Out[3]: True
```

```python
In [4]: pd.DataFrame([[False]]).bool()
Out[4]: False
```
28.1.1 Bitwise boolean

Bitwise boolean operators like `==` and `!=` will 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.

28.1.2 Using the `in` operator

Using the Python `in` operator on a Series tests for membership in the index, not membership among the values.

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()`:

For DataFrames, likewise, `in` applies to the column axis, testing for membership in the list of column names.

28.2 NaN, Integer NA values and NA type promotions

28.2.1 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
- 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 `isnull` and `notnull` 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.

28.2.2 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 [5]: s = pd.Series([1, 2, 3, 4, 5], index=list('abcde'))

In [6]: s
Out[6]:
a   1
b   2
c   3
```

884 Chapter 28. Caveats and Gotchas
This trade-off is made largely for memory and performance reasons, and also so that the resulting Series continues to be “numeric”. One possibility is to use \texttt{dtype=object} arrays instead.

### 28.2.3 NA type promotions

When introducing NAs into an existing Series or DataFrame via \texttt{reindex} or some other means, boolean and integer types will be promoted to a different dtype in order to store the NAs. These are summarized by 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, in practice I have found very few cases where this is an issue in practice. Some explanation for the motivation here in the next section.

### 28.2.4 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 \texttt{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 \texttt{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.

### 28.3 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 only label-based indexing is possible with the standard tools like .ix. The following code will generate exceptions:

```python
s = pd.Series(range(5))
s[-1]
df = pd.DataFrame(np.random.randn(5, 4))
df
df.ix[-2:]
```

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).

### 28.4 Label-based slicing conventions

#### 28.4.1 Non-monotonic indexes require exact matches

#### 28.4.2 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:

```
In [11]: s = pd.Series(np.random.randn(6), index=list('abcdef'))
In [12]: s
Out[12]:
a  1.544821
b -1.708552
c  1.545458
d -0.735738
e -0.649091
f -0.403878
dtype: float64
```

Suppose we wished to slice from c to e, using integers this would be

```
In [13]: s[2:5]
Out[13]:
c  1.545458
d -0.735738
```
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:

\[
s.ix['c':'e'+1]
\]

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 decision to make label-based slicing include both endpoints:

\[
\text{In [14]: } s.ix['c':'e']
\]

\[
\text{Out [14]: }
c \quad 1.545458
d \quad -0.735738
e \quad -0.649091
dtype: float64
\]

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.

### 28.5 Miscellaneous indexing gotchas

#### 28.5.1 Reindex versus ix gotchas

Many users will find themselves using the \( ix \) indexing capabilities as a concise means of selecting data from a pandas object:

\[
\text{In [15]: } df = pd.DataFrame(np.random.randn(6, 4), columns=['one', 'two', 'three', 'four'],
\]

\[
\text{index=list('abcdef'))}
\]

\[
\text{In [16]: } df
\]

\[
\text{Out [16]:}
\]

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>one</td>
<td>two</td>
<td>three</td>
<td>four</td>
<td></td>
</tr>
<tr>
<td>a</td>
<td>-2.474932</td>
<td>0.975891</td>
<td>-0.204206</td>
<td>0.452707</td>
</tr>
<tr>
<td>b</td>
<td>3.478418</td>
<td>-0.591538</td>
<td>-0.508560</td>
<td>0.047946</td>
</tr>
<tr>
<td>c</td>
<td>-0.170009</td>
<td>-1.615606</td>
<td>-0.894382</td>
<td>1.334681</td>
</tr>
<tr>
<td>d</td>
<td>-0.418002</td>
<td>-0.690649</td>
<td>0.128522</td>
<td>0.429260</td>
</tr>
<tr>
<td>e</td>
<td>1.207515</td>
<td>-1.308877</td>
<td>-0.548792</td>
<td>-1.520879</td>
</tr>
<tr>
<td>f</td>
<td>1.153696</td>
<td>0.609378</td>
<td>-0.825763</td>
<td>0.218223</td>
</tr>
</tbody>
</table>

\[
\text{In [17]: } df.ix[['b', 'c', 'e']]
\]

\[
\text{Out [17]:}
\]

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>one</td>
<td>two</td>
<td>three</td>
<td>four</td>
</tr>
<tr>
<td>b</td>
<td>3.478418</td>
<td>-0.591538</td>
<td>-0.508560</td>
</tr>
<tr>
<td>c</td>
<td>-0.170009</td>
<td>-1.615606</td>
<td>-0.894382</td>
</tr>
<tr>
<td>e</td>
<td>1.207515</td>
<td>-1.308877</td>
<td>-0.548792</td>
</tr>
</tbody>
</table>

This is, of course, completely equivalent in this case to using the \texttt{reindex} method:

\[
\text{In [18]: } df.reindex(['b', 'c', 'e'])
\]

\[
\text{Out [18]:}
\]

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>one</td>
<td>two</td>
<td>three</td>
<td>four</td>
</tr>
<tr>
<td>b</td>
<td>3.478418</td>
<td>-0.591538</td>
<td>-0.508560</td>
</tr>
<tr>
<td>c</td>
<td>-0.170009</td>
<td>-1.615606</td>
<td>-0.894382</td>
</tr>
<tr>
<td>e</td>
<td>1.207515</td>
<td>-1.308877</td>
<td>-0.548792</td>
</tr>
</tbody>
</table>
Some might conclude that `ix` and `reindex` are 100% equivalent based on this. This is indeed true except in the case of integer indexing. For example, the above operation could alternately have been expressed as:

```
In [19]: df.ix[[1, 2, 4]]
Out[19]:
     one   two   three   four
b  3.478418 -0.591538  0.508560  0.047946
c -0.170009  1.615606  0.894382  1.334681
e  1.207515 -1.308877 -0.548792 -1.520879
```

If you pass `[1, 2, 4]` to `reindex` you will get another thing entirely:

```
In [20]: df.reindex([1, 2, 4])
Out[20]:
     one   two   three   four
1  NaN  NaN  NaN  NaN
2  NaN  NaN  NaN  NaN
4  NaN  NaN  NaN  NaN
```

So it’s important to remember that `reindex` is strict label indexing only. This can lead to some potentially surprising results in pathological cases where an index contains, say, both integers and strings:

```
In [21]: s = pd.Series([1, 2, 3], index=['a', 0, 1])
In [22]: s
Out[22]:
    a  1
    0  2
    1  3
dtype: int64
In [23]: s.ix[[0, 1]]
Out[23]:
   0  2
   1  3
dtype: int64
In [24]: s.reindex([0, 1])
Out[24]:
   0  2
   1  3
dtype: int64
```

Because the index in this case does not contain solely integers, `ix` falls back on integer indexing. By contrast, `reindex` only looks for the values passed in the index, thus finding the integers 0 and 1. While it would be possible to insert some logic to check whether a passed sequence is all contained in the index, that logic would exact a very high cost in large data sets.

### 28.5.2 Reindex potentially changes underlying Series dtype

The use of `reindex_like` can potentially change the `dtype` of a `Series`.

```
In [25]: series = pd.Series([1, 2, 3])
In [26]: x = pd.Series([True])
In [27]: x.dtype
Out[27]: dtype('bool')
```
In [28]: x = pd.Series([True]).reindex_like(series)

In [29]: x.dtype
Out[29]: dtype('O')

This is because `reindex_like` 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](https://github.com/pandas-dev/pandas/issues/4137) for a more detailed discussion.

### 28.6 Timestamp limitations

#### 28.6.1 Minimum and maximum timestamps

Since pandas represents timestamps in nanosecond resolution, the timespan that can be represented using a 64-bit integer is limited to approximately 584 years:

In [30]: begin = pd.Timestamp.min

In [31]: begin
Out[31]: Timestamp('1677-09-22 00:12:43.145225')

In [32]: end = pd.Timestamp.max

In [33]: end
Out[33]: Timestamp('2262-04-11 23:47:16.854775807')

See [here](https://pandas.pydata.org/pandas-docs/stable/user_guide/timeseries.html#dates/) for ways to represent data outside these bounds.

### 28.7 Parsing Dates from Text Files

When parsing multiple text file columns into a single date column, the new date column is prepended to the data and then `index_col` specification is indexed off of the new set of columns rather than the original ones:

In [34]: 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 [35]: date_spec = {'nominal': [1, 2], 'actual': [1, 3]}  
In [36]: df = pd.read_csv('tmp.csv', header=None,  
                   ....: parse_dates=date_spec,  
                   ....: keep_date_col=True,  
                   ....: index_col=0)

# index_col=0 refers to the combined column "nominal" and not the original  
# first column of 'KORD' strings
In [37]: df
### 28.8 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.

### 28.9 Thread-safety

As of pandas 0.11, pandas is not 100% thread safe. The known issues relate to the `DataFrame.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.

### 28.10 HTML Table Parsing

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.

**Issues with using Anaconda**

- Anaconda ships with lxml version 3.2.0; the following workaround for Anaconda was successfully used to deal with the versioning issues surrounding lxml and BeautifulSoup4.

**Note:** Unless you have both:

- A strong restriction on the upper bound of the runtime of some code that incorporates read_html()

- Complete knowledge that the HTML you will be parsing will be 100% valid at all times

then you should install html5lib and things will work swimmingly without you having to muck around with conda. If you want the best of both worlds then install both html5lib and lxml. If you do install lxml then you need to perform the following commands to ensure that lxml will work correctly:

```
# remove the included version
conda remove lxml

# install the latest version of lxml
pip install 'git+git://github.com/lxml/lxml.git'

# install the latest version of beautifulsoup4
pip install 'bzr+lp:beautifulsoup'
```

Note that you need bzr and git installed to perform the last two operations.

**28.11 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/DataFrame/Panel constructors using something similar to the following:

In [38]: x = np.array(list(range(10)), 'i4')  # big endian
In [39]: newx = x.byteswap().newbyteorder()  # force native byteorder
In [40]: s = pd.Series(newx)

See the NumPy documentation on byte order for more details.
Warning: In v0.16.0, the pandas.rpy interface has been deprecated and will be removed in a future version. Similar functionality can be accessed through the rpy2 project. See the updating section for a guide to port your code from the pandas.rpy to rpy2 functions.

29.1 Updating your code to use rpy2 functions

In v0.16.0, the pandas.rpy module has been deprecated and users are pointed to the similar functionality in rpy2 itself (rpy2 >= 2.4).

Instead of importing `import pandas.rpy.common as com`, the following imports should be done to activate the pandas conversion support in rpy2:

```python
from rpy2.robjects import pandas2ri
pandas2ri.activate()
```

Converting data frames back and forth between rpy2 and pandas should be largely automated (no need to convert explicitly, it will be done on the fly in most rpy2 functions).

To convert explicitly, the functions are `pandas2ri.py2ri()` and `pandas2ri.ri2py()`. So these functions can be used to replace the existing functions in pandas:

- `com.convert_to_r_dataframe(df)` should be replaced with `pandas2ri.py2ri(df)`
- `com.convert_robj(rdf)` should be replaced with `pandas2ri.ri2py(rdf)`

Note: these functions are for the latest version (rpy2 2.5.x) and were called `pandas2ri.pandas2ri()` and `pandas2ri.ri2pandas()` previously.

Some of the other functionality in `pandas.rpy` can be replaced easily as well. For example to load R data as done with the `load_data` function, the current method:

```python
df_iris = com.load_data('iris')
```

can be replaced with:

```python
from rpy2.robjects import r
r.data('iris')
df_iris = pandas2ri.ri2py(r['name'])
```

The `convert_to_r_matrix` function can be replaced by the normal `pandas2ri.py2ri` to convert dataframes, with a subsequent call to `R.as.matrix` function.
Warning: Not all conversion functions in rpy2 are working exactly the same as the current methods in pandas. If you experience problems or limitations in comparison to the ones in pandas, please report this at the issue tracker.

See also the documentation of the rpy2 project.

29.2 R interface with rpy2

If your computer has R and rpy2 (> 2.2) installed (which will be left to the reader), you will be able to leverage the below functionality. On Windows, doing this is quite an ordeal at the moment, but users on Unix-like systems should find it quite easy. rpy2 evolves in time, and is currently reaching its release 2.3, while the current interface is designed for the 2.2.x series. We recommend to use 2.2.x over other series unless you are prepared to fix parts of the code, yet the rpy2-2.3.0 introduces improvements such as a better R-Python bridge memory management layer so it might be a good idea to bite the bullet and submit patches for the few minor differences that need to be fixed.

# if installing for the first time
hg clone http://bitbucket.org/lgautier/rpy2

cd rpy2
hg pull
hg update version_2.2.x
sudo python setup.py install

Note: To use R packages with this interface, you will need to install them inside R yourself. At the moment it cannot install them for you.

Once you have done installed R and rpy2, you should be able to import pandas.rpy.common without a hitch.

29.3 Transferring R data sets into Python

The load_data function retrieves an R data set and converts it to the appropriate pandas object (most likely a DataFrame):

```
In [1]: import pandas.rpy.common as com

In [2]: infert = com.load_data('infert')

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

```
Out[3]:
       education  age  parity  induced  case  spontaneous  stratum  pooled.stratum
0   0-5yrs   0-5yrs 26    6      1    1        2        1         3
1   0-5yrs   0-5yrs 42    1      1    1        0        2         1
2   0-5yrs   0-5yrs 39    6      2    1        0        3         4
3   0-5yrs   0-5yrs 34    4      2    1        0        4         2
4   0-5yrs   0-5yrs 35    3      1    1        1        5         3
```

29.4 Converting DataFrames into R objects

New in version 0.8.
Starting from pandas 0.8, there is **experimental** support to convert DataFrames into the equivalent R object (that is, `data.frame`):

```python
In [4]: df = pd.DataFrame({'A': [1, 2, 3], 'B': [4, 5, 6], 'C':[7,8,9]},
    ...
    index=['one', 'two', 'three'])
    ...

In [5]: r_dataframe = com.convert_to_r_dataframe(df)

In [6]: print(type(r_dataframe))
<class 'rpy2.robjects.vectors.DataFrame'>

In [7]: print(r_dataframe)
   A B C
one 1 4 7
two 2 5 8
three 3 6 9
```

The DataFrame’s index is stored as the `rownames` attribute of the data.frame instance.

You can also use `convert_to_r_matrix` to obtain a `Matrix` instance, but bear in mind that it will only work with homogeneously-typed DataFrames (as R matrices bear no information on the data type):

```python
In [8]: r_matrix = com.convert_to_r_matrix(df)

In [9]: print(type(r_matrix))
<class 'rpy2.robjects.vectors.Matrix'>

In [10]: print(r_matrix)
   A B C
one 1 4 7
two 2 5 8
three 3 6 9
```

### 29.5 Calling R functions with pandas objects

### 29.6 High-level interface to R estimators
Increasingly, packages are being built on top of pandas to address specific needs in data preparation, analysis and visualization. This is encouraging because it means pandas is not only helping users to handle their data tasks but also that it provides a better starting point for developers to build powerful and more focused data tools. The creation of libraries that complement pandas’ functionality also allows pandas development to remain focused around it’s original requirements.

This is an in-exhaustive list of projects that build on pandas in order to provide tools in the PyData space.

We’d like to make it easier for users to find these project, if you know of other substantial projects that you feel should be on this list, please let us know.

### 30.1 Statistics and Machine Learning

#### 30.1.1 Statsmodels

Statsmodels is the prominent python “statistics and econometrics library” and it has a long-standing special relationship with pandas. Statsmodels provides powerful statistics, econometrics, analysis and modeling functionality that is out of pandas’ scope. Statsmodels leverages pandas objects as the underlying data container for computation.

#### 30.1.2 sklearn-pandas

Use pandas DataFrames in your scikit-learn ML pipeline.

### 30.2 Visualization

#### 30.2.1 Bokeh

Bokeh is a Python interactive visualization library for large datasets that natively uses the latest web technologies. Its goal is to provide elegant, concise construction of novel graphics in the style of Protovis/D3, while delivering high-performance interactivity over large data to thin clients.

#### 30.2.2 yhat/ggplot

Hadley Wickham’s ggplot2 is a foundational exploratory visualization package for the R language. Based on “The Grammar of Graphics” it provides a powerful, declarative and extremely general way to generate bespoke plots of any kind of data. It’s really quite incredible. Various implementations to other languages are available, but a faithful
implementation for python users has long been missing. Although still young (as of Jan-2014), the yhat/ggplot project has been progressing quickly in that direction.

30.2.3 Seaborn

Although pandas has quite a bit of “just plot it” functionality built-in, visualization and in particular statistical graphics is a vast field with a long tradition and lots of ground to cover. The Seaborn project builds on top of pandas and matplotlib to provide easy plotting of data which extends to more advanced types of plots then those offered by pandas.

30.2.4 Vincent

The Vincent project leverages Vega (that in turn, leverages d3) to create plots. It has great support for pandas data objects.

30.2.5 Plotly

Plotly’s Python API enables interactive figures and web shareability. Maps, 2D, 3D, and live-streaming graphs are rendered with WebGL and D3.js. The library supports plotting directly from a pandas DataFrame and cloud-based collaboration. Users of matplotlib, ggplot for Python, and Seaborn can convert figures into interactive web-based plots. Plots can be drawn in IPython Notebooks, edited with R or MATLAB, modified in a GUI, or embedded in apps and dashboards. Plotly is free for unlimited sharing, and has cloud, offline, or on-premise accounts for private use.

30.3 IDE

30.3.1 IPython

IPython is an interactive command shell and distributed computing environment. IPython Notebook is a web application for creating IPython notebooks. An IPython notebook is a JSON document containing an ordered list of input/output cells which can contain code, text, mathematics, plots and rich media. IPython notebooks can be converted to a number of open standard output formats (HTML, HTML presentation slides, LaTeX, PDF, ReStructuredText, Markdown, Python) through ‘Download As’ in the web interface and ipython nbconvert in a shell.

Pandas DataFrames implement _repr_html_ methods which are utilized by IPython Notebook for displaying (abbreviated) HTML tables. (Note: HTML tables may or may not be compatible with non-HTML IPython output formats.)

30.3.2 quantopian/qgrid

qgrid is “an interactive grid for sorting and filtering DataFrames in IPython Notebook” built with SlickGrid.

30.3.3 Spyder

Spyder is a cross-platform Qt-based open-source Python IDE with editing, testing, debugging, and introspection features. Spyder can now introspect and display Pandas DataFrames and show both “column wise min/max and global min/max coloring.”
30.4 API

30.4.1 quandl/Python

Quandl API for Python wraps the Quandl REST API to return Pandas DataFrames with timeseries indexes.

30.4.2 pydatastream

PyDatastream is a Python interface to the Thomson Dataworks Enterprise (DWE/Datastream) SOAP API to return indexed Pandas DataFrames or Panels with financial data. This package requires valid credentials for this API (non-free).

30.4.3 pandaSDMX

pandaSDMX is an extensible library to retrieve and acquire statistical data and metadata disseminated in SDMX 2.1. This standard is currently supported by the European statistics office (Eurostat) and the European Central Bank (ECB). Datasets may be returned as pandas Series or multi-indexed DataFrames.

30.4.4 fredapi

fredapi is a Python interface to the Federal Reserve Economic Data (FRED) provided by the Federal Reserve Bank of St. Louis. It works with both the FRED database and ALFRED database that contains point-in-time data (i.e. historic data revisions). fredapi provides a wrapper in python to the FRED HTTP API, and also provides several convenient methods for parsing and analyzing point-in-time data from ALFRED. fredapi makes use of pandas and returns data in a Series or DataFrame. This module requires a FRED API key that you can obtain for free on the FRED website.

30.5 Domain Specific

30.5.1 Geopandas

Geopandas extends pandas data objects to include geographic information which support geometric operations. If your work entails maps and geographical coordinates, and you love pandas, you should take a close look at Geopandas.

30.5.2 xray

xray brings the labeled data power of pandas to the physical sciences by providing N-dimensional variants of the core pandas data structures. It aims to provide a pandas-like and pandas-compatible toolkit for analytics on multi-dimensional arrays, rather than the tabular data for which pandas excels.

30.6 Out-of-core

30.6.1 Blaze

Blaze provides a standard API for doing computations with various in-memory and on-disk backends: NumPy, Pandas, SQLAlchemy, MongoDB, PyTables, PySpark.
30.6.2 Odo

Odo provides a uniform API for moving data between different formats. It uses pandas own `read_csv` for CSV IO and leverages many existing packages such as PyTables, h5py, and pymongo to move data between non pandas formats. Its graph based approach is also extensible by end users for custom formats that may be too specific for the core of odo.
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.

### 31.1 Base R

#### 31.1.1 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

```
In [1]: df = pd.DataFrame(np.random.randn(10, 3), columns=list('abc'))
```

```
In [2]: df[['a', 'c']]
Out[2]:
   a      c
0 -1.039575 -0.424972
1  0.567020 -1.087401
2 -0.673690 -1.478427
3  0.524988  0.577046
4 -1.715002 -0.370647
5 -1.157892  0.844885
6  1.075770  1.643563
```
In [3]: df.loc[:, ['a', 'c']]
Out[3]:
    a     c
0 -1.039575 -0.424972
1  0.567020 -1.087401
2 -0.673690 -1.478427
3  0.524988  0.577046
4 -1.715002 -0.370647
5 -1.157892  0.844885
6  1.075770  1.643563
7 -1.469388 -0.674600
8 -1.776904 -1.294524
9  0.413738 -0.472035

Selecting multiple noncontiguous columns by integer location can be achieved with a combination of the `iloc` indexer attribute and `numpy.r_`.

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  -0.013960 -0.362543 -0.006154 -0.923061  0.895717  0.805244 -1.206412
    1   0.545952 -1.219217 -1.226825  0.769804 -1.281247 -0.727707 -0.121306
    2   2.396780  0.014871  3.357427 -0.317441 -1.236269  0.896171 -0.487602
    3  -0.988387  0.094055  1.262731  1.289997  0.082423 -0.055758  0.536580
    4  -1.340896  1.846883 -1.328865  1.682706 -1.717693  0.888782  0.228440
    5   0.464000  0.227371 -0.496922  0.306389 -2.290613 -1.134623 -1.561819
    6 -0.507516 -0.230096  0.394500 -1.934370 -1.652499  1.488753 -0.896484
    ...  ...  ...  ...  ...  ...  ...  ...
   23 -0.083272 -0.273955 -0.772369 -1.242807 -0.386336 -0.182486  0.164816
   24  2.071413 -1.364763  1.122066  0.066847  1.751987  0.419071 -1.118283
   25  0.036609  0.359986  1.211905  0.850427  1.559457 -0.884633 -1.508808
   26 -1.179240  0.238923  1.756671 -0.747571  0.543625 -0.159609 -0.051458
   27  0.025645  0.932436 -1.694531 -0.182236 -1.072710  0.466764  0.072673
   28  0.439086  0.812684 -0.128932 -0.142506 -1.137207  0.462001 -0.159466
   29 -0.909806 -0.312006  0.383630 -0.631606  1.321415 -0.047999 -2.008210

    a     b     c     d     e     f     g
   7  2.565646  1.431256  1.340309  0.875906 -2.211372  0.974466 -2.006747
   8 -1.097883  0.695775  0.341734 -1.743161 -0.826591 -0.345352  1.314232
   9  0.860245 -0.182271  1.262862  1.289977 -0.623572 -0.164170  0.408204
  10  0.036962  0.369374 -0.034571  0.221471 -0.744471  0.758527  1.729689
  11  0.901805  1.171216  0.520260  0.650776 -1.461665 -1.137707 -0.891060
  12 -0.260383  0.281957  1.523962 -0.008434  1.952541 -1.056652  0.533946
  13  0.576897  1.146000  1.487349  2.015523 -1.833722  1.771740 -0.670027
  14  0.065624  0.307665 -1.898358  1.389045 -0.873585 -0.699862  0.812477

Chapter 31. Comparison with R / R libraries
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 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.

```r
In [9]: df = pd.DataFrame{
    ...:     'v1': [1,3,5,7,8,3,5,na,nan,4,5,7,9],
    ...:     'v2': [11,33,55,77,88,33,55,na,nan,44,55,77,99],
    ...:     'by1': ['red','blue',1,2,na,"big",1,2,"red",1,na,12],
    ...:     'by2': ['wet','dry',99,95,na,"damp",95,99,"red",99,na,na],
    ...:     np.nan
    ...: }

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

In [11]: g[['v1','v2']].mean()
Out[11]:
   by1  by2
v1  
1  95  5  55
99  5  55
```

31.1.2 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 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.

```r
In [9]: df = pd.DataFrame{
    ...:     'v1': [1,3,5,7,8,3,5,na,nan,4,5,7,9],
    ...:     'v2': [11,33,55,77,88,33,55,na,nan,44,55,77,99],
    ...:     'by1': ['red','blue',1,2,na,"big",1,2,"red",1,na,12],
    ...:     'by2': ['wet','dry',99,95,na,"damp",95,99,"red",99,na,na],
    ...:     np.nan
    ...: }

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

In [11]: g[['v1','v2']].mean()
Out[11]:
   by1  by2
v1  
1  95  5  55
99  5  55
```
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:

```r
In [12]: s = pd.Series(np.arange(5), dtype=np.float32)
In [13]: s.isin([2, 4])
Out[13]:
0   False
1   False
2    True
3   False
4    True
dtype: bool
```

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

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

The `apply()` method can be used to replicate this:

```r
In [14]: s = pd.Series(np.arange(5), dtype=np.float32)
In [15]: pd.Series(pd.match(s, [2, 4], np.nan))
Out[15]:
0   NaN
1   NaN
2    0
3   NaN
4    1
dtype: float64
```

For more details and examples see the reshaping documentation.

### 31.1.4 `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`: 
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:

In [16]: import random
In [17]: import string
In [18]:
    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 [19]:
    baseball.pivot_table(values='batting avg', columns='team', aggfunc=np.max)

Out[19]:
      team
    team 1 0.394457
    team 2 0.395730
    team 3 0.343015
    team 4 0.388863
    team 5 0.377379
Name: batting avg, dtype: float64

For more details and examples see the reshaping documentation.

31.1.5 subset

New in version 0.13.

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:

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:

In [20]:
    df = pd.DataFrame({'a': np.random.randn(10), 'b': np.random.randn(10)})

In [21]:
    df.query('a <= b')
Out[21]:
      a         b
0 -1.003455 -0.990738
1  0.083515  0.548796
3 -0.524392  0.904400
4 -0.837804  0.746374
8 -0.507219  0.245479

31.1. Base R
In [22]: df[df.a <= df.b]
Out[22]:
       a      b
0 -1.003455 -0.990738
1  0.083515  0.548796
3 -0.524392  0.904400
4 -0.837804  0.746374
8 -0.507219  0.245479

In [23]: df.loc[df.a <= df.b]
Out[23]:
       a      b
0 -1.003455 -0.990738
1  0.083515  0.548796
3 -0.524392  0.904400
4 -0.837804  0.746374
8 -0.507219  0.245479

For more details and examples see the query documentation.

31.1.6 with

New in version 0.13.

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

df <- data.frame(a=rnorm(10), b=rnorm(10))
with(df, a + b)
df$a + df$b # same as the previous expression

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

In [24]: df = pd.DataFrame({'a': np.random.randn(10), 'b': np.random.randn(10)})
In [25]: df.eval('a + b')
Out[25]:
   0     -0.920205
   1     -0.860236
   2      1.154370
   3      0.188140
   4     -1.163718
   5      0.001397
   6     -0.825694
   7     -1.138198
   8     -1.708034
   9      1.148616

In [26]: df.a + df.b # same as the previous expression
Out[26]:
   0     -0.920205
   1     -0.860236
   2      1.154370
   3      0.188140
   4     -1.163718
   5      0.001397
   6     -0.825694
In certain cases eval() will be much faster than evaluation in pure Python. For more details and examples see the eval documentation.

31.2 zoo

31.3 xts

31.4 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>

31.4.1 ddply

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)
)

ddply(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 [27]: 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 [28]: grouped = df.groupby(['month','week'])
```
In [29]: print grouped['x'].agg([np.mean, np.std])

<table>
<thead>
<tr>
<th>month</th>
<th>week</th>
<th>mean</th>
<th>std</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>1</td>
<td>71.840596</td>
<td>52.886392</td>
</tr>
<tr>
<td>2</td>
<td>71.904794</td>
<td>55.786805</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>89.845632</td>
<td>49.892367</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>97.730877</td>
<td>52.442172</td>
</tr>
<tr>
<td>2</td>
<td>93.369836</td>
<td>47.178389</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>96.592088</td>
<td>58.773744</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>1</td>
<td>59.255715</td>
<td>43.442336</td>
</tr>
<tr>
<td>2</td>
<td>69.634012</td>
<td>28.607369</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>84.510992</td>
<td>59.761096</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>1</td>
<td>104.787666</td>
<td>31.745437</td>
</tr>
<tr>
<td>2</td>
<td>69.717872</td>
<td>53.747188</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>79.892221</td>
<td>52.950459</td>
<td></td>
</tr>
</tbody>
</table>

For more details and examples see the groupby documentation.

### 31.5 reshape / reshape2

#### 31.5.1 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.

In [30]: a = np.array(list(range(1,24))+[np.NAN]).reshape(2,3,4)

In [31]: pd.DataFrame([tuple(list(x)+[val]) for x, val in np.ndenumerate(a)])

Out[31]:

<table>
<thead>
<tr>
<th>0 1 2 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 0 0 0 1</td>
</tr>
<tr>
<td>1 0 0 1 2</td>
</tr>
<tr>
<td>2 0 0 2 3</td>
</tr>
<tr>
<td>3 0 0 3 4</td>
</tr>
<tr>
<td>4 0 1 0 5</td>
</tr>
<tr>
<td>5 0 1 1 6</td>
</tr>
<tr>
<td>6 0 1 2 7</td>
</tr>
<tr>
<td>.. .. .. ..</td>
</tr>
<tr>
<td>17 1 1 1 18</td>
</tr>
<tr>
<td>18 1 1 2 19</td>
</tr>
<tr>
<td>19 1 1 3 20</td>
</tr>
<tr>
<td>20 1 2 0 21</td>
</tr>
<tr>
<td>21 1 2 1 22</td>
</tr>
<tr>
<td>22 1 2 2 23</td>
</tr>
<tr>
<td>23 1 2 3 NaN</td>
</tr>
</tbody>
</table>

[24 rows x 4 columns]

#### 31.5.2 melt.list

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

In [32]: a = list(enumerate(list(range(1,5))+[np.NAN]))

In [33]: pd.DataFrame(a)
Out[33]:
    0 1
0  0 1
1  1 2
2  2 3
3  3 4
4  4 NaN

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

31.5.3 melt.data.frame

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

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:

In [34]: cheese = pd.DataFrame({'first' : ['John', 'Mary'],
                            'last' : ['Doe', 'Bo'],
                            'height' : [5.5, 6.0],
                            'weight' : [130, 150]})

In [35]: pd.melt(cheese, id_vars=['first', 'last'])
Out[35]:
   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 [36]: cheese.set_index(['first', 'last']).stack() # alternative way
Out[36]:
   first  last
John Doe height  5.5
     weight 130.0
Mary Bo height  6.0
     weight 150.0
dtype: float64

For more details and examples see the reshaping documentation.
31.5.4 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 [37]: 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 [38]: mdf = pd.melt(df, id_vars=['month', 'week'])
In [39]: pd.pivot_table(mdf, values='value', index=['variable','week'],
                        columns=['month'], aggfunc=np.mean)
Out[39]:
```

<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>114.001700</td>
<td>132.227290</td>
<td>65.808204</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>124.669553</td>
<td>147.495706</td>
<td>82.882820</td>
</tr>
<tr>
<td>y</td>
<td>1</td>
<td>225.636630</td>
<td>301.864228</td>
<td>91.706834</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>57.692665</td>
<td>215.851669</td>
<td>218.004383</td>
</tr>
<tr>
<td>z</td>
<td>1</td>
<td>17.793871</td>
<td>7.124644</td>
<td>17.679823</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>15.068355</td>
<td>13.873974</td>
<td>9.394966</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)
# Alternative method using base R
with(df, tapply(Amount, list(Animal, FeedType), sum))
```

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

```python
In [40]: 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],
  })
```

In [41]: df.pivot_table(values='Amount', index=['Animal', 'FeedType'],
                        columns=['amount'], aggfunc=np.sum)
Out[41]:
```

<table>
<thead>
<tr>
<th>Animal</th>
<th>FeedType</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Animal1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Animal2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Animal3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
```

In [42]: df['Amount'].sum()  # Summarize the entire DataFrame
```

Alternatively, using `groupby()`

```python
In [43]: df['Amount'].groupby(['Animal', 'FeedType']).sum()
Out[43]:
```

<table>
<thead>
<tr>
<th>Animal</th>
<th>FeedType</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Animal1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Animal2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Animal3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
```
In [41]: df.pivot_table(values='Amount', index='Animal', columns='FeedType', aggfunc='sum')
Out[41]:
           FeedType  A  B
Animal1     Animal1  10  5
Animal2     Animal2  2  13
Animal3     Animal3  6  NaN

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

In [42]: df.groupby(['Animal', 'FeedType'])['Amount'].sum()
Out[42]:
   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.

### 31.5.5 factor

New in version 0.15.

pandas has a data type for categorical data.

```python
import pandas as pd
cut(pd.Series([1, 2, 3, 4, 5, 6]), 3)
factor(pd.Series([1, 2, 3, 2, 2, 3]))
```

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

```python
In [43]: pd.cut(pd.Series([1, 2, 3, 4, 5, 6]), 3)
Out[43]:
0 (0.995, 2.667]
1 (0.995, 2.667]
2 (2.667, 4.333]
3 (2.667, 4.333]
4 (4.333, 6]
5 (4.333, 6]
dtype: category
Categories (3, object): [0.995, 2.667] < (2.667, 4.333] < (4.333, 6]]

In [44]: pd.Series([1, 2, 3, 2, 2, 3]).astype("category")
Out[44]:
0 1
1 2
2 3
3 2
4 2
5 3
```
dtype: category
Categories (3, int64): [1, 2, 3]

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:

```
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.

```
In [3]: url = 'https://raw.github.com/pydata/pandas/master/pandas/tests/data/tips.csv'
In [4]: tips = pd.read_csv(url)
In [5]: tips.head()
```

### 32.1 SELECT

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

```
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:

```
In [6]: tips[['total_bill', 'tip', 'smoker', 'time']].head(5)
Out[6]:
```

<table>
<thead>
<tr>
<th>total_bill</th>
<th>tip</th>
<th>smoker</th>
<th>time</th>
</tr>
</thead>
<tbody>
<tr>
<td>16.99</td>
<td>1.01</td>
<td>Female</td>
<td>No</td>
</tr>
<tr>
<td>10.34</td>
<td>1.66</td>
<td>Male</td>
<td>No</td>
</tr>
<tr>
<td>21.01</td>
<td>3.50</td>
<td>Male</td>
<td>No</td>
</tr>
<tr>
<td>23.68</td>
<td>3.31</td>
<td>Male</td>
<td>No</td>
</tr>
<tr>
<td>24.59</td>
<td>3.61</td>
<td>Female</td>
<td>No</td>
</tr>
</tbody>
</table>
3  23.68  3.31  No Dinner
4  24.59  3.61  No Dinner

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

### 32.2 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 [7]: tips[tips['time'] == 'Dinner'].head(5)
Out[7]:
   total_bill  tip     sex smoker  day time  size
0  16.9900   1.01  Female    No  Sun  Dinner  2
1  10.3400   1.66     Male    No  Sun  Dinner  3
2  21.0100   3.50     Male    No  Sun  Dinner  3
3  23.6800   3.31     Male    No  Sun  Dinner  2
4  24.5900   3.61  Female    No  Sun  Dinner  4
```

The above statement is simply passing a `Series` of True/False objects to the DataFrame, returning all rows with True.

```python
In [8]: is_dinner = tips['time'] == 'Dinner'
In [9]: is_dinner.value_counts()
Out[9]:
False    68
   True  176
Name: time, dtype: int64
```

```python
In [10]: tips[is_dinner].head(5)
Out[10]:
   total_bill  tip     sex smoker  day time  size
0  16.9900   1.01  Female    No  Sun  Dinner  2
1  10.3400   1.66     Male    No  Sun  Dinner  3
2  21.0100   3.50     Male    No  Sun  Dinner  3
3  23.6800   3.31     Male    No  Sun  Dinner  2
4  24.5900   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).

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

```python
# tips of more than $5.00 at Dinner meals
In [11]: tips[(tips['time'] == 'Dinner') & (tips['tip'] > 5.00)]
Out[11]:
   total_bill  tip     sex smoker  day time  size
23  39.4200   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  Sat Dinner  4
116  29.93  5.07 Female  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  Male    Yes  Sun Dinner  4
239  29.03  5.92  Male    No  Sun 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;

# tips by parties of at least 5 diners OR bill total was more than $45

In [12]: tips[(tips['size'] >= 5) | (tips['total_bill'] > 45)]
Out[12]:

<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>Dinner 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>Lunch 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>Lunch 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>Lunch 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>Lunch 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>Dinner 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>Dinner 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>Dinner 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>Dinner 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>Dinner 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>Dinner 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>Dinner 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>Dinner 3</td>
</tr>
</tbody>
</table>

NULL checking is done using the notnull() and isnull() methods.

                           'col2': ['F', np.NaN, 'G', 'H', 'I']})

In [14]: frame
Out[14]:

<table>
<thead>
<tr>
<th></th>
<th>col1</th>
<th>col2</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>A</td>
<td>F</td>
</tr>
<tr>
<td>1</td>
<td>B</td>
<td>NaN</td>
</tr>
<tr>
<td>2</td>
<td>NaN</td>
<td>G</td>
</tr>
<tr>
<td>3</td>
<td>C</td>
<td>H</td>
</tr>
<tr>
<td>4</td>
<td>D</td>
<td>I</td>
</tr>
</tbody>
</table>

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:

SELECT *
FROM frame
WHERE col2 IS NULL;
In [15]: frame[frame['col2'].isnull()]
Out[15]:
   col1 col2
0   B   NaN

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

SELECT * 
FROM frame
WHERE col1 IS NOT NULL;

In [16]: frame[frame['col1'].notnull()]
Out[16]:
   col1 col2
0   A   F
1   B   NaN
3   C   H
4   D   I

### 32.3 GROUP BY

In pandas, SQL's GROUP BY operations 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 [17]: tips.groupby('sex').size()
Out[17]:
   sex
Female  87
 Male   157
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 [18]: tips.groupby('sex').count()
Out[18]:
   sex
   total_bill tip smoker day time size
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:
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.

```python
In [20]: tips.groupby('day').agg({'tip': np.mean, 'day': np.size})
Out[20]:
   tip   day
Fri 2.734737  19
Sat 2.993103  87
Sun 3.255132  76
Thur 2.771452  62
```

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

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

JOINs can be performed with `join()` or `merge()`. By default, `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).

```python
In [22]: df1 = pd.DataFrame({'key': ['A', 'B', 'C', 'D'],
                      ....:            'value': np.random.randn(4)})
......:

In [23]: df2 = pd.DataFrame({'key': ['B', 'D', 'D', 'E'],
                      ....:            'value': np.random.randn(4)})
......:
```

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.

32.4.1 INNER JOIN

```sql
SELECT *
FROM df1
INNER JOIN df2
  ON df1.key = df2.key;
```

```python
In [24]: pd.merge(df1, df2, on='key')
```

<table>
<thead>
<tr>
<th>key</th>
<th>value_x</th>
<th>value_y</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>B</td>
<td>-0.318214 0.543581</td>
</tr>
<tr>
<td>1</td>
<td>D</td>
<td>2.169960  -0.426067</td>
</tr>
<tr>
<td>2</td>
<td>D</td>
<td>2.169960  1.138079</td>
</tr>
</tbody>
</table>

`merge()` also offers parameters for cases when you’d like to join one DataFrame’s column with another DataFrame’s index.

```python
In [25]: indexed_df2 = df2.set_index('key')

In [26]: pd.merge(df1, indexed_df2, left_on='key', right_index=True)
```

<table>
<thead>
<tr>
<th>key</th>
<th>value_x</th>
<th>value_y</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>B</td>
<td>-0.318214 0.543581</td>
</tr>
<tr>
<td>3</td>
<td>D</td>
<td>2.169960  -0.426067</td>
</tr>
<tr>
<td>3</td>
<td>D</td>
<td>2.169960  1.138079</td>
</tr>
</tbody>
</table>

32.4.2 LEFT OUTER JOIN

```sql
-- show all records from df1
SELECT *
FROM df1
LEFT OUTER JOIN df2
  ON df1.key = df2.key;
```
# show all records from df1
In [27]: pd.merge(df1, df2, on='key', how='left')
Out[27]:
   key  value_x  value_y
0  A   0.116174  NaN
1  B  -0.318214  0.543581
2  C   0.285261  NaN
3  D  2.169960  -0.426067
4  D  2.169960   1.138079

32.4.3 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 [28]: pd.merge(df1, df2, on='key', how='right')
Out[28]:
   key  value_x  value_y
0  B  -0.318214  0.543581
1  D   2.169960  -0.426067
2  D   2.169960   1.138079
3  E   NaN      0.086073

32.4.4 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 [29]: pd.merge(df1, df2, on='key', how='outer')
Out[29]:
   key  value_x  value_y
0  A   0.116174  NaN
1  B  -0.318214  0.543581
2  C   0.285261  NaN
3  D  2.169960  -0.426067
4  D  2.169960   1.138079
5  E   NaN      0.086073

32.5 UNION

UNION ALL can be performed using concat().
In [30]: df1 = pd.DataFrame({'city': ['Chicago', 'San Francisco', 'New York City'],
....:                    'rank': range(1, 4))
....:
In [31]: df2 = pd.DataFrame({'city': ['Chicago', 'Boston', 'Los Angeles'],
....:                    'rank': [1, 4, 5])
....:
SELECT city, rank
FROM df1
UNION ALL
SELECT city, rank
FROM df2;
/*
city rank
Chicago 1
San Francisco 2
New York City 3
Chicago 1
Boston 4
Los Angeles 5
*/
In [32]: pd.concat([df1, df2]).drop_duplicates()
Out[32]:
    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.

SELECT city, rank
FROM df1
UNION
SELECT city, rank
FROM df2;
-- notice that there is only one Chicago record this time
/*
city rank
Chicago 1
San Francisco 2
New York City 3
Boston 4
Los Angeles 5
*/
In pandas, you can use concat() in conjunction with drop_duplicates().

In [33]: pd.concat([df1, df2]).drop_duplicates()
Out[33]:
    city  rank
0  Chicago     1
1  San Francisco     2
2  New York City     3
1  Boston     4
32.6 UPDATE

32.7 DELETE
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;
```

### 33.1 Data Structures

#### 33.1.1 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>

#### 33.1.2 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.
33.1.3 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 row 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.

33.2 Data Input / Output

33.2.1 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.

```sas
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.

```python
In [3]: df = pd.DataFrame({
    ...:     'x': [1, 3, 5],
    ...:     'y': [2, 4, 6]})
```

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

33.2.2 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.

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

The pandas method is `read_csv()`, which works similarly.
In [5]: url = 'https://raw.github.com/pydata/pandas/master/pandas/tests/data/tips.csv'

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

In [7]: tips.head()
Out[7]:
   total_bill  tip  sex  smoker  day   time  size
0     16.99  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 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:

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 for more details.

### 33.2.3 Exporting Data

The inverse of PROC IMPORT in SAS is PROC EXPORT

```sas
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')
```

### 33.3 Data Operations

#### 33.3.1 Operations on Columns

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

```sas
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()
```
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]:
<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>14.99</td>
<td>1.01</td>
<td>Female</td>
<td>No</td>
<td>Sun</td>
<td>Dinner 2</td>
<td>7.495</td>
</tr>
<tr>
<td>19.01</td>
<td>3.50</td>
<td>Male</td>
<td>No</td>
<td>Sun</td>
<td>Dinner 3</td>
<td>9.505</td>
</tr>
<tr>
<td>21.68</td>
<td>3.31</td>
<td>Male</td>
<td>No</td>
<td>Sun</td>
<td>Dinner 2</td>
<td>10.840</td>
</tr>
<tr>
<td>22.59</td>
<td>3.61</td>
<td>Female</td>
<td>No</td>
<td>Sun</td>
<td>Dinner 4</td>
<td>11.295</td>
</tr>
<tr>
<td>23.29</td>
<td>4.71</td>
<td>Male</td>
<td>No</td>
<td>Sun</td>
<td>Dinner 4</td>
<td></td>
</tr>
</tbody>
</table>

### 33.3.3 If/Then Logic

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

```sas
data tips;
    set tips;
    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]:
<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>bucket</th>
</tr>
</thead>
<tbody>
<tr>
<td>14.99</td>
<td>1.01</td>
<td>Female</td>
<td>No</td>
<td>Sun</td>
<td>Dinner 2</td>
<td>high</td>
<td></td>
</tr>
<tr>
<td>8.34</td>
<td>1.66</td>
<td>Male</td>
<td>No</td>
<td>Sun</td>
<td>Dinner 3</td>
<td>low</td>
<td></td>
</tr>
</tbody>
</table>
33.3.4 Date Functionality

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

```sas
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 and custom offsets) - see the timeseries documentation for 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          2  2013-02-01           25
```

33.3.5 Selection of Columns

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

```sas
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   14.99    1.01
1    Male     8.34    1.66
2    Male    19.01    3.50
3    Male    21.68    3.31
4  Female    22.59    3.61

# drop
In [22]: tips.drop('sex', axis=1).head()
Out[22]:
     total_bill  tip  smoker  day  time  size
0  14.99      1.01   No  Sun  Dinner  2
1  8.34       1.66   No  Sun  Dinner  3
2 19.01       3.50   No  Sun  Dinner  3
3 21.68       3.31   No  Sun  Dinner  2
4 22.59       3.61   No  Sun  Dinner  4

# rename
In [23]: tips.rename(columns={'total_bill':'total_bill_2'}).head()
Out[23]:
      total_bill_2  tip  sex  smoker  day  time  size
0  14.99        1.01 Female   No  Sun  Dinner  2
1  8.34         1.66    Male   No  Sun  Dinner  3
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

33.3.6 Sorting by Values

Sorting in SAS is accomplished via PROC SORT

```sas
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.

```python
In [24]: tips = tips.sort_values(['sex', 'total_bill'])
In [25]: tips.head()
```
33.4 Merging

The following tables will be used in the merge examples

In [26]: df1 = pd.DataFrame({'key': ['A', 'B', 'C', 'D'],
                         'value': np.random.randn(4)})

In [27]: df1
Out[27]:
   key   value
0   A -0.857326
1   B  1.075416
2   C  0.371727
3   D  1.065735

In [28]: df2 = pd.DataFrame({'key': ['B', 'D', 'D', 'E'],
                         'value': np.random.randn(4)})

In [29]: df2
Out[29]:
   key   value
0   B -0.227314
1   D  2.102726
2   D -0.092796
3   E  0.094694

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.

```r
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.

```
In [30]: inner_join = df1.merge(df2, on=['key'], how='inner')

In [31]: inner_join
Out[31]:
   key  value_x  value_y
0   B  1.075416 -0.227314
1   D  1.065735  2.102726
2   D  1.065735 -0.092796

In [32]: left_join = df1.merge(df2, on=['key'], how='left')

In [33]: left_join
Out[33]:
   key  value_x  value_y
0   A  -0.857326    NaN
1   B  1.075416 -0.227314
2   C  0.371727    NaN
3   D  1.065735  2.102726
4   D  1.065735 -0.092796

In [34]: right_join = df1.merge(df2, on=['key'], how='right')

In [35]: right_join
Out[35]:
   key  value_x  value_y
0   B  1.075416 -0.227314
1   D  1.065735  2.102726
2   D  1.065735 -0.092796
3   E    NaN   0.094694

In [36]: outer_join = df1.merge(df2, on=['key'], how='outer')

In [37]: outer_join
Out[37]:
   key  value_x  value_y
0   A  -0.857326    NaN
1   B  1.075416 -0.227314
2   C  0.371727    NaN
3   D  1.065735  2.102726
4   D  1.065735 -0.092796
5   E    NaN   0.094694

### 33.5 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 [38]: outer_join
Out[38]:
   key  value_x  value_y
0   A  -0.857326    NaN
1   B  1.075416 -0.227314
```
2  C  0.371727   NaN
3  D  1.065735  2.102726
4  D  1.065735 -0.092796
5  E   NaN   0.094694

In [39]: outer_join['value_x'] + outer_join['value_y']
Out[39]:
0    NaN
1  0.848102
2   NaN
3   3.168461
4  0.972939
5   NaN
dtype: float64

In [40]: outer_join['value_x'].sum()
Out[40]: 2.7212865354426206

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 in pandas. Instead, the `pd.isnull` or `pd.notnull` functions should be used for comparisons.

In [41]: outer_join[pd.isnull(outer_join['value_x'])]
Out[41]:
    key  value_x  value_y
      E   NaN    0.094694

In [42]: outer_join[pd.notnull(outer_join['value_x'])]
Out[42]:
    key  value_x  value_y
      0    -0.857326  NaN
      1    1.075416 -0.227314
      2    0.371727  NaN
      3   1.065735  2.102726
      4   1.065735 -0.092796

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 [43]: outer_join.dropna()
Out[43]:
    key  value_x  value_y
      1    1.075416 -0.227314
      3   1.065735  2.102726
      4   1.065735 -0.092796
In [44]: outer_join.fillna(method='ffill')
Out[44]:
   key  value_x  value_y
0  A    -0.857326    NaN
1  B    1.075416  -0.227314
2  C    0.371727  -0.227314
3  D    1.065735   2.102726
4  D    1.065735  -0.092796
5  E    1.065735   0.094694

In [45]: outer_join['value_x'].fillna(outer_join['value_x'].mean())
Out[45]:
0   -0.857326
1    1.075416
2    0.371727
3    1.065735
4    1.065735
5    0.544257
Name: value_x, dtype: float64

33.6 GroupBy

33.6.1 Aggregation

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

```sas
proc summary data=tips nway;
   class sex smoker;
   var total_bill tip;
   output out=tips_summed sum=;
run;
```

pandas provides a flexible groupby mechanism that allows similar aggregations. See the groupby documentation for more details and examples.

In [46]: tips_summed = tips.groupby([sex, smoker])['total_bill', 'tip'].sum()

In [47]: tips_summed.head()
Out[47]:
   sex  smoker  total_bill  tip
Female No        869.68  149.77
   Yes       527.27   96.74
Male  No       1725.75  302.00
      Yes     1217.07  183.07

33.6.2 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;
```
```r
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.

In [48]: gb = tips.groupby('smoker')['total_bill']

In [49]: tips['adj_total_bill'] = tips['total_bill'] - gb.transform('mean')

In [50]: tips.head()
Out[50]:
<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>Female</td>
<td>Yes</td>
<td>Sat</td>
<td>Dinner</td>
<td>1</td>
<td>-17.686344</td>
</tr>
<tr>
<td>92</td>
<td>3.75</td>
<td>Female</td>
<td>Yes</td>
<td>Fri</td>
<td>Dinner</td>
<td>2</td>
<td>-15.006344</td>
</tr>
<tr>
<td>111</td>
<td>5.25</td>
<td>Female</td>
<td>No</td>
<td>Sat</td>
<td>Dinner</td>
<td>1</td>
<td>-11.938278</td>
</tr>
<tr>
<td>145</td>
<td>6.35</td>
<td>Female</td>
<td>No</td>
<td>Thur</td>
<td>Lunch</td>
<td>2</td>
<td>-10.838278</td>
</tr>
<tr>
<td>135</td>
<td>6.51</td>
<td>Female</td>
<td>No</td>
<td>Thur</td>
<td>Lunch</td>
<td>2</td>
<td>-10.678278</td>
</tr>
</tbody>
</table>

33.6.3 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.

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:

In [51]: tips.groupby(['sex', 'smoker']).first()
Out[51]:
<table>
<thead>
<tr>
<th>sex</th>
<th>smoker</th>
<th>total_bill</th>
<th>tip</th>
<th>day</th>
<th>time</th>
<th>size</th>
<th>adj_total_bill</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>No</td>
<td>5.25</td>
<td>1.00</td>
<td>Sat</td>
<td>Dinner</td>
<td>1</td>
<td>-11.938278</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>1.07</td>
<td>1.00</td>
<td>Sat</td>
<td>Dinner</td>
<td>1</td>
<td>-17.686344</td>
</tr>
<tr>
<td>Male</td>
<td>No</td>
<td>5.51</td>
<td>2.00</td>
<td>Thur</td>
<td>Lunch</td>
<td>2</td>
<td>-11.678278</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>5.25</td>
<td>5.15</td>
<td>Sun</td>
<td>Dinner</td>
<td>2</td>
<td>-13.506344</td>
</tr>
</tbody>
</table>
```
33.7 Other Considerations

33.7.1 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.

33.7.2 Data Interop

pandas provides a read_sas() method that can read SAS data saved in the XPORT format. The ability to read SAS’s binary format is planned for a future release.

```python
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')
```

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
# version 0.17, 10M rows

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
```
34.1 Input/Output

34.1.1 Pickling

```
pandas.read_pickle(path)  # Load pickled pandas object (or any other pickled object) from the specified file path
```

**pandas.read_pickle**

```
pandas.read_pickle(path)
```

Load pickled pandas object (or any other pickled object) from the specified file path

Warning: Loading pickled data received from untrusted sources can be unsafe. See: http://docs.python.org/2.7/library/pickle.html

**Parameters**

- **path**: string
  - File path

**Returns**

- **unpickled**: type of object stored in file

34.1.2 Flat File

```
read_table(filepath_or_buffer[, sep, ...])  # Read general delimited file into DataFrame
read_csv(filepath_or_buffer[, sep, dialect, ...])  # Read CSV (comma-separated) file into DataFrame
read_fwf(filepath_or_buffer[, colspecs, widths])  # Read a table of fixed-width formatted lines into DataFrame
```

935
pandas: powerful Python data analysis toolkit, Release 0.17.0

pandas.read_table

pandas.read_table(filepath_or_buffer, sep='\t', dialect=None, compression='infer', doublequote=True, escapechar=None, quoting=0, skipinitialspace=False, lineterminator=None, header='infer', index_col=None, names=None, prefix=None, skiprows=None, skipfooter=None, skip_footer=0, na_values=None, true_values=None, false_values=None, delimiter=None, converters=None, dtype=None, usecols=None, engine=None, delim_whitespace=False, as_recarray=False, na_filter=True, compact_ints=False, use_unsigned=False, low_memory=True, buffer_lines=None, warn_bad_lines=True, error_bad_lines=True, keep_default_na=True, thousands=None, comment=None, decimal='.', parse_dates=False, keep_date_col=False, dayfirst=False, date_parser=None, memory_map=False, float_precision=None, nrows=None, iterator=False, chunksize=None, verbose=False, encoding=None, squeeze=False, mangle_dupe_cols=True, tupleize_cols=False, infer_datetime_format=False, skip_blank_lines=True)

Read general delimited file into DataFrame

Also supports optionally iterating or breaking of the file into chunks.

**Parameters**

- **filepath_or_buffer**: 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.csv

- **sep**: string, default t (tab-stop)
  - Delimiter to use. Regular expressions are accepted.

- **engine**: {'c', 'python'}
  - Parser engine to use. The C engine is faster while the python engine is currently more feature-complete.

- **lineterminator**: string (length 1), default None
  - Character to break file into lines. Only valid with C parser

- **quotechar**: string (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 None
  - Control field quoting behavior per csv.QUOTE_* constants. Use one of QUOTE_MINIMAL (0), QUOTE_ALL (1), QUOTE_NONNUMERIC (2) or QUOTE_NONE (3). Default (None) results in QUOTE_MINIMAL behavior.

- **skipinitialspace**: boolean, default False
  - Skip spaces after delimiter

- **escapechar**: string (length 1), default None
  - One-character string used to escape delimiter when quoting is QUOTE_NONE.

- **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')

- **compression**: {'gzip', 'bz2', 'infer', None}, default 'infer'
  -
For on-the-fly decompression of on-disk data. If ‘infer’, then use gzip or bz2 if filepath_or_buffer is a string ending in ‘.gz’ or ‘.bz2’, respectively, and no decompression otherwise. Set to None for no decompression.

dialect : string or csv.Dialect instance, default None

If None defaults to Excel dialect. Ignored if sep longer than 1 char See csv.Dialect documentation for more details

header : int, list of ints, default ‘infer’

Row number(s) to use as the column names, and the start of the data. Defaults to 0 if no names passed, otherwise 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 are 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.

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

index_col : int or sequence or False, default None

Column to use as the row labels of the DataFrame. If a sequence is given, a MultiIndex is used. If you have a malformed file with delimiters at the end of each line, you might consider index_col=False to force pandas to _not_ use the first column as the index (row names)

names : array-like, default None

List of column names to use. If file contains no header row, then you should explicitly pass header=None

prefix : string, default None

Prefix to add to column numbers when no header, e.g ‘X’ for X0, X1, ...

na_values : str, list-like or dict, default None

Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values

true_values : list, default None

Values to consider as True

false_values : list, default None

Values to consider as False

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

parse_dates : boolean, list of ints or names, 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. {‘foo’ : [1, 3]} -> parse columns 1, 3 as date and call result ‘foo’ A fast-path exists for iso8601-formatted dates.

keep_date_col : boolean, default False

34.1. Input/Output
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

thousands : str, default None

Thousands separator

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 '#emptyna,b,cn1,2,3' with header=0 will result in 'a,b,c' being treated as the header.

decimal : str, default '.

Character to recognize as decimal point. E.g. use ',' for European data

nrows : int, default None

Number of rows of file to read. Useful for reading pieces of large files

iterator : boolean, default False

Return TextFileReader object

chunksize : int, default None

Return TextFileReader object for iteration

skipfooter : int, default 0

Number of lines at bottom of file to skip (Unsupported with engine='c')

converters : dict, default None

Dict of functions for converting values in certain columns. Keys can either be integers or column labels

verbose : boolean, default False

Indicate number of NA values placed in non-numeric columns

delimiter : string, default None

Alternative argument name for sep. Regular expressions are accepted.

encoding : string, default None

Encoding to use for UTF when reading/writing (ex. ‘utf-8’). List of Python standard encodings
squeeze : boolean, default False

If the parsed data only contains one column then return a Series

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

usecols : array-like, default None

Return a subset of the columns. Results in much faster parsing time and lower memory usage.

mangle_dupe_cols : boolean, default True

Duplicate columns will be specified as ‘X.0’...'X.N’, rather than ‘X'...'X'

tupleize_cols : boolean, default False

Leave a list of tuples on columns as is (default is to convert to a Multi Index on the columns)

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. (Only valid with C parser)

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. (Only valid with C parser).

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

skip_blank_lines : boolean, default True

If True, skip over blank lines rather than interpreting as NaN values

Returns result : DataFrame or TextParser

pandas.read_csv

pandas.read_csv(filepath_or_buffer, sep='; ', dialect=None, compression='infer', doublequote=True, escapechar=None, quotechar='', quoting=0, skipinitialspace=False, lineterminator=None, header='infer', index_col=None, names=None, prefix=None, skiprows=None, skipfooter=0, skip_blank_lines=True, na_values=None, true_values=None, false_values=None, delimiter=None, converters=None, dtype=None, usecols=None, engine=None, delimiter_whitespace=False, as_recarray=False, na_filter=True, compact_ints=False, use_unsigned=False, low_memory=True, buffer_lines=None, warn_bad_lines=True, error_bad_lines=True, keep_default_na=True, thousands=None, comment=None, decimal='.', parse_dates=False, keep_date_col=False, dayfirst=False, date_parser=None, memory_map=False, float_precision=None, nrows=None, iterator=False, chunksize=None, verbose=False, encoding=None, squeeze=False, mangle_dupe_cols=True, tupleize_cols=False, infer_datetime_format=False, skip_blank_lines=True)

Read CSV (comma-separated) file into DataFrame
Also supports optionally iterating or breaking of the file into chunks.

**Parameters**

filepath_or_buffer : 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://local-host/path/to/table.csv

sep : string, default ‘,’

Delimiter to use. If sep is None, will try to automatically determine this. Regular expressions are accepted.

ginparse : {'c', 'python'}

Parser engine to use. The C engine is faster while the python engine is currently more feature-complete.

lineterminator : string (length 1), default None

Character to break file into lines. Only valid with C parser

quotechar : string (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 None

Control field quoting behavior per csv.QUOTE_* constants. Use one of QUOTE_MINIMAL (0), QUOTE_ALL (1), QUOTE_NONNUMERIC (2) or QUOTE_NONE (3). Default (None) results in QUOTE_MINIMAL behavior.

skipinitialspace : boolean, default False

Skip spaces after delimiter

escapechar : string (length 1), default None

One-character string used to escape delimiter when quoting is QUOTE_NONE.

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')

compression : {'gzip', 'bz2', 'infer', None}, default 'infer'

For on-the-fly decompression of on-disk data. If ‘infer’, then use gzip or bz2 if filepath_or_buffer is a string ending in ‘.gz’ or ‘.bz2’, respectively, and no decompression otherwise. Set to None for no decompression.

dialect : string or csv.Dialect instance, default None

If None defaults to Excel dialect. Ignored if sep longer than 1 char See csv.Dialect documentation for more details

header : int, list of ints, default ‘infer’

Row number(s) to use as the column names, and the start of the data. Defaults to 0 if no names passed, otherwise 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 are 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.
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

index_col : int or sequence or False, default None

Column to use as the row labels of the DataFrame. If a sequence is given, a MultiIndex is used. If you have a malformed file with delimiters at the end of each line, you might consider index_col=False to force pandas to _not_ use the first column as the index (row names)

names : array-like, default None

List of column names to use. If file contains no header row, then you should explicitly pass header=None

prefix : string, default None

Prefix to add to column numbers when no header, e.g ‘X’ for X0, X1, ...

na_values : str, list-like or dict, default None

Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values

true_values : list, default None

Values to consider as True

false_values : list, default None

Values to consider as False

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

parse_dates : boolean, list of ints or names, 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. {‘foo’ : [1, 3]} -> parse columns 1, 3 as date and call result ‘foo’ A fast-path exists for iso8601-formatted dates.

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

thousands : str, default None
Thousands separator

**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 ‘#emptyna,b,cn1,2,3’ with `header=0` will result in ‘a,b,c’ being treated as the header.

**decimal** : str, default ‘.’

Character to recognize as decimal point. E.g. use ‘,’ for European data

**nrows** : int, default None

Number of rows of file to read. Useful for reading pieces of large files

**iterator** : boolean, default False

Return TextFileReader object

**chunksize** : int, default None

Return TextFileReader object for iteration

**skipfooter** : int, default 0

Number of lines at bottom of file to skip (Unsupported with engine=’c’)

**converters** : dict, default None

Dict of functions for converting values in certain columns. Keys can either be integers or column labels

**verbose** : boolean, default False

Indicate number of NA values placed in non-numeric columns

**delimiter** : string, default None

Alternative argument name for sep. Regular expressions are accepted.

**encoding** : string, default None

Encoding to use for UTF when reading/writing (ex. ‘utf-8’). List of Python standard encodings

**squeeze** : boolean, default False

If the parsed data only contains one column then return a Series

**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

**usecols** : array-like, default None

Return a subset of the columns. Results in much faster parsing time and lower memory usage.

**mangle_dupe_cols** : boolean, default True

Duplicate columns will be specified as ‘X.0’...'X.N’, rather than ‘X’...'X'

**tupleize_cols** : boolean, default False
Leave a list of tuples on columns as is (default is to convert to a Multi Index on the columns)

**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. (Only valid with C parser)

**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. (Only valid with C parser).

**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

**skip_blank_lines** : boolean, default True

If True, skip over blank lines rather than interpreting as NaN values

**Returns**

result : DataFrame or TextParser

**pandas.read_fwf**

pandas.read_fwf(filepath_or_buffer, colspecs='infer', widths=None, **kwds)

Read a table of fixed-width formatted lines into DataFrame

Also supports optionally iterating or breaking of the file into chunks.

**Parameters**

filepath_or_buffer : 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.csv

colspecs : list of pairs (int, int) or ‘infer’. optional

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=‘infer’).

widths : list of ints. optional

A list of field widths which can be used instead of ‘colspecs’ if the intervals are contiguous.

lineterminator : string (length 1), default None

Character to break file into lines. Only valid with C parser

quotechar : string (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 None

Control field quoting behavior per csv.QUOTE_* constants. Use one of QUOTE_MINIMAL (0), QUOTE_ALL (1), QUOTE_NONNUMERIC (2) or QUOTE_NONE (3). Default (None) results in QUOTE_MINIMAL behavior.
skipinitialspace : boolean, default False

Skip spaces after delimiter

escapechar : string (length 1), default None

One-character string used to escape delimiter when quoting is QUOTE_NONE.

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')

compression : {'gzip', 'bz2', 'infer', None}, default 'infer'

For on-the-fly decompression of on-disk data. If ‘infer’, then use gzip or bz2 if filepath_or_buffer is a string ending in ‘.gz’ or ‘.bz2’, respectively, and no decompression otherwise. Set to None for no decompression.

dialect : string or csv.Dialect instance, default None

If None defaults to Excel dialect. Ignored if sep longer than 1 char See csv.Dialect documentation for more details

header : int, list of ints, default ‘infer’

Row number(s) to use as the column names, and the start of the data. Defaults to 0 if no names passed, otherwise 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 are 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.

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

index_col : int or sequence or False, default None

Column to use as the row labels of the DataFrame. If a sequence is given, a MultiIndex is used. If you have a malformed file with delimiters at the end of each line, you might consider index_col=False to force pandas to _not_ use the first column as the index (row names)

names : array-like, default None

List of column names to use. If file contains no header row, then you should explicitly pass header=None

prefix : string, default None

Prefix to add to column numbers when no header, e.g ‘X’ for X0, X1, ...

na_values : str, list-like or dict, default None

Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values

true_values : list, default None

Values to consider as True

false_values : list, default None

Values to consider as False
**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.

**parse_dates**: boolean, list of ints or names, 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. {'foo': [1, 3]} -> parse columns 1, 3 as date and call result ‘foo’ A fast-path exists for iso8601-formatted dates.

**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 (rowwise) 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

**thousands**: str, default None

Thousands separator

**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 ‘#emptyna,b,cn1,2,3’ with header=0 will result in ‘a,b,c’ being treated as the header.

**decimal**: str, default ‘.’

Character to recognize as decimal point. E.g. use ‘,’ for European data

**nrows**: int, default None

Number of rows of file to read. Useful for reading pieces of large files

**iterator**: boolean, default False

Return TextFileReader object

**chunksize**: int, default None

Return TextFileReader object for iteration

**skipfooter**: int, default 0

Number of lines at bottom of file to skip (Unsupported with engine=’c’)

**converters**: dict, default None
Dict of functions for converting values in certain columns. Keys can either be integers or column labels.

**verbose**: boolean, default False

Indicate number of NA values placed in non-numeric columns.

**delimiter**: string, default None

Alternative argument name for sep. Regular expressions are accepted.

**encoding**: string, default None

Encoding to use for UTF when reading/writing (ex. ‘utf-8’). List of Python standard encodings.

**squeeze**: boolean, default False

If the parsed data only contains one column then return a Series.

**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.

**usecols**: array-like, default None

Return a subset of the columns. Results in much faster parsing time and lower memory usage.

**mangle_dupe_cols**: boolean, default True

Duplicate columns will be specified as ‘X.0’...'X.N’, rather than ‘X'...'X’

**tupleize_cols**: boolean, default False

Leave a list of tuples on columns as is (default is to convert to a Multi Index on the columns).

**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. (Only valid with C parser)

**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. (Only valid with C parser).

**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.

**skip_blank_lines**: boolean, default True

If True, skip over blank lines rather than interpreting as NaN values.

**Returns result**: DataFrame or TextParser

Also, ‘delimiter’ is used to specify the filler character of the fields if it is not spaces (e.g., ‘~’).
34.1.3 Clipboard

```
pandas.read_clipboard(**kwargs)  # Read text from clipboard and pass to read_table.
```

**pandas.read_clipboard**

Read text from clipboard and pass to read_table. See read_table for the full argument list.

- If unspecified, `sep` defaults to ‘s’

**Returns** `parsed` : DataFrame

34.1.4 Excel

```
pandas.read_excel(io[, sheetname, header, ...])  # Read an Excel table into a pandas DataFrame
ExcelFile.parse([sheetname, header, ...])  # Parse specified sheet(s) into a DataFrame
```

**pandas.read_excel**

Read an Excel table into a pandas DataFrame.

- **Parameters**
  - `io` : string, file-like object, pandas ExcelFile, or xlrd workbook.
    - 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/workbook.xlsx
  - `sheetname` : string, int, mixed list of strings/int lists, 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.
    - str/int -> DataFrame is returned. list|None -> Dict of DataFrames is returned, with keys representing sheets.
    - **Available Cases**
      - Defaults to 0 -> 1st sheet as a DataFrame
      - 1 -> 2nd sheet as a DataFrame
      - “Sheet1” -> 1st sheet as a DataFrame
      - [0,1,”Sheet5"] -> 1st, 2nd & 5th sheet as a dictionary of DataFrames
      - None -> All sheets as a dictionary of DataFrames
  - `header` : int, list of ints, 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
**skiprows** : list-like

Rows to skip at the beginning (0-indexed)

**skip_footer** : int, default 0

Rows at the end to skip (0-indexed)

**index_col** : int, list of ints, 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

**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.

**parse_cols** : int or list, default None

- If None then parse all columns,
- If int then indicates last column to be parsed
- If list of ints then indicates list of column numbers to be parsed
- If string then indicates comma separated list of column names and column ranges (e.g. “A:E” or “A,C,E:F”)

**na_values** : list-like, default None

List of additional strings to recognize as NA/NaN

**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.

**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

**verbose** : boolean, default False

Indicate number of NA values placed in non-numeric columns

**engine** : string, default None

If io is not a buffer or path, this must be set to identify io. Acceptable values are None or xlr

**convert_float** : boolean, 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

**has_index_names** : boolean, default None

DEPRECATED: for version 0.17+ index names will be automatically inferred based on index_col. To read Excel output from 0.16.2 and prior that had saved index names, use True.

**Returns** parsed : DataFrame or Dict of DataFrames
DataFrame from the passed in Excel file. See notes in sheetname argument for more information on when a Dict of Dataframes is returned.

**pandas.ExcelFile.parse**

ExcelFile.parse(sheetname=0, header=0, skiprows=None, skip_footer=0, index_col=None, parse_cols=None, parse_dates=False, date_parser=None, na_values=None, thousands=None, convert_float=True, has_index_names=None, converters=None, **kwds)

Parse specified sheet(s) into a DataFrame

Equivalent to read_excel(ExcelFile, ...) See the read_excel docstring for more info on accepted parameters

### 34.1.5 JSON

**pandas.read_json**

pandas.read_json(path_or_buf=None, orient=None, typ='frame', dtype=True, convert_axes=True, convert_dates=True, keep_default_dates=True, numpy=False, precise_float=False, date_unit=None)

Convert a JSON string to pandas object

**Parameters**

- **path_or_buf**: a valid JSON string or file-like, default: None
  - 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

- **orient**
  - default is ‘index’
  - allowed values are: {'split', 'records', 'index'}
  - The Series index must be unique for orient ‘index’.
  - default is ‘columns’
  - allowed values are: {'split', 'records', 'index', 'columns', 'values'}
  - The DataFrame index must be unique for orient ‘columns’.
  - The DataFrame columns must be unique for orient ‘columns’, and ‘records’.
  - 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 -> {index -> value}}
– values : just the values array

typ : type of object to recover (series or frame), default ‘frame’
dtype : boolean or dict, default True

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.

convert_axes : boolean, default True

Try to convert the axes to the proper dtypes.

convert_dates : boolean, default True

List of columns to parse for dates; If True, then try to parse datelike columns default is
True; 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’

keep_default_dates : boolean, default True

If parsing dates, then parse the default datelike columns

numpy : boolean, 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.

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, default None

The timestamp unit to detect if converting dates. The default behaviour is to try and de-
tect 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.

Returns result : Series or DataFrame

```
json_normalize(data[, record_path, meta, ...])  “Normalize” semi-structured JSON data into a flat table
```

### pandas.io.json.json_normalize

```
pandas.io.json.json_normalize(data, record_path=None, meta=None, meta_prefix=None, record_prefix=None)
```

“Normalize” semi-structured JSON data into a flat table

Parameters data : dict or list of dicts

Unserialized JSON objects

record_path : string or list of strings, 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 (string or list of strings), default None

Fields to use as metadata for each record in resulting table

**record_prefix**: string, default None

If True, prefix records with dotted (?) path, e.g. foo.bar.field if path to records is [‘foo’, ‘bar’]

**meta_prefix**: string, default None

**Returns**

frame : DataFrame

**Examples**

```python
>>> data = [{'state': 'Florida',
...   'shortname': 'FL',
...   'info': {
...     'governor': 'Rick Scott'
...   },
...   'counties': [{'name': 'Dade', 'population': 12345},
...     {'name': 'Broward', 'population': 40000},
...     {'name': 'Palm Beach', 'population': 60000}]
... },
... {'state': 'Ohio',
...   'shortname': 'OH',
...   'info': {
...     'governor': 'John Kasich'
...   },
...   'counties': [{'name': 'Summit', 'population': 1234},
...     {'name': 'Cuyahoga', 'population': 1337}]}
>>> from pandas.io.json import json_normalize
>>> result = json_normalize(data, 'counties', [state, 'shortname',
...   'info', 'governor'])
>>> result
     name population info.governor state shortname
0     Dade     12345        Rick Scott  Florida    FL
1   Broward     40000        Rick Scott  Florida    FL
2  Palm Beach     60000        Rick Scott  Florida    FL
3    Summit      1234        John Kasich  Ohio      OH
4  Cuyahoga     1337        John Kasich  Ohio      OH
```

### HTML

**read_html(io[, match, flavor, header, ...])** Read HTML tables into a list of DataFrame objects.

**pandas.read_html**

read_html (io, match=’.+’, flavor=None, header=None, index_col=None, skiprows=None, attrs=None, parse_dates=False, tupleize_cols=False, thousands=’,’, encoding=None)

Read HTML tables into a list of DataFrame objects.

**Parameters**

* io : str or file-like

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 or None, container of strings

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 or None, optional

The row (or list of rows for a MultiIndex) to use to make the columns headers.

**index_col** : int or list-like or None, optional

The column (or list of columns) to use to create the index.

**skiprows** : int or list-like or slice or None, optional

0-based. Number of rows to skip after parsing the column integer. 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 or None, 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,

```python
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.

```python
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.

**tupleize_cols** : bool, optional

If False try to parse multiple header rows into a MultiIndex, otherwise return raw
tuples. Defaults to False.

**thousands** : str, optional

Separator to use to parse thousands. Defaults to ‘,’.
encoding : str or None, 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).

Returns dfs : list of DataFrames

See also:
pandas.read_csv

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”.

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.

34.1.7 HDFStore: PyTables (HDF5)

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>pandas.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>
</tbody>
</table>

pandas.read_hdf

pandas.read_hdf (path_or_buf, key=None, **kwargs)

read from the store, close it if we opened it

Retrieve pandas object stored in file, optionally based on where criteria

Parameters path_or_buf : path (string), or buffer to read from

key : group identifier in the store. Can be omitted a HDF file contains a single pandas object.

where : list of Term (or convertible) objects, optional

start : optional, integer (defaults to None), row number to start
selection

stop : optional, integer (defaults to None), row number to stop

selection

columns : optional, a list of columns that if not None, will limit the
return columns

iterator : optional, boolean, return an iterator, default False

chunksize : optional, nrows to include in iteration, return an iterator

Returns  The selected object

pandas.HDFStore.put

HDFStore.put (key, value, format=None, append=False, **kwargs)
Store object in HDFStore

Parameters  key : object

value : {Series, DataFrame, Panel}

format : ‘fixed(f)table(t)’, default is ‘fixed’

fixed(f)  [Fixed format] Fast writing/reading. Not-appendable, nor searchable

table(t)  [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 : boolean, default False

This will force Table format, append the input data to the existing.

encoding : default None, provide an encoding for strings

dropna : boolean, default False, do not write an ALL nan row to
the store settable by the option ‘io.hdf.dropna_table’

pandas.HDFStore.append

HDFStore.append (key, value, format=None, append=True, columns=None, dropna=None, **kwargs)
Append to Table in file. Node must already exist and be Table format.

Parameters  key : object

value : {Series, DataFrame, Panel, Panel4D}

format: ‘table’ is the default

table(t)  [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 : boolean, default True, append the input data to the
existing

data_columns : list of columns to create as data columns, or True to
use all columns
min_itemsize : dict of columns that specify minimum string sizes
nan_rep : string to use as string nan representation
chunksize : size to chunk the writing
expectedrows : expected TOTAL row size of this table
encoding : default None, provide an encoding for strings
dropna : boolean, 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 : object
Returns obj : type of 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, **kwargs)
Retrieve pandas object stored in file, optionally based on where criteria
Parameters key : object
    where : list of Term (or convertable) objects, optional
    start : integer (defaults to None), row number to start selection
    stop : integer (defaults to None), row number to stop selection
    columns : a list of columns that if not None, will limit the return
columns
    iterator : boolean, return an iterator, default False
    chunksize : nrows to include in iteration, return an iterator
    auto_close : boolean, should automatically close the store when
    finished, default is False
Returns The selected object

34.1.8 SAS

read_sas(filepath_or_buffer[, format, ...])  Read a SAS file into a DataFrame.
pandas.read_sas

```python
pandas.read_sas(filepath_or_buffer, format='xport', index=None, encoding='ISO-8859-1',
chunksize=None, iterator=False)
```

Read a SAS file into a DataFrame.

**Parameters**

- `filepath_or_buffer` : string or file-like object
  Path to SAS file or object implementing binary read method.
- `format` : string
  File format, only *xport* is currently supported.
- `index` : identifier of index column
  Identifier of column that should be used as index of the DataFrame.
- `encoding` : string
  Encoding for text data.
- `chunksize` : int
  Read file *chunksize* lines at a time, returns iterator.
- `iterator` : boolean, default False
  Return XportReader object for reading file incrementally.

**Returns**

DataFrame or XportReader

**Examples**

Read a SAS Xport file:

```python
>>> df = pandas.read_sas('filename.XPT')
```

Read a Xport file in 10,000 line chunks:

```python
>>> itr = pandas.read_sas('filename.XPT', chunksize=10000)
>>> for chunk in itr:
...     do_something(chunk)
```

New in version 0.17.0.

34.1.9 SQL

```python
read_sql_table(table_name, con[, schema, ...])
read_sql_query(sql, con[, index_col, ...])
read_sql(sql, con[, index_col, ...])
```

Read SQL database table into a DataFrame. This function does not support DBAPI connections.

**pandas.read_sql_table**

```python
pandas.read_sql_table(table_name, con, schema=None, index_col=None, coerce_float=True,
parse_dates=None, columns=None, chunksize=None)
```

Read SQL database table into a DataFrame.

Given a table name and an SQLAlchemy connectable, returns a DataFrame.
**Parameters**

**table_name** : string
Name of SQL table in database

**con** : SQLAlchemy connectable (or database string URI)
Sqlite DBAPI connection mode not supported

**schema** : string, default None
Name of SQL schema in database to query (if database flavor supports this). If None, use default schema (default).

**index_col** : string, optional, default: None
Column to set as index

**coerce_float** : boolean, default True
Attempt to convert values to 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 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

**chunksize** : int, default None
If specified, return an iterator where chunksize is the number of rows to include in each chunk.

**Returns**

Dataframe

**See also**

read_sql_query Read SQL query into a DataFrame.

read_sql

**Notes**

Any datetime values with time zone information will be converted to UTC

**pandas.read_sql_query**

pandas.read_sql_query(sql, con, index_col=None, coerce_float=True, params=None, parse_dates=None, chunksize=None)

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`: string SQL query or SQLAlchemy Selectable (select or text object) to be executed.
- `con`: SQLAlchemy connectable (engine/connection) or database string URI or sqlite3 DBAPI2 connection. Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.
- `index_col`: string, optional, default: None
  - Column name to use as index for the returned DataFrame object.
- `coerce_float`: boolean, default True
  - Attempt to convert values to 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}` 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

**See also:**

`read_sql_table` Read SQL database table into a DataFrame

**Notes**

Any datetime values with time zone information parsed via the `parse_dates` parameter will be converted to UTC.

**pandas.read_sql**

```python
def pandas.read_sql(sql, con, index_col=None, coerce_float=True, params=None, parse_dates=None, columns=None, chunksize=None)
```

Read SQL query or database table into a DataFrame.

**Parameters**

- `sql`: string SQL query or SQLAlchemy Selectable (select or text object)
to be executed, or database table name.

**con**: SQLAlchemy connectable(engine/connection) or database string URI

or DBAPI2 connection (fallback mode) Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

**index_col**: string, optional, default: None

column name to use as index for the returned DataFrame object.

**coerce_float**: boolean, default True

Attempt to convert values to 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, ns) 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

**See also**:

read_sql_table Read SQL database table into a DataFrame

read_sql_query Read SQL query into a DataFrame

**Notes**

This function is a convenience wrapper around read_sql_table and read_sql_query (and for backward compatibility) and will delegate to the specific function depending on the provided input (database table name or sql query). The delegated function might have more specific notes about their functionality not listed here.

### 34.1.10 Google BigQuery
pandas: powerful Python data analysis toolkit, Release 0.17.0

**read_gbq**
```python
read_gbq(query[, project_id, index_col, ...])
```
Load data from Google BigQuery.

**to_gbq**
```python
to_gbq(dataframe, destination_table, project_id)
```
Write a DataFrame to a Google BigQuery table.

---

**pandas.io.gbq.read_gbq**

`pandas.io.gbq.read_gbq(query, project_id=None, index_col=None, col_order=None, reauth=False, verbose=True)`

Load data from Google BigQuery.

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The main method a user calls to execute a Query in Google BigQuery and read results into a pandas DataFrame using the v2 Google API client for Python. Documentation for the API is available at https://developers.google.com/api-client-library/python/. Authentication to the Google BigQuery service is via OAuth 2.0 using the product name ‘pandas GBQ’.

**Parameters**

- `query` : str
  SQL-Like Query to return data values

- `project_id` : str
  Google BigQuery Account project ID.

- `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` : boolean (default False)
  Force Google BigQuery to reauthenticate the user. This is useful if multiple accounts are used.

- `verbose` : boolean (default True)
  Verbose output

**Returns**

- `df` : DataFrame
  DataFrame representing results of query

---

**pandas.io.gbq.to_gbq**

`pandas.io.gbq.to_gbq(dataframe, destination_table, project_id, chunksize=10000, verbose=True, reauth=False, if_exists='fail')`

Write a DataFrame to a Google BigQuery table.

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**Parameters**

- `dataframe` : DataFrame
  DataFrame to be written

- `destination_table` : string
  Name of table to be written, in the form ‘dataset.tablename’

- `project_id` : str
Google BigQuery Account project ID.

chunksize : int (default 10000)

Number of rows to be inserted in each chunk from the dataframe.

verbose : boolean (default True)

Show percentage complete

reauth : boolean (default False)

Force Google BigQuery to reauthenticate the user. This is useful if multiple accounts are used.

if_exists : {'fail', 'replace', 'append'}, default 'fail'

‘fail’: If table exists, do nothing. ‘replace’: If table exists, drop it, recreate it, and insert data. ‘append’: If table exists, insert data. Create if does not exist.

### 34.1.11 STATA

```
pandas.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, encoding=None, index=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 : string or file-like object
  
  Path to .dta file or object implementing a binary read() functions

* convert_dates : boolean, defaults to True
  
  Convert date variables to DataFrame time values

* convert_categoricals : boolean, defaults to True
  
  Read value labels and convert columns to Categorical/Factor variables

* encoding : string, None or encoding
  
  Encoding used to parse the files. Note that Stata doesn’t support unicode. None defaults to iso-8859-1.

* index : identifier of index column
  
  identifier of column that should be used as index of the DataFrame

* convert_missing : boolean, defaults to False
  
  Flag indicating whether to convert missing values to their Stata representations. If False, missing values are replaced with nans. If True, columns containing missing values are returned with object data types and missing values are represented by StataMissing-Value objects.

* preserve_dtypes : boolean, defaults to 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 : boolean, defaults to 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 : boolean, default False
Return StataReader object

**Examples**

Read a Stata dta file: >> df = pandas.read_stata('filename.dta')

Read a Stata dta file in 10,000 line chunks: >> itr = pandas.read_stata('filename.dta', chunksize=10000) >> for
chunk in itr: >> do_something(chunk)

StataReader.data(**kwargs) DEPRECATED: Reads observations from Stata file, converting them into a dataframe
StataReader.data_label() Returns data label of Stata file
StataReader.value_labels() Returns a dict, associating each variable name a dict, associating
StataReader.variable_labels() Returns variable labels as a dict, associating each variable name
StataWriter.write_file()

**pandas.io.stata.StataReader.data**

StataReader.data(**kwargs) DEPRECATED: Reads observations from Stata file, converting them into a dataframe
This is a legacy method. Use read in new code.

**Parameters**

convert_dates : boolean, defaults to True
Convert date variables to DataFrame time values

convert_categoricals : boolean, defaults to True
Read value labels and convert columns to Categorical/Factor variables

index : identifier of index column
identifier of column that should be used as index of the DataFrame

convert_missing : boolean, defaults to False
Flag indicating whether to convert missing values to their Stata representations. If False, missing values are replaced with nans. If True, columns containing missing values are returned with object data types and missing values are represented by StataMissing-Value objects.

preserve_dtypes : boolean, defaults to 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 : boolean, defaults to True

Flag indicating whether converted categorical data are ordered.

Returns DataFrame

pandas.io.stata.StataReader.data_label

StataReader .data_label ()

Returns data label of Stata file

pandas.io.stata.StataReader.value_labels

StataReader .value_labels ()

Returns a dict, associating each variable name a dict, associating each value its corresponding label

pandas.io.stata.StataReader.variable_labels

StataReader .variable_labels ()

Returns variable labels as a dict, associating each variable name with corresponding label

pandas.io.stata.StataWriter.write_file

StataWriter .write_file ()

34.2 General functions

34.2.1 Data manipulations

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>melt</td>
<td>“Unpivots” a DataFrame from wide format to long format, optionally leaving identifier variables set.</td>
</tr>
<tr>
<td>pivot</td>
<td>Produce ‘pivot’ table based on 3 columns of this DataFrame.</td>
</tr>
<tr>
<td>pivot_table</td>
<td>Create a spreadsheet-style pivot table as a DataFrame.</td>
</tr>
<tr>
<td>crosstab</td>
<td>Compute a simple cross-tabulation of two (or more) factors.</td>
</tr>
<tr>
<td>cut</td>
<td>Return indices of half-open bins to which each value of x belongs.</td>
</tr>
<tr>
<td>qcut</td>
<td>Quantile-based discretization function.</td>
</tr>
<tr>
<td>merge</td>
<td>Merge DataFrame objects by performing a database-style join operation by columns or indexes.</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</td>
<td>Convert categorical variable into dummy/indicator variables.</td>
</tr>
<tr>
<td>factorize</td>
<td>Encode input values as an enumerated type or categorical variable.</td>
</tr>
</tbody>
</table>

pandas.melt

pandas .melt (frame [, id_vars=None, value_vars=None, var_name=None, value_name='value', col_level=None)  

“Unpivots” a DataFrame from wide format to long format, optionally leaving identifier variables 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**

- **frame** : DataFrame
  - **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 string, optional
    If columns are a MultiIndex then use this level to melt.

**See also:**
- `pivot_table`
- `DataFrame.pivot`

**Examples**

```python
>>> import pandas as pd
>>> 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:
pandas: powerful Python data analysis toolkit, Release 0.17.0

```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

If you have multi-index columns:

```python
groupby['A']
df.columns = [list('ABC'), list('DEF')]
df
   A   B   C   D   E   F
0 a  1   2   0   1   2
1 b  3   4   1   3   4
2 c  5   6   2   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(index, columns, values)`

Produce 'pivot' table based on 3 columns of this DataFrame. Uses unique values from index / columns and fills with values.

- **Parameters**
  - `index` : ndarray
    Labels to use to make new frame’s index
  - `columns` : ndarray
    Labels to use to make new frame’s columns
  - `values` : ndarray
    Values to use for populating new frame’s values

- **Returns**
  DataFrame

- **Notes**
  Obviously, all 3 of the input arguments must have the same length

**pandas.pivot_table**

`pandas.pivot_table(data, values=, index=None, columns=None, aggfunc='mean', fill_value=None, margins=False, dropna=True)`

Create a spreadsheet-style pivot table as a DataFrame. The levels in the pivot table will be stored in MultiIndex

34.2. General functions
objects (hierarchical indexes) on the index and columns of the result DataFrame

**Parameters**
- **data**: DataFrame
  - **values**: column to aggregate, optional
  - **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, default numpy.mean, or list of functions
    - 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)
  - **fill_value**: scalar, default None
    - Value to replace missing values with
  - **margins**: boolean, default False
    - Add all row / columns (e.g. for subtotal / grand totals)
  - **dropna**: boolean, default True
    - Do not include columns whose entries are all NaN

**Returns**
- **table**: DataFrame

**Examples**

```python
>>> df
   A    B  C     D
0  foo  one  small  1
1  foo  one  large  2
2  foo  one  large  2
3  foo  two  small  3
4  foo  two  small  3
5  bar  one  large  4
6  bar  one  small  5
7  bar  two  small  6
8  bar  two  large  7

>>> table = pivot_table(df, values='D', index=['A', 'B'],
                      columns=['C'], aggfunc=np.sum)

>>> table
   small     large
foo  one  1     4
     two  6     NaN
bar  one  5     4
     two  6     7
```
pandas.crosstab

pandas.crosstab(index, columns, values=None, rownames=None, colnames=None, aggfunc=None, margins=False, dropna=True)
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
- **aggfunc**: function, optional
  - If no values array is passed, computes a frequency table
- **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
- **margins**: boolean, default False
  - Add row/column margins (subtotals)
- **dropna**: boolean, default True
  - Do not include columns whose entries are all NaN

**Returns**

- **crosstab**: DataFrame

**Notes**

Any Series passed will have their name attributes used unless row or column names for the cross-tabulation are specified

**Examples**

```python
>>> a
array([foo, foo, foo, foo, bar, bar,
       bar, bar, foo, foo, foo], dtype=object)
>>> b
array([one, one, one, two, one, one,
       one, two, two, two, one], dtype=object)
>>> c
array([dull, dull, shiny, dull, dull, shiny,
       shiny, dull, shiny, shiny, shiny], dtype=object)

>>> crosstab(a, [b, c], rownames=['a'], colnames=['b', 'c'])
b  one  two
c  dull   shiny
da   dull   shiny
```
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<table>
<thead>
<tr>
<th>bar</th>
<th>1</th>
<th>2</th>
<th>1</th>
<th>0</th>
</tr>
</thead>
<tbody>
<tr>
<td>foo</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

**pandas.cut**

pandas.cut(x, bins, right=True, labels=None, retbins=False, precision=3, include_lowest=False)

Return indices of half-open bins to which each value of x belongs.

**Parameters**

- **x**: array-like
  - Input array to be binned. It has to be 1-dimensional.
- **bins**: int or sequence of scalars
  - If bins is an int, it defines the number of equal-width bins in the range of x. However, in this case, the range of x is extended by .1% on each side to include the min or max values of x. If bins is a sequence it defines the bin edges allowing for non-uniform bin width. No extension of the range of x is done in this case.
- **right**: bool, optional
  - Indicates whether the bins include the rightmost edge or not. If right == True (the default), then the bins [1,2,3,4] indicate (1,2], (2,3], (3,4].
- **labels**: array or boolean, 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.
- **retbins**: bool, optional
  - Whether to return the bins or not. Can be useful if bins is given as a scalar.
- **precision**: int
  - The precision at which to store and display the bins labels
- **include_lowest**: bool
  - Whether the first interval should be left-inclusive or not.

**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**

The cut function can be useful for going from a continuous variable to a categorical variable. For example, cut could convert ages to groups of age ranges.

Any NA values will be NA in the result. Out of bounds values will be NA in the resulting Categorical object.
Examples

```python
good, good, good, medium, bad, good
Categories (3, object): [good < medium < bad]
```
```python
>>> pd.qcut(range(5), 4)
[[0, 1], [0, 1], (1, 2], (2, 3], (3, 4])
Categories (4, object): [(0, 1) < (1, 2) < (2, 3) < (3, 4)]

>>> pd.qcut(range(5), 3, labels=['good','medium','bad'])
[good, good, medium, bad, bad]
Categories (3, object): [good < medium < bad]

>>> pd.qcut(range(5), 4, labels=False)
array([0, 0, 1, 2, 3], dtype=int64)
```

### pandas.merge

**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)

Merge DataFrame objects by performing a database-style join operation by 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
  - how : {'left', 'right', 'outer', 'inner'}, default ‘inner’
    - 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)
  - on : label or list
    - Field names to join on. Must be found in both DataFrames. If on is None and not merging on indexes, then it merges on the intersection of the columns by default.
  - 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_index : boolean, 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 : boolean, default False
    - Use the index from the right DataFrame as the join key. Same caveats as left_index
  - sort : boolean, default False
    - Sort the join keys lexicographically in the result DataFrame
  - suffixes : 2-length sequence (tuple, list, ...)
    - Suffix to apply to overlapping column names in the left and right side, respectively
  - copy : boolean, default True
If False, do not copy data unnecessarily

**indicator** : boolean or string, default False

If True, adds a column to output DataFrame called “_merge” with information on the source of each row. If string, column with information on source of each row will be added to output DataFrame, and column will be named value of string. Information column is Categorical-type and takes on a value of “left_only” for observations whose merge key only appears in ‘left’ DataFrame, “right_only” for observations whose merge key only appears in ‘right’ DataFrame, and “both” if the observation’s merge key is found in both.

New in version 0.17.0.

**Returns**  
merged : DataFrame

The output type will the be same as ‘left’, if it is a subclass of DataFrame.

**Examples**

```python
>>> A
lkey value
0 foo 1
1 bar 2
2 baz 3
3 foo 4

>>> B
rkey value
0 foo 5
1 bar 6
2 qux 7

>>> merge(A, B, left_on='lkey', right_on='rkey', how='outer')
lkey value_x rkey value_y
0 foo 1 foo 5
1 foo 4 foo 5
2 bar 2 bar 6
3 bar 2 bar 8
4 baz 3 NaN NaN
5 NaN NaN qux 7
```

**pandas.concat**

pandas.concat(objs, axis=0, join='outer', join_axes=None, ignore_index=False, keys=None, levels=None, names=None, verify_integrity=False, copy=True)

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, DataFrame, or Panel 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 outer axis(es)

- **join_axes** : list of Index objects
Specific indexes to use for the other n - 1 axes instead of performing inner/outer set logic

**verify_integrity** : boolean, default False

Check whether the new concatenated axis contains duplicates. This can be very expensive relative to the actual data concatenation

**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

**ignore_index** : boolean, 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 the index values on the other axes are still respected in the join.

**copy** : boolean, default True

If False, do not copy data unnecessarily

Returns **concatenated** : type of objects

**Notes**

The keys, levels, and names arguments are all optional

#### pandas.get_dummies

**pandas.get_dummies** *(data, prefix=None, prefix_sep='_', dummy_na=False, columns=None, sparse=False)*

Convert categorical variable into dummy/indicator variables

**Parameters**

- **data** : array-like, Series, or DataFrame
- **prefix** : string, list of strings, or dict of strings, 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. Alternativly, prefix can be a dictionary mapping column names to prefixes.

- **prefix_sep** : string, 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 columns should be sparse or not. Returns SparseDataFrame if `data` is a Series or if all columns are included. Otherwise returns a DataFrame with some SparseBlocks.

New in version 0.16.1.

**Returns** dummies : DataFrame or SparseDataFrame

**Examples**

```python
>>> import pandas as pd
>>> s = pd.Series(list('abca'))

>>> get_dummies(s)
   a  b  c
0  1  0  0
1  0  1  0
2  0  0  1
3  1  0  0

>>> s1 = ['a', 'b', np.nan]

>>> get_dummies(s1)
   a  b
0  1  0
1  0  1
2  0  0

>>> get_dummies(s1, dummy_na=True)
   a  b  NaN
0  1  0  0
1  0  1  0
2  0  0  1

>>> df = DataFrame({'A': ['a', 'b', 'a'], 'B': ['b', 'a', 'c'], 'C': [1, 2, 3]})

>>> 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

See also `Series.str.get_dummies`.
```

**pandas.factorize**

`pandas.factorize(values, sort=False, order=None, na_sentinel=-1, size_hint=None)`

Encode input values as an enumerated type or categorical variable

**Parameters** values : ndarray (1-d)

Sequence
sort : boolean, default False
    Sort by values
order : deprecated
na_sentinel : int, default -1
    Value to mark “not found”
size_hint : hint to the hashtable sizer

Returns labels : the indexer to the original array
uniques : ndarray (1-d) or Index
    the unique values. Index is returned when passed values is Index or Series
note: an array of Periods will ignore sort as it returns an always sorted PeriodIndex

34.2.2 Top-level missing data

<table>
<thead>
<tr>
<th>isnull(obj)</th>
<th>Detect missing values (NaN in numeric arrays, None/NaN in object arrays)</th>
</tr>
</thead>
<tbody>
<tr>
<td>notnull(obj)</td>
<td>Replacement for numpy.isfinite / -numpy.isnan which is suitable for use on object arrays.</td>
</tr>
</tbody>
</table>

**pandas.isnull**

**pandas.isnull(obj)**
Detect missing values (NaN in numeric arrays, None/NaN in object arrays)

**Parameters**

arr : ndarray or object value
    Object to check for null-ness

**Returns**

isnull: array-like of bool or bool
    Array or bool indicating whether an object is null or if an array is given which of the element is null.

**See also:**

**pandas.notnull** boolean inverse of pandas.isnull

**pandas.notnull**

**pandas.notnull(obj)**
Replacement for numpy.isfinite / -numpy.isnan which is suitable for use on object arrays.

**Parameters**

arr : ndarray or object value
    Object to check for not-null-ness

**Returns**

isnull: array-like of bool or bool
    Array or bool indicating whether an object is not null or if an array is given which of the element is not null.

**See also:**

**pandas.isnull** boolean inverse of pandas.notnull
### 34.2.3 Top-level conversions

| `to_numeric(arg[, errors])` | Convert argument to a numeric type. |

#### pandas.to_numeric

```
pandas.to_numeric(arg, errors='raise')
```

Convert argument to a numeric type.

**Parameters**

- `arg` : list, tuple or array of objects, or Series
- `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

**Returns**

- `ret` : numeric if parsing succeeded.

Return type depends on input. Series if Series, otherwise ndarray

**Examples**

Take separate series and convert to numeric, coercing when told to

```python
>>> import pandas as pd
>>> s = pd.Series(['1.0', '2', -3])
>>> pd.to_numeric(s)
>>> s = pd.Series(['apple', '1.0', '2', -3])
>>> pd.to_numeric(s, errors='ignore')
>>> pd.to_numeric(s, errors='coerce')
```

### 34.2.4 Top-level dealing with datetimelike

| `to_datetime(*args, **kwargs)` | Convert argument to datetime. |
| `to_timedelta(*args, **kwargs)` | Convert argument to timedelta |
| `date_range([start, end, periods, freq, tz, ...])` | Return a fixed frequency datetime index, with day (calendar) as the default |
| `bdate_range([start, end, periods, freq, tz, ...])` | Return a fixed frequency datetime index, with business day as the default |
| `period_range([start, end, periods, freq, name])` | Return a fixed frequency datetime index, with day (calendar) as the default |
| `timedelta_range([start, end, periods, freq, ...])` | Return a fixed frequency timedelta index, with day as the default |
| `infer_freq(index[, warn])` | Infer the most likely frequency given the input index. |

#### pandas.to_datetime

```
pandas.to_datetime(*args, **kwargs)
```

Convert argument to datetime.

**Parameters**

- `arg` : string, datetime, array of strings (with possible NAs)
- `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 : boolean, 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 : boolean, 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). Warning: yearfirst=True is not strict, but will prefer to parse with year first (this is a known bug, based on dateutil behavior).

utc : boolean, default None

Return UTC DatetimeIndex if True (converting any tz-aware datetime.datetime objects as well).

box : boolean, default True

• If True returns a DatetimeIndex
• If False returns ndarray of values.

format : string, default None

strftime to parse time, eg “%d/%m/%Y”, note that “%f” will parse all the way up to nanoseconds.

exact : boolean, True by default

• If True, require an exact format match.
• If False, allow the format to match anywhere in the target string.

unit : unit of the arg (D,s,ms,us,ns) denote the unit in epoch

(e.g. a unix timestamp), which is an integer/float number.

infer_datetime_format : boolean, default False

If no format is given, try to infer the format based on the first datetime string. Provides a large speed-up in many cases.

Returns ret : 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 corresponing array/Series).

Examples

Take separate series and convert to datetime
>>> import pandas as pd
>>> i = pd.date_range('20000101', periods=100)
>>> df = pd.DataFrame(dict(year = i.year, month = i.month, day = i.day))
>>> pd.to_datetime(df.year*10000 + df.month*100 + df.day, format='%Y%m%d')
0   2000-01-01
1   2000-01-02
...
98  2000-04-08
99  2000-04-09
Length: 100, dtype: datetime64[ns]

Or from strings
>>> df = df.astype(str)
>>> pd.to_datetime(df.day + df.month + df.year, format='%d%m%Y')
0   2000-01-01
1   2000-01-02
...
98  2000-04-08
99  2000-04-09
Length: 100, dtype: datetime64[ns]

Date that does not meet timestamp limitations:
>>> pd.to_datetime('13000101', format='%Y%m%d')
datetime.datetime(1300, 1, 1, 0, 0)
>>> pd.to_datetime('13000101', format='%Y%m%d', errors='coerce')
NaT

pandas.to_timedelta

pandas.to_timedelta(*args, **kwargs)
Convert argument to timedelta

Parameters arg : string, timedelta, array of strings (with possible NAs)

   unit : unit of the arg (D,h,m,s,ms,us,ns) denote the unit, which is an integer/float number

   box : boolean, default True
   • If True returns a Timedelta/TimedeltaIndex of the results
   • if False returns a np.timedelta64 or ndarray of values of dtype timedelta64[ns]

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 ret : timedelta64/arrays of timedelta64 if parsing succeeded

pandas.date_range

pandas.date_range(start=None, end=None, periods=None, freq='D', tz=None, normalize=False, name=None, closed=None)
Return a fixed frequency datetime index, with day (calendar) as the default frequency
Parameters

- **start**: string or datetime-like, default None
  - Left bound for generating dates
- **end**: string or datetime-like, default None
  - Right bound for generating dates
- **periods**: integer or None, default None
  - If None, must specify start and end
- **freq**: string or DateOffset, default ‘D’ (calendar daily)
  - Frequency strings can have multiples, e.g. ‘5H’
- **tz**: string or None
  - Time zone name for returning localized DatetimeIndex, for example Asia/Hong_Kong
- **normalize**: bool, default False
  - Normalize start/end dates to midnight before generating date range
- **name**: str, default None
  - Name of the resulting index
- **closed**: string or None, default None
  - Make the interval closed with respect to the given frequency to the ‘left’, ‘right’, or both sides (None)

Returns **rng**: DatetimeIndex

Notes

2 of start, end, or periods must be specified

**pandas.bdate_range**

Return a fixed frequency datetime index, with business day as the default frequency

Parameters

- **start**: string or datetime-like, default None
  - Left bound for generating dates
- **end**: string or datetime-like, default None
  - Right bound for generating dates
- **periods**: integer or None, default None
  - If None, must specify start and end
- **freq**: string or DateOffset, default ‘B’ (business daily)
  - Frequency strings can have multiples, e.g. ‘5H’
- **tz**: string 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 for the resulting index

**closed**: string or None, default None

Make the interval closed with respect to the given frequency to the ‘left’, ‘right’, or both sides (None)

**Returns**

rng : DatetimeIndex

**Notes**

2 of start, end, or periods must be specified

**pandas.period_range**

pandas.period_range(start=None, end=None, periods=None, freq='D', name=None)

Return a fixed frequency datetime index, with day (calendar) as the default frequency

**Parameters**

**start**: starting value, period-like, optional

**end**: ending value, period-like, optional

**periods**: int, default None

Number of periods in the index

**freq**: str/DateOffset, default ‘D’

Frequency alias

**name**: str, default None

Name for the resulting PeriodIndex

**Returns**

prng : PeriodIndex

**pandas.timedelta_range**

pandas.timedelta_range(start=None, end=None, periods=None, freq='D', name=None, closed=None)

Return a fixed frequency timedelta index, with day as the default frequency

**Parameters**

**start**: string or timedelta-like, default None

Left bound for generating dates

**end**: string or datetime-like, default None

Right bound for generating dates

**periods**: integer or None, default None

If None, must specify start and end

**freq**: string or DateOffset, default ‘D’ (calendar daily)

Frequency strings can have multiples, e.g. ‘5H’
name: str, default None

Name of the resulting index

closed: string or None, default None

Make the interval closed with respect to the given frequency to the ‘left’, ‘right’, or both sides (None)

Returns rng: TimedeltaIndex

Notes

2 of start, end, or periods must be specified

pandas.infer_freq

pandas.infer_freq(index, warn=True)

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: boolean, default True

Returns freq: string or None

None if no discernible frequency TypeError if the index is not datetime-like ValueError if there are less than three values.

34.2.5 Top-level evaluation

expr[, parser, engine, truediv, ...]) Evaluate a Python expression as a string using various backends.

pandas.eval

pandas.eval(expr, parser='pandas', engine='numexpr', truediv=True, local_dict=None, global_dict=None, resolvers=(), level=0, target=None)

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 or unicode

The expression to evaluate. This string cannot contain any Python statements, only Python expressions.

parser: string, default ‘pandas’, {'pandas', ‘python’}

The parser to use to construct the syntax tree 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** : string, default `'numexpr'`, {'python', 'numexpr'}

The engine used to evaluate the expression. Supported engines are

- `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

**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 `index` and `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** : a target object for assignment, optional, default is None

essentially this is a passed in resolver

**Returns**  
`ndarray`, numeric scalar, DataFrame, Series

See also:

`pandas.DataFrame.query`, `pandas.DataFrame.eval`

**Notes**

The `dtype` of any objects involved in an arithmetic `%` operation are recursively cast to `float64`.

See the `enhancing performance` documentation for more details.

### 34.2.6 Standard moving window functions

- **rolling_count** *(arg, window[, freq, center, how])*  
  Rolling count of number of non-NaN observations inside provided window.

- **rolling_sum** *(arg, window[, min_periods, ...])*  
  Moving sum.

- **rolling_mean** *(arg, window[, min_periods, ...])*  
  Moving mean.

- **rolling_median** *(arg, window[, min_periods, ...])*  
  O(N log(window)) implementation using skip list

- **rolling_var** *(arg, window[, min_periods, ...])*  
  Numerically stable implementation using Welford’s method.

- **rolling_std** *(arg, window[, min_periods, ...])*  
  Moving standard deviation.

- **rolling_min** *(arg, window[, min_periods, ...])*  
  Moving min of 1d array of dtype=float64 along axis=0 ignoring NaNs.
Table 34.19 – continued from previous page

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>rolling_max</code></td>
<td>Moving max of 1d array of dtype=float64 along axis=0 ignoring NaNs.</td>
</tr>
<tr>
<td><code>rolling_corr</code></td>
<td>Moving sample correlation.</td>
</tr>
<tr>
<td><code>rolling_corr_pairwise</code></td>
<td>Deprecated.</td>
</tr>
<tr>
<td><code>rolling_cov</code></td>
<td>Unbiased moving covariance.</td>
</tr>
<tr>
<td><code>rolling_skew</code></td>
<td>Unbiased moving skewness.</td>
</tr>
<tr>
<td><code>rolling_kurt</code></td>
<td>Unbiased moving kurtosis.</td>
</tr>
<tr>
<td><code>rolling_apply</code></td>
<td>Generic moving function application.</td>
</tr>
<tr>
<td><code>rolling_quantile</code></td>
<td>Moving quantile.</td>
</tr>
<tr>
<td><code>rolling_window</code></td>
<td>Applies a moving window of type <code>window_type</code> and size <code>window</code> on the data</td>
</tr>
</tbody>
</table>

**pandas.rolling_count**

The `rolling_count` function counts the number of non-NaN observations inside a provided window.

**Parameters**

- `arg` : DataFrame or numpy ndarray-like
- `window` : int
  - Size of the moving window. This is the number of observations used for calculating the statistic.
- `freq` : string or DateOffset object, optional (default None)
  - Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.
- `center` : boolean, default False
  - Whether the label should correspond with center of window
- `how` : string, default 'mean'
  - Method for down- or re-sampling

**Returns**

- `rolling_count` : type of caller

**Notes**

The `freq` keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the mean).

**pandas.rolling_sum**

The `rolling_sum` function calculates the moving sum.

**Parameters**

- `arg` : Series, DataFrame
- `window` : int
  - Size of the moving window. This is the number of observations used for calculating the statistic.
- `min_periods` : int, default None
  - Minimum number of observations in window required to have a value (otherwise results are NaN).
Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)
Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False
Set the labels at the center of the window.

how : string, default ‘None’
Method for down- or re-sampling

Returns y : type of input argument

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.

The freq keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of resample() (i.e. using the mean).

**pandas.rolling_mean**

pandas.rolling_mean(arg, window, min_periods=None, freq=None, center=False, how=None, **kwargs)
Moving mean.

Parameters arg : Series, DataFrame

window : int
Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None
Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)
Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False
Set the labels at the center of the window.

how : string, default ‘None’
Method for down- or re-sampling

Returns y : type of input argument
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.

The freq keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of resample() (i.e. using the mean).

**pandas.rolling_median**

```python
pandas.rolling_median(arg, window, min_periods=None, freq=None, center=False, how='median', **kwargs)
```

O(N log(window)) implementation using skip list

Moving median.

**Parameters**

- *arg*: Series, DataFrame
- *window*: int
  - Size of the moving window. This is the number of observations used for calculating the statistic.
- *min_periods*: int, default None
  - Minimum number of observations in window required to have a value (otherwise result is NA).
- *freq*: string or DateOffset object, optional (default None)
  - Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.
- *center*: boolean, default False
  - Set the labels at the center of the window.
- *how*: string, default ‘median’
  - Method for down- or re-sampling

**Returns**

- *y*: type of input argument

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.

The freq keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of resample() (i.e. using the mean).

**pandas.rolling_var**

```python
pandas.rolling_var(arg, window, min_periods=None, freq=None, center=False, how=None, **kwargs)
```

Numerically stable implementation using Welford’s method.

Moving variance.
**Parameters**

- **arg**: Series, DataFrame
  - **window**: int
    Size of the moving window. This is the number of observations used for calculating the statistic.
  - **min_periods**: int, default None
    Minimum number of observations in window required to have a value (otherwise result is NA).
  - **freq**: string or DateOffset object, optional (default None)
    Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.
  - **center**: boolean, default False
    Set the labels at the center of the window.
  - **how**: string, default ‘None’
    Method for down- or re-sampling
  - **ddof**: int, default 1
    Delta Degrees of Freedom. The divisor used in calculations is \( N - \text{ddof} \), where \( N \) represents the number of elements.

**Returns**

- **y**: type of input argument

**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`.

The `freq` keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the `mean`).

### pandas.rolling_std

**pandas.rolling_std** *(arg, window, min_periods=None, freq=None, center=False, how=None, **kwargs)*

Moving standard deviation.

**Parameters**

- **arg**: Series, DataFrame
  - **window**: int
    Size of the moving window. This is the number of observations used for calculating the statistic.
  - **min_periods**: int, default None
    Minimum number of observations in window required to have a value (otherwise result is NA).
  - **freq**: string or DateOffset object, optional (default None)
    Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.
center : boolean, default False
    Set the labels at the center of the window.
how : string, default ‘None’
    Method for down- or re-sampling
ddf : int, default 1
    Delta Degrees of Freedom. The divisor used in calculations is N – ddf, where N represents the number of elements.
Returns y : type of input argument

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.
The freq keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of resample() (i.e. using the mean).

pandas.rolling_min

pandas.rolling_min(arg, window, min_periods=None, freq=None, center=False, how='min', **kwargs)
Moving min of 1d array of dtype=float64 along axis=0 ignoring NaNs. Moving minimum.

Parameters arg : Series, DataFrame
    window : int
        Size of the moving window. This is the number of observations used for calculating the statistic.
min_periods : int, default None
    Minimum number of observations in window required to have a value (otherwise result is NA).
freq : string or DateOffset object, optional (default None)
    Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.
center : boolean, default False
    Set the labels at the center of the window.
how : string, default ‘min’
    Method for down- or re-sampling
Returns y : type of input argument

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.
The `freq` keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the `mean`).

**pandas.rolling_max**

```python
pandas.rolling_max(arg, window, min_periods=None, freq=None, center=False, how='max', **kwargs)
```

Moving max of 1d array of dtype=float64 along axis=0 ignoring NaNs. Moving maximum.

**Parameters**

- `arg` : Series, DataFrame
  - `window` : int
    Size of the moving window. This is the number of observations used for calculating the statistic.
  - `min_periods` : int, default None
    Minimum number of observations in window required to have a value (otherwise result is NA).
  - `freq` : string or DateOffset object, optional (default None)
    Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.
  - `center` : boolean, default False
    Set the labels at the center of the window.
  - `how` : string, default ‘max’
    Method for down- or re-sampling

**Returns**

- `y` : type of input argument

**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`.

The `freq` keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the `mean`).

**pandas.rolling_corr**

```python
pandas.rolling_corr(arg1, arg2=None, window=None, min_periods=None, freq=None, center=False, pairwise=None, how=None)
```

Moving sample correlation.

**Parameters**

- `arg1` : Series, DataFrame, or ndarray
  - `arg2` : Series, DataFrame, or ndarray, optional
    if not supplied then will default to `arg1` and produce pairwise output
  - `window` : int
    Size of the moving window. This is the number of observations used for calculating the statistic.
**min_periods**: int, default None
Minimum number of observations in window required to have a value (otherwise result is NA).

**freq**: string or DateOffset object, optional (default None)
Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

**center**: boolean, default False
Set the labels at the center of the window.

**how**: string, default ‘None’
Method for down- or re-sampling

**pairwise**: bool, default False
If False then only matching columns between arg1 and arg2 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 Panel in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

**Returns**

- **y**: type depends on inputs
  - DataFrame / DataFrame -> DataFrame (matches on columns) or Panel (pairwise)
  - DataFrame / Series -> Computes result for each column
  - Series / Series -> Series

**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`.

The `freq` keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the `mean`).

### pandas.rolling_corr_pairwise

**Parameters**

- **df1**: DataFrame
- **df2**: DataFrame
- **window**: int
  Size of the moving window. This is the number of observations used for calculating the statistic.
- **min_periods**: int, default None
  Minimum number of observations in window required to have a value (otherwise result is NA).
- **freq**: string or DateOffset object, optional (default None)
Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

**center** : boolean, default False

Set the labels at the center of the window.

**how** : string, default ‘None’

Method for down- or re-sampling

**Returns**  
*y* : Panel whose items are df1.index values

**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`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

**pandas.rolling_cov**

```python
pandas.rolling_cov(arg1, arg2=None, window=None, min_periods=None, freq=None, center=False, pairwise=None, how=None, ddof=1)
```

Unbiased moving covariance.

**Parameters**

**arg1** : Series, DataFrame, or ndarray

**arg2** : Series, DataFrame, or ndarray, optional

if not supplied then will default to arg1 and produce pairwise output

**window** : int

Size of the moving window. This is the number of observations used for calculating the statistic.

**min_periods** : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

**freq** : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

**center** : boolean, default False

Set the labels at the center of the window.

**how** : string, default ‘None’

Method for down- or re-sampling

**pairwise** : bool, default False

If False then only matching columns between arg1 and arg2 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 Panel 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 \( N - \text{ddof} \), where \( N \) represents the number of elements.

**Returns**: y : type depends on inputs

- DataFrame / DataFrame -> DataFrame (matches on columns) or Panel (pairwise)
- DataFrame / Series -> Computes result for each column
- Series / Series -> Series

**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`.

The `freq` keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the `mean`).

**pandas.rolling_skew**

`pandas.rolling_skew(arg, window, min_periods=None, freq=None, center=False, how=None, **kwargs)`

Unbiased moving skewness.

**Parameters**

- **arg**: Series, DataFrame
- **window**: int
  
  Size of the moving window. This is the number of observations used for calculating the statistic.
- **min_periods**: int, default None
  
  Minimum number of observations in window required to have a value (otherwise result is NA).
- **freq**: string or DateOffset object, optional (default None)
  
  Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.
- **center**: boolean, default False
  
  Set the labels at the center of the window.
- **how**: string, default ‘None’
  
  Method for down- or re-sampling

**Returns**

- y : type of input argument

**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`.

The `freq` keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the `mean`).
pandas.rolling_kurt

**pandas.rolling_kurt**(arg, window, min_periods=None, freq=None, center=False, how=None, **kwargs)

Unbiased moving kurtosis.

**Parameters**
- **arg**: Series, DataFrame

  - **window**: int
    Size of the moving window. This is the number of observations used for calculating the statistic.
  - **min_periods**: int, default None
    Minimum number of observations in window required to have a value (otherwise result is NA).
  - **freq**: string or DateOffset object, optional (default None)
    Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.
  - **center**: boolean, default False
    Set the labels at the center of the window.
  - **how**: string, default ‘None’
    Method for down- or re-sampling

**Returns**
- **y**: type of input argument

**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`.

The `freq` keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the `mean`).

pandas.rolling_apply

**pandas.rolling_apply**(arg, window, func, min_periods=None, freq=None, center=False, args=(), kwargs={})

Generic moving function application.

**Parameters**
- **arg**: Series, DataFrame

  - **window**: int
    Size of the moving window. This is the number of observations used for calculating the statistic.
  - **func**: function
    Must produce a single value from an ndarray input
  - **min_periods**: int, default None
    Minimum number of observations in window required to have a value (otherwise result is NA).
freq : string or DateOffset object, optional (default None)
    Frequency to conform the data to before computing the statistic. Specified as a fre-
    quency string or DateOffset object.

center : boolean, default False
    Whether the label should correspond with center of window

args : tuple
    Passed on to func

kwarg : dict
    Passed on to func

Returns y : type of input argument

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.

The freq keyword is used to conform time series data to a specified frequency by resampling the data. This is
done with the default parameters of resample() (i.e. using the mean).

pandas.rolling_quantile

pandas.rolling_quantile(arg, window, quantile, min_periods=None, freq=None, center=False)
Moving quantile.

Parameters arg : Series, DataFrame

window : int
    Size of the moving window. This is the number of observations used for calculating the
    statistic.

quantile : float
    0 <= quantile <= 1

min_periods : int, default None
    Minimum number of observations in window required to have a value (otherwise result
    is NA).

freq : string or DateOffset object, optional (default None)
    Frequency to conform the data to before computing the statistic. Specified as a fre-
    quency string or DateOffset object.

center : boolean, default False
    Whether the label should correspond with center of window

Returns y : type of input argument
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.

The freq keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of resample() (i.e. using the mean).

pandas.rolling_window

pandas.rolling_window(arg, window=None, win_type=None, min_periods=None, freq=None, center=False, mean=True, axis=0, how=None, **kwargs)

Applies a moving window of type window_type and size window on the data.

Parameters arg : Series, DataFrame

window : int or ndarray
    Weighting window specification. If the window is an integer, then it is treated as the window length and win_type is required

win_type : str, default None
    Window type (see Notes)

min_periods : int, default None
    Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)
    Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False
    Whether the label should correspond with center of window

mean : boolean, default True
    If True computes weighted mean, else weighted sum

axis : {0, 1}, default 0

how : string, default ‘mean’
    Method for down- or re-sampling

Returns y : type of input argument

Notes

The recognized window types are:

• boxcar
• triang
• blackman
• hamming
• bartlett
• parzen
• bohman
• blackmanharris
• nuttall
• barthann
• kaiser (needs beta)
• gaussian (needs std)
• general_gaussian (needs power, width)
• slepian (needs width).

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.

The freq keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of resample() (i.e. using the mean).

### 34.2.7 Standard expanding window functions

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>expanding_count</td>
<td>Expanding count of number of non-NaN observations.</td>
</tr>
<tr>
<td>expanding_sum</td>
<td>Expanding sum.</td>
</tr>
<tr>
<td>expanding_mean</td>
<td>Expanding mean.</td>
</tr>
<tr>
<td>expanding_median</td>
<td>O(N log(window)) implementation using skip list</td>
</tr>
<tr>
<td>expanding_var</td>
<td>Numerically stable implementation using Welford’s method.</td>
</tr>
<tr>
<td>expanding_min</td>
<td>Moving min of 1d array of dtype=\text{float64} along axis=0 ignoring NaNs.</td>
</tr>
<tr>
<td>expanding_max</td>
<td>Moving max of 1d array of dtype=\text{float64} along axis=0 ignoring NaNs.</td>
</tr>
<tr>
<td>expanding_corr</td>
<td>Expanding sample correlation.</td>
</tr>
<tr>
<td>expanding_corr_pairwise</td>
<td>Deprecated.</td>
</tr>
<tr>
<td>expanding_cov</td>
<td>Unbiased expanding covariance.</td>
</tr>
<tr>
<td>expanding_skew</td>
<td>Unbiased expanding skewness.</td>
</tr>
<tr>
<td>expanding_kurt</td>
<td>Unbiased expanding kurtosis.</td>
</tr>
<tr>
<td>expanding_apply</td>
<td>Generic expanding function application.</td>
</tr>
<tr>
<td>expanding_quantile</td>
<td>Expanding quantile.</td>
</tr>
</tbody>
</table>

**pandas.expanding_count**

Expanding count of number of non-NaN observations.

**Parameters**

- **arg**: DataFrame or numpy ndarray-like
- **freq**: string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

**Returns**

- **expanding_count**: type of caller
Notes

The freq keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of resample() (i.e. using the mean).

**pandas.expanding_sum**

pandas.<expanding_sum>(arg, min_periods=1, freq=None, **kwargs)
Expanding sum.

**Parameters**
- **arg**: Series, DataFrame
- **min_periods**: int, default None
  - Minimum number of observations in window required to have a value (otherwise result is NA).
- **freq**: string or DateOffset object, optional (default None)
  - Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

**Returns**
- **y**: type of input argument

**pandas.expanding_mean**

pandas.<expanding_mean>(arg, min_periods=1, freq=None, **kwargs)
Expanding mean.

**Parameters**
- **arg**: Series, DataFrame
- **min_periods**: int, default None
  - Minimum number of observations in window required to have a value (otherwise result is NA).
- **freq**: string or DateOffset object, optional (default None)
  - Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

**Returns**
- **y**: type of input argument

**pandas.expanding_median**

pandas.<expanding_median>(arg, min_periods=1, freq=None, **kwargs)
O(N log(window)) implementation using skip list
Expanding median.

**Parameters**
- **arg**: Series, DataFrame
- **min_periods**: int, default None
  - Minimum number of observations in window required to have a value (otherwise result is NA).
- **freq**: string or DateOffset object, optional (default None)
Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns \( y \) : type of input argument

**pandas.expanding_var**

```python
pandas.expanding_var(arg, min_periods=1, freq=None, **kwargs)
```

Numerically stable implementation using Welford's method.

Expanding variance.

Parameters
- **arg** : Series, DataFrame
- **min_periods** : int, default None
  - Minimum number of observations in window required to have a value (otherwise result is NA).
- **freq** : string or DateOffset object, optional (default None)
  - Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.
- **ddof** : int, default 1
  - Delta Degrees of Freedom. The divisor used in calculations is \( N - ddof \), where \( N \) represents the number of elements.

Returns \( y \) : type of input argument

**pandas.expanding_std**

```python
pandas.expanding_std(arg, min_periods=1, freq=None, **kwargs)
```

Expanding standard deviation.

Parameters
- **arg** : Series, DataFrame
- **min_periods** : int, default None
  - Minimum number of observations in window required to have a value (otherwise result is NA).
- **freq** : string or DateOffset object, optional (default None)
  - Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.
- **ddof** : int, default 1
  - Delta Degrees of Freedom. The divisor used in calculations is \( N - ddof \), where \( N \) represents the number of elements.

Returns \( y \) : type of input argument

**pandas.expanding_min**

```python
pandas.expanding_min(arg, min_periods=1, freq=None, **kwargs)
```

Moving min of 1d array of dtype=float64 along axis=0 ignoring NaNs. Expanding minimum.
Parameters arg : Series, DataFrame

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns y : type of input argument

**pandas.expanding_max**

pandas.expanding_max(arg, min_periods=1, freq=None, **kwargs)

Moving max of 1d array of dtype=float64 along axis=0 ignoring NaNs. Expanding maximum.

Parameters arg : Series, DataFrame

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns y : type of input argument

**pandas.expanding_corr**

pandas.expanding_corr(arg1, arg2=None, min_periods=1, freq=None, pairwise=None)

Expanding sample correlation.

Parameters arg1 : Series, DataFrame, or ndarray

arg2 : Series, DataFrame, or ndarray, optional

if not supplied then will default to arg1 and produce pairwise output

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

pairwise : bool, default False

If False then only matching columns between arg1 and arg2 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 Panel in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

Returns y : type depends on inputs
DataFrame / DataFrame -> DataFrame (matches on columns) or Panel (pairwise)
DataFrame / Series -> Computes result for each column Series / Series -> Series

**pandas.expanding_corr_pairwise**

**pandas.expanding_corr_pairwise** *(df1, df2=None, min_periods=1, freq=None)*

Deprecated. Use expanding_corr(..., pairwise=True) instead.

Pairwise expanding sample correlation

**Parameters**

*df1* : DataFrame

*df2* : DataFrame

*min_periods* : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

*freq* : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

**Returns**

*y* : Panel whose items are df1.index values

**pandas.expanding_cov**

**pandas.expanding_cov** *(arg1, arg2=None, min_periods=1, freq=None, pairwise=None, ddof=1)*

Unbiased expanding covariance.

**Parameters**

*arg1* : Series, DataFrame, or ndarray

*arg2* : Series, DataFrame, or ndarray, optional

if not supplied then will default to arg1 and produce pairwise output

*min_periods* : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

*freq* : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

*pairwise* : bool, default False

If False then only matching columns between arg1 and arg2 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 Panel 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.

**Returns**

*y* : type depends on inputs

DataFrame / DataFrame -> DataFrame (matches on columns) or Panel (pairwise)
DataFrame / Series -> Computes result for each column Series / Series -> Series
pandas.expanding_skew

**pandas.expanding_skew**(arg, min_periods=1, freq=None, **kwargs)

Unbiased expanding skewness.

**Parameters**

- **arg**: Series, DataFrame
  - **min_periods**: int, default None
    - Minimum number of observations in window required to have a value (otherwise result is NA).
  - **freq**: string or DateOffset object, optional (default None)
    - Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

**Returns**

- **y**: type of input argument

---

pandas.expanding_kurt

**pandas.expanding_kurt**(arg, min_periods=1, freq=None, **kwargs)

Unbiased expanding kurtosis.

**Parameters**

- **arg**: Series, DataFrame
  - **min_periods**: int, default None
    - Minimum number of observations in window required to have a value (otherwise result is NA).
  - **freq**: string or DateOffset object, optional (default None)
    - Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

**Returns**

- **y**: type of input argument

---

pandas.expanding_apply

**pandas.expanding_apply**(arg, func, min_periods=1, freq=None, args=(), kwargs={})

Generic expanding function application.

**Parameters**

- **arg**: Series, DataFrame
  - **func**: function
    - Must produce a single value from an ndarray input
  - **min_periods**: int, default None
    - Minimum number of observations in window required to have a value (otherwise result is NA).
  - **freq**: string or DateOffset object, optional (default None)
    - Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.
  - **args**: tuple
    - Passed on to func
  - **kwargs**: dict
    - Passed on to func

---
**kwargs**: dict

Passed on to func

Returns **y**: type of input argument

**Notes**

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

**pandas.expanding_quantile**

```
pandas.expanding_quantile(arg, quantile, min_periods=1, freq=None)
```

Expanding quantile.

**Parameters**

- **arg**: Series, DataFrame
- **quantile**: float
  
  0 <= quantile <= 1
- **min_periods**: int, default None
  
  Minimum number of observations in window required to have a value (otherwise result is NA).
- **freq**: string or DateOffset object, optional (default None)
  
  Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns **y**: type of input argument

**Notes**

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

### 34.2.8 Exponentially-weighted moving window functions

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>ewma(arg[, com, span, halflife, ...])</code></td>
<td>Exponentially-weighted moving average</td>
</tr>
<tr>
<td><code>ewmstd(arg[, com, span, halflife, ...])</code></td>
<td>Exponentially-weighted moving std</td>
</tr>
<tr>
<td><code>ewmvar(arg[, com, span, halflife, ...])</code></td>
<td>Exponentially-weighted moving variance</td>
</tr>
<tr>
<td><code>ewmcorr(arg1[, arg2, com, span, halflife, ...])</code></td>
<td>Exponentially-weighted moving correlation</td>
</tr>
<tr>
<td><code>ewmcov(arg1[, arg2, com, span, halflife, ...])</code></td>
<td>Exponentially-weighted moving covariance</td>
</tr>
</tbody>
</table>

**pandas.ewma**

```
pandas.ewma(arg, com=None, span=None, halflife=None, min_periods=0, freq=None, adjust=True, how=None, ignore_na=False)
```

Exponentially-weighted moving average

**Parameters**

- **arg**: Series, DataFrame
com : float. optional
    Center of mass: \( \alpha = 1/(1 + \text{com}) \),

span : float, optional
    Specify decay in terms of span, \( \alpha = 2/(\text{span} + 1) \)

halflife : float, optional
    Specify decay in terms of halflife, \( \alpha = 1 - \exp\left(\frac{\log(0.5)}{\text{halflife}}\right) \)

min_periods : int, default 0
    Minimum number of observations in window required to have a value (otherwise result is NA).

decay : None or string alias / date offset object, default=None
    Frequency to conform to before computing statistic

adjust : boolean, default True
    Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average)

how : string, default 'mean'
    Method for down- or re-sampling

ignore_na : boolean, default False
    Ignore missing values when calculating weights; specify True to reproduce pre-0.15.0 behavior

Returns y : type of input argument

Notes

Either center of mass, span or halflife must be specified

EWMA is sometimes specified using a “span” parameter \( s \), we have that the decay parameter \( \alpha \) is related to the span as \( \alpha = 2/(s + 1) = 1/(1 + c) \)

where \( c \) is the center of mass. Given a span, the associated center of mass is \( c = (s - 1)/2 \)

So a “20-day EWMA” would have center 9.5.

**When adjust is True (default), weighted averages are calculated using weights**
(1-alpha)**(n-1), (1-alpha)**(n-2), ..., 1-alpha, 1.

**When adjust is False, weighted averages are calculated recursively as:**
weighted_average[0] = arg[0];
weighted_average[i] = (1-alpha)*weighted_average[i-1] + alpha*arg[i].

When ignore_na is False (default), weights are based on absolute positions. For example, the weights of x and y used in calculating the final weighted average of [x, None, y] are (1-alpha)**2 and 1 (if adjust is True), and (1-alpha)**2 and alpha (if adjust is False).

When ignore_na is True (reproducing pre-0.15.0 behavior), weights are based on relative positions. For example, the weights of x and y used in calculating the final weighted average of [x, None, y] are 1-alpha and 1 (if adjust is True), and 1-alpha and alpha (if adjust is False).
pandas: powerful Python data analysis toolkit, Release 0.17.0

pandas.ewmstd

pandas.ewmstd(arg, com=None, span=None, halflife=None, min_periods=0, bias=False, ignore_na=False, adjust=True)

Exponentially-weighted moving std

Parameters

arg : Series, DataFrame

com : float, optional

Center of mass: \( \alpha = 1/(1 + \text{com}) \),

span : float, optional

Specify decay in terms of span, \( \alpha = 2/(\text{span} + 1) \)

halflife : float, optional

Specify decay in terms of halflife, \( \alpha = 1 - \exp(\log(0.5)/\text{halflife}) \)

min_periods : int, default 0

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

adjust : boolean, default True

Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average)

how : string, default ‘mean’

Method for down- or re-sampling

ignore_na : boolean, default False

Ignore missing values when calculating weights; specify True to reproduce pre-0.15.0 behavior

bias : boolean, default False

Use a standard estimation bias correction

Returns

y : type of input argument

Notes

Either center of mass, span or halflife must be specified

EWMA is sometimes specified using a “span” parameter \( s \), we have that the decay parameter \( \alpha \) is related to the span as \( \alpha = 2/(s + 1) = 1/(1 + c) \)

where \( c \) is the center of mass. Given a span, the associated center of mass is \( c = (s - 1)/2 \)

So a “20-day EWMA” would have center 9.5.

When adjust is True (default), weighted averages are calculated using weights \( (1-\alpha)^{*(n-1)}, (1-\alpha)^{*(n-2)}, ..., 1-\alpha, 1. \)

When adjust is False, weighted averages are calculated recursively as: \( \text{weighted_average}[0] = \text{arg}[0]; \) \( \text{weighted_average}[i] = (1-\alpha)\times\text{weighted_average}[i-1] + \alpha\times\text{arg}[i]. \)
When ignore_na is False (default), weights are based on absolute positions. For example, the weights of x and y used in calculating the final weighted average of [x, None, y] are (1-alpha)**2 and 1 (if adjust is True), and (1-alpha)**2 and alpha (if adjust is False).

When ignore_na is True (reproducing pre-0.15.0 behavior), weights are based on relative positions. For example, the weights of x and y used in calculating the final weighted average of [x, None, y] are 1-alpha and 1 (if adjust is True), and 1-alpha and alpha (if adjust is False).

**pandas.ewmvar**

*pandas.ewmvar*(arg, com=None, span=None, halflife=None, min_periods=0, bias=False, freq=None, how=None, ignore_na=False, adjust=True)

Exponentially-weighted moving variance

**Parameters**

arg : Series, DataFrame

com : float, optional

Center of mass: \( \alpha = 1/(1 + \text{com}) \),

span : float, optional

Specify decay in terms of span, \( \alpha = 2/(\text{span} + 1) \)

halflife : float, optional

Specify decay in terms of halflife, \( \alpha = 1 - \exp(0.5/\text{halflife}) \)

min_periods : int, default 0

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

adjust : boolean, default True

Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average)

how : string, default ‘mean’

Method for down- or re-sampling

ignore_na : boolean, default False

Ignore missing values when calculating weights; specify True to reproduce pre-0.15.0 behavior

bias : boolean, default False

Use a standard estimation bias correction

**Returns**

y : type of input argument

**Notes**

Either center of mass, span or halflife must be specified

EWMA is sometimes specified using a “span” parameter \( S \), we have that the decay parameter \( \alpha \) is related to the span as \( \alpha = 2/(S + 1) = 1/(1 + c) \)
where \( c \) is the center of mass. Given a span, the associated center of mass is \( c = (s - 1)/2 \)

So a “20-day EWMA” would have center 9.5.

**When adjust is True (default), weighted averages are calculated using weights**
\[
(1-\alpha)^*\text{span}(n-1), \quad \ldots, \quad (1-\alpha)^*2, \quad (1-\alpha), \quad 1.
\]

**When adjust is False, weighted averages are calculated recursively as:**
\[
\text{weighted_average}[0] = \text{arg}[0];
\text{weighted_average}[i] = (1-\alpha)^*\text{weighted_average}[i-1] + \alpha^*\text{arg}[i].
\]

When ignore_na is False (default), weights are based on absolute positions. For example, the weights of \( x \) and \( y \) used in calculating the final weighted average of \([x, \text{None}, y]\) are \((1-\alpha)^*2\) and 1 (if adjust is True), and \((1-\alpha)^*2\) and \(\alpha\) (if adjust is False).

When ignore_na is True (reproducing pre-0.15.0 behavior), weights are based on relative positions. For example, the weights of \( x \) and \( y \) used in calculating the final weighted average of \([x, \text{None}, y]\) are \(1-\alpha\) and 1 (if adjust is True), and 1-\(\alpha\) and \(\alpha\) (if adjust is False).

---

**pandas.ewmcorr**

\[
\text{pandas.ewmcorr}(\text{arg1}, \text{arg2}=\text{None}, \text{com}=\text{None}, \text{span}=\text{None}, \text{halflife}=\text{None}, \text{min_periods}=0, \text{freq}=\text{None}, \text{pairwise}=\text{None}, \text{how}=\text{None}, \text{ignore_na}=\text{False}, \text{adjust}=\text{True})
\]

Exponentially-weighted moving correlation

**Parameters arg1**: Series, DataFrame, or ndarray

arg2 : Series, DataFrame, or ndarray, optional

if not supplied then will default to arg1 and produce pairwise output

com : float, optional

Center of mass: \( \alpha = 1/(1 + com) \),

span : float, optional

Specify decay in terms of span, \( \alpha = 2/(span + 1) \)

halflife : float, optional

Specify decay in terms of halflife, \( \alpha = 1 - \exp(log(0.5)/\text{halflife}) \)

min_periods : int, default 0

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

adjust : boolean, default True

Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average)

how : string, default ‘mean’

Method for down- or re-sampling

ignore_na : boolean, default False

Ignore missing values when calculating weights; specify True to reproduce pre-0.15.0 behavior

pairwise : bool, default False
If False then only matching columns between arg1 and arg2 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 Panel in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

**Returns** y : type of input argument

**Notes**

Either center of mass, span or halflife must be specified

EWMA is sometimes specified using a “span” parameter $s$, we have that the decay parameter $\alpha$ is related to the span as $\alpha = 2/(s + 1) = 1/(1 + c)$

where $c$ is the center of mass. Given a span, the associated center of mass is $c = (s - 1)/2$

So a “20-day EWMA” would have center 9.5.

**When adjust is True (default), weighted averages are calculated using weights** (1-$\alpha$)***(n-1), (1-$\alpha$)***(n-2), ..., 1-$\alpha$, 1.

**When adjust is False, weighted averages are calculated recursively as:** weighted_average[0] = arg[0]; weighted_average[i] = (1-$\alpha$)*weighted_average[i-1] + $\alpha$*arg[i].

When ignore_na is False (default), weights are based on absolute positions. For example, the weights of x and y used in calculating the final weighted average of [x, None, y] are (1-$\alpha$)**2 and 1 (if adjust is True), and (1-$\alpha$)**2 and alpha (if adjust is False).

When ignore_na is True (reproducing pre-0.15.0 behavior), weights are based on relative positions. For example, the weights of x and y used in calculating the final weighted average of [x, None, y] are 1-$\alpha$ and 1 (if adjust is True), and 1-$\alpha$ and alpha (if adjust is False).

**pandas.ewmcov**

**pandas.ewmcov** arg1, arg2=None, com=None, span=None, halflife=None, min_periods=0, bias=False, freq=None, pairwise=None, how=None, ignore_na=False, adjust=True

Exponentially-weighted moving covariance

**Parameters** arg1 : Series, DataFrame, or ndarray

arg2 : Series, DataFrame, or ndarray, optional

if not supplied then will default to arg1 and produce pairwise output

com : float, optional

Center of mass: $\alpha = 1/(1 + com)$.

span : float, optional

Specify decay in terms of span, $\alpha = 2/(span + 1)$

halflife : float, optional

Specify decay in terms of halflife, $\alpha = 1 - \exp(log(0.5)/halflife)$

min_periods : int, default 0

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : None or string alias / date offset object, default=None

34.2. General functions
Frequency to conform to before computing statistic

**adjust** : boolean, default True

Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average)

**how** : string, default ‘mean’

Method for down- or re-sampling

**ignore_na** : boolean, default False

Ignore missing values when calculating weights; specify True to reproduce pre-0.15.0 behavior

**pairwise** : bool, default False

If False then only matching columns between arg1 and arg2 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 Panel in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

**Returns** y : type of input argument

**Notes**

Either center of mass, span or halflife must be specified

EWMA is sometimes specified using a “span” parameter $s$, we have that the decay parameter $\alpha$ is related to the span as $\alpha = \frac{2}{(s + 1)} = \frac{1}{1 + c}$

where $c$ is the center of mass. Given a span, the associated center of mass is $c = \frac{s - 1}{2}$

So a “20-day EWMA” would have center 9.5.

**When adjust is True (default), weighted averages are calculated using weights**  
(1-$\alpha$)**(n-1), (1-$\alpha$)**(n-2), ..., 1-$\alpha$, 1.

**When adjust is False, weighted averages are calculated recursively as:**  
weighted_average[0] = arg[0]; weighted_average[i] = (1-$\alpha$)*weighted_average[i-1] + $\alpha$*arg[i].

When ignore_na is False (default), weights are based on absolute positions. For example, the weights of x and y used in calculating the final weighted average of [x, None, y] are (1-$\alpha$)**2 and 1 (if adjust is True), and (1-$\alpha$)**2 and alpha (if adjust is False).

When ignore_na is True (reproducing pre-0.15.0 behavior), weights are based on relative positions. For example, the weights of x and y used in calculating the final weighted average of [x, None, y] are 1-$\alpha$ and 1 (if adjust is True), and 1-$\alpha$ and alpha (if adjust is False).

**34.3 Series**

**34.3.1 Constructor**

```python
Series([data, index, dtype, name, copy, ...])  
One-dimensional ndarray with axis labels (including time series).
```
pandas.Series

class pandas.Series(data=None, index=None, dtype=None, name=None, copy=False, fastpath=False)
One-dimensional ndarray with axis labels (including time series).

Labels need not be unique but must be any 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, dict, or scalar value
Contains data stored in Series

index : array-like or Index (1d)
Values must be unique and hashable, same length as data. Index object (or other iterable of same length as data) Will default to np.arange(len(data)) if not provided. If both a dict and index sequence are used, the index will override the keys found in the dict.

dtype : numpy.dtype or None
If None, dtype will be inferred

copy : boolean, default False
Copy input data

Attributes

T
return the transpose, which is by definition self

at
Fast label-based scalar accessor

axes
Return a list of the row axis labels

base
return the base object if the memory of the underlying data is shared

blocks
Internal property, property synonym for as_blocks()

data
return the data pointer of the underlying data

dtype
return the dtype object of the underlying data

dtypes
return the dtypes object of the underlying data

empty
True if NDFrame is entirely empty [no items]

flags

ftype
return if the data is sparseldense

ftypes
return if the data is sparseldense

hasnans

iat
Fast integer location scalar accessor.

iloc
Purely integer-location based indexing for selection by position.

imag

is_copy

is_time_series

itemsize
return the size of the dtypes of the item of the underlying data

ix
A primarily label-location based indexer, with integer position fallback.

loc
Purely label-location based indexer for selection by label.

 nbytes
return the number of bytes in the underlying data

 ndim
return the number of dimensions of the underlying data, by definition 1

real
Continued on next page
Table 34.23 – continued from previous page

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<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>strides</td>
<td>return the strides of the underlying data</td>
</tr>
<tr>
<td>values</td>
<td>Return Series as ndarray or ndarray-like</td>
</tr>
</tbody>
</table>

**pandas.Series.T**

Series.T
- return the transpose, which is by definition self

**pandas.Series.at**

Series.at
- Fast label-based scalar accessor
  - Similarly to loc, at provides label based scalar lookups. You can also set using these indexers.

**pandas.Series.axes**

Series.axes
- Return a list of the row axis labels

**pandas.Series.base**

Series.base
- return the base object if the memory of the underlying data is shared

**pandas.Series.blocks**

Series.blocks
- Internal property, property synonym for as_blocks()

**pandas.Series.data**

Series.data
- return the data pointer of the underlying data

**pandas.Series.dtype**

Series.dtype
- return the dtype object of the underlying data

**pandas.Series.dtypes**

Series.dtypes
- return the dtype object of the underlying data
pandas.Series.empty

Series.empty
True if NDFrame is entirely empty [no items]

pandas.Series.flags

Series.flags

pandas.Series.ftype

Series.ftype
return if the data is sparseldense

pandas.Series.ftypes

Series.ftypes
return if the data is sparseldense

pandas.Series.hasnans

Series.hasnans = None

pandas.Series.iat

Series.iat
Fast integer location scalar accessor.

Similarly to iloc, iat provides integer based lookups. You can also set using these indexers.

pandas.Series.iloc

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.

.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
pandas.Series.imag

Series.imag

pandas.Series.is_copy

Series.is_copy = None

pandas.Series.is_time_series

Series.is_time_series

pandas.Series.itemsize

Series.itemsize
return the size of the dtype of the item of the underlying data

pandas.Series.ix

Series.ix
A primarily label-location based indexer, with integer position fallback.

.ix[] supports mixed integer and label based access. It is primarily label based, but will fall back to
integer positional access unless the corresponding axis is of integer type.

.ix is the most general indexer and will support any of the inputs in .loc and .iloc. ix also supports
floating point label schemes. .ix is exceptionally useful when dealing with mixed positional and label
based hierachical indexes.

However, when an axis is integer based, ONLY label based access and not positional access is supported.
Thus, in such cases, it’s usually better to be explicit and use .iloc or .loc.

See more at Advanced Indexing.

pandas.Series.loc

Series.loc
Purely label-location based indexer for selection by label.

.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' (note that contrary to usual python slices, both the start and
  the stop are included!).

•A boolean array.
.loc will raise a KeyError when the items are not found.

See more at Selection by Label

pandas.Series.nbytes

Series.nbytes
return the number of bytes in the underlying data

pandas.Series.ndim

Series.ndim
return the number of dimensions of the underlying data, by definition 1

pandas.Series.real

Series.real

pandas.Series.shape

Series.shape
return a tuple of the shape of the underlying data

pandas.Series.size

Series.size
return the number of elements in the underlying data

pandas.Series.strides

Series.strides
return the strides of the underlying data

pandas.Series.values

Series.values
Return Series as ndarray or ndarray-like depending on the dtype

Returns arr : numpy.ndarray or ndarray-like

Examples

>>> 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, a, b, c]
Categories (3, object): [a, b, c]

Timezone aware datetime data is converted to UTC:

>>> pd.Series(pd.date_range('20130101', periods=3, tz='US/Eastern')).values
array(['2013-01-01T00:00:00.000000000-0500',
       '2013-01-02T00:00:00.000000000-0500',
       '2013-01-03T00:00:00.000000000-0500'], dtype='datetime64[ns]')

Methods

abs()  
Addition of series and other, element-wise (binary operator add).
add(other[, level, fill_value, axis])  
Concatenate prefix string with panel items names.
add_prefix(prefix)  
Concatenate suffix string with panel items names
add_suffix(suffix)  
Align two object on their axes with the
align(other[, join, axis, level, copy, ...])  
Return whether all elements are True over requested axis
all([axis, bool_only, skipna, level])  
Return whether any element is True over requested axis
any([axis, bool_only, skipna, level])  
 Concatenate two or more Series.
argmax([axis, out, skipna])  
Invoke function on values of Series.
argmin([axis, out, skipna])  
Index of first occurrence of maximum of values.
argsort([axis, kind, order])  
Index of first occurrence of minimum of values.
as_blocks([copy])  
Overrides ndarray.argsort.
as_matrix([columns])  
Convert the frame to a dict of dtype -> Constructor Types that each has a homogen
astype(dtype[, copy, raise_on_error])  
Convert the frame to its Numpy-array representation.
at_time(time[, asof])  
Convert all TimeSeries inside to specified frequency using DateOffset objects.
autocorr([lag])  
Return last good (non-NaN) value in Series if value is NaN for requested date.
bfill([axis, inplace, limit, downcast()])  
Cast object to input numpy.dtype
bool()  
Select values at particular time of day (e.g.
clip([lower, upper, out, axis])  
Lag-N autocorrelation
clip_lower(threshold[, axis])  
Select values between particular times of the day (e.g., 9:00-9:30 AM)
clip_upper(threshold[, axis])  
Synonym for NDFrame.fillna(method='bfill')
combine(other, func[, fill_value])  
Return the bool of a single element PandasObject
combine_first(other)  
Trim values at input threshold(s)
compound([axis, skipna, level])  
Return copy of the input with values below given value(s) truncated
compress(condition[, axis, out])  
Return copy of input with values above given value(s) truncated
consolidate([inplace])  
Perform elementwise binary operation on two Series using given function
convert_objects([convert_dates, ...])  
Combine Series values, choosing the calling Series’s values first.
corr(other[, method, min_periods])  
Return the compound percentage of the values for the requested axis
count([level])  
Return selected slices of an array along given axis as a Series
conv(other[, min_periods])  
Compute NDFrame with “consolidated” internals (data of each dtype grouped to
cummax([axis, dtype, out, skipna])  
Attempt to infer better dtype for object columns
cummin([axis, dtype, out, skipna])  
Make a copy of this object
copy([deep])  
Compute correlation with other Series, excluding missing values
corr([level])  
Return number of non-NA/null observations in the Series
cov(other[, min_periods])  
Compute covariance with Series, excluding missing values
count([level])  
Return cumulative max over requested axis.
cummax([axis, dtype, out, skipna])  
Return cumulative min over requested axis.
<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>cumprod</code></td>
<td>Return cumulative prod over requested axis.</td>
</tr>
<tr>
<td><code>cumsum</code></td>
<td>Return cumulative sum over requested axis.</td>
</tr>
<tr>
<td><code>describe</code></td>
<td>Generate various summary statistics, excluding NaN values.</td>
</tr>
<tr>
<td><code>diff</code></td>
<td>1st discrete difference of object</td>
</tr>
<tr>
<td><code>div</code></td>
<td>Floating division of series and other, element-wise (binary operator <code>truediv</code>).</td>
</tr>
<tr>
<td><code>divide</code></td>
<td>Floating division of series and other, element-wise (binary operator <code>truediv</code>).</td>
</tr>
<tr>
<td><code>dot</code></td>
<td>Matrix multiplication with DataFrame or inner-product with Series</td>
</tr>
<tr>
<td><code>drop</code></td>
<td>Return new object with labels in requested axis removed</td>
</tr>
<tr>
<td><code>drop_duplicates</code></td>
<td>Return Series with duplicate values removed</td>
</tr>
<tr>
<td><code>dropna</code></td>
<td>Return Series without null values</td>
</tr>
<tr>
<td><code>dt</code></td>
<td>alias of <code>CombinedDatetimelikeProperties</code></td>
</tr>
<tr>
<td><code>duplicated</code></td>
<td>Return boolean Series denoting duplicate values</td>
</tr>
<tr>
<td><code>eq</code></td>
<td>Determines if two NDFrame objects contain the same elements.</td>
</tr>
<tr>
<td><code>factorize</code></td>
<td>Encode the object as an enumerated type or categorical variable</td>
</tr>
<tr>
<td><code>ffill</code></td>
<td>Synonym for NDFrame.fillna(method='ffill')</td>
</tr>
<tr>
<td><code>fillna</code></td>
<td>Fill NA/NaN values using the specified method</td>
</tr>
<tr>
<td><code>get</code></td>
<td>Get item from object for given key (DataFrame column, Panel slice, etc.).</td>
</tr>
<tr>
<td><code>get_dtype_counts</code></td>
<td>Return the counts of dtypes in this object</td>
</tr>
<tr>
<td><code>get_ftype_counts</code></td>
<td>Return the counts of ftypes in this object</td>
</tr>
<tr>
<td><code>get_values</code></td>
<td>Quickly retrieve single value at passed index label same as values (but handles sparseness conversions); is a view</td>
</tr>
<tr>
<td><code>groupby</code></td>
<td>Group series using mapper (dict or key function, apply given function)</td>
</tr>
<tr>
<td><code>head</code></td>
<td>Returns first n rows</td>
</tr>
<tr>
<td><code>hist</code></td>
<td>Draw histogram of the input series using matplotlib</td>
</tr>
<tr>
<td><code>idxmax</code></td>
<td>Index of first occurrence of maximum of values.</td>
</tr>
<tr>
<td><code>idxmin</code></td>
<td>Index of first occurrence of minimum of values.</td>
</tr>
<tr>
<td><code>iget</code></td>
<td>DEPRECATED. Interpolate values according to different methods.</td>
</tr>
<tr>
<td><code>interpolate</code></td>
<td>Interpolate values according to different methods.</td>
</tr>
<tr>
<td><code>isnull</code></td>
<td>Return a boolean Series showing whether each element in the Series is NaN</td>
</tr>
<tr>
<td><code>iteritems</code></td>
<td>Lazily iterate over (index, value) tuples</td>
</tr>
<tr>
<td><code>iterkv</code></td>
<td>iteritems alias used to get around 2to3. Deprecated</td>
</tr>
<tr>
<td><code>kurt</code></td>
<td>Return unbiased kurtosis over requested axis using Fishers definition of kurtosis</td>
</tr>
<tr>
<td><code>kurtosis</code></td>
<td>Return unbiased kurtosis over requested axis using Fishers definition of kurtosis</td>
</tr>
<tr>
<td><code>last</code></td>
<td>Return label for last non-NA/null value</td>
</tr>
<tr>
<td><code>mad</code></td>
<td>Return the mean absolute deviation of the values for the requested axis</td>
</tr>
</tbody>
</table>
**map**(arg[, na_action])

Map values of Series using input correspondence (which can be
function, see docstring there).

**mask**(cond[, other, inplace, axis, level, ...])

Return an object of same shape as self and whose corresponding entries are from
this method returns the maximum of the values in the object.

**max**(axis, skipna, level, numeric_only)

Return the mean of the values for the requested axis
This method returns the minimum of the values in the object.

**mean**(axis, skipna, level, numeric_only)

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**median**(axis, skipna, level, numeric_only)

Modulo of series and other, element-wise (binary operator mod).

**min**(axis, skipna, level, numeric_only)

Returns the mode(s) of the dataset.

**mod**(other[, level, fill_value, axis])

Multiplication of series and other, element-wise (binary operator mul).

**mode**()

Multiplication of series and other, element-wise (binary operator mul).

**mul**(other[, level, fill_value, axis])

Return the largest n elements.

**multiply**(other[, level, fill_value, axis])

Return the indices of the elements that are non-zero
Return a boolean same-sized object indicating if the values are
Return the smallest n elements.

**ne**(other[, axis])

Return number of unique elements in the object.

**notnull**()

DEPRECATED: use Series.sort_values()
Percent change over given number of periods.
Apply func(self, *args, **kwargs)
alias of SeriesPlotMethods
Return item and drop from frame.

**nsmallest**(args, **kwargs)

Return exponent power of series and other, element-wise (binary operator pow).

**nunique**(dropna)

Return the product of the values for the requested axis
Return the product of the values for the requested axis

**order**(na_last, ascending, kind, ...)

Return a boolean same-sized object indicating if the values are
Return the smallest n elements.

**pct_change**(periods, fill_method, limit, freq)

Addition of series and other, element-wise (binary operator radd).
Compute data ranks (1 through n).
Return the flattened underlying data as an ndarray
Floating division of series and other, element-wise (binary operator rtruediv).
Conform Series to new index with optional filling logic, placing NA/NaN in loci
for compatibility with higher dims
return an object with matching indices to myself
Alter axes input function or functions.
Alter index and / or columns using input function or functions.
Return a new Series with the values repeated reps times
Replace values given in 'to_replace' with 'value'.

**percentile**(q)

Convenience method for frequency conversion and resampling of regular time-series
Analogous to the pandas.DataFrame.reset_index() function, see doc
replace an ndarray with the values put
Return value at the given quantile, a la numpy.percentile.

**plot**()

Addition of series and other, element-wise (binary operator radd).
Return a boolean same-sized object indicating if the values are
Return the smallest n elements.

**pop**(item)

Compute data ranks (1 through n).
Return the flattened underlying data as an ndarray
Floating division of series and other, element-wise (binary operator rtruediv).
Conform Series to new index with optional filling logic, placing NA/NaN in loci
for compatibility with higher dims
return an object with matching indices to myself
Alter axes input function or functions.
Alter index and / or columns using input function or functions.
Return a new Series with the values repeated reps times
Replace values given in ‘to_replace’ with ‘value’. 

**pow**(other[, level, fill_value, axis])

Convenience method for frequency conversion and resampling of regular time-series
Analogous to the pandas.DataFrame.reset_index() function, see doc
replace an ndarray with the values shape
Integer division of series and other, element-wise (binary operator rdivmod).
Modulo of series and other, element-wise (binary operator rmod).
Multiplication of series and other, element-wise (binary operator rmul).
Return a with each element rounded to the given number of decimals.
Exponential power of series and other, element-wise (binary operator rpow).
Subtraction of series and other, element-wise (binary operator rsub).
Floating division of series and other, element-wise (binary operator rtruediv).
Returns a random sample of items from an axis of object.
Find indices where elements should be inserted to maintain order.
Return data corresponding to axis labels matching criteria

**prod**(axis, skipna, level, numeric_only)

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**product**(axis, skipna, level, numeric_only)

Return an object of same shape as self and whose corresponding entries are from
This method returns the maximum of the values in the object.

**ptp**(axis, out)

Return the mean of the values for the requested axis
This method returns the minimum of the values in the object.

**put**(args, **kwargs)

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**quantile**(q)

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**radd**(other[, level, fill_value, axis])

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**rdiv**(other[, level, fill_value, axis])

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**rdivmod**(other[, level, fill_value, axis])

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**rdiff**(other[, level, fill_value, axis])

Return the quantile of the values in the object.

**reindex**(index)

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**reindex_axis**(labels[, axis])

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**reindex_like**(other[, method, copy, limit, ...])

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**rename**(mapper[, axis, copy, inplace])

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**rename_axis**(mapper[, axis, copy, inplace])

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**reorder_levels**(order)

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**repeat**(reps)

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**replace**(to_replace, value, inplace, limit, ...)

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**resample**(rule[, how, axis, fill_method, ...])

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**reset_index**(level, drop, name, inplace)

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**reshape**(args, **kwargs)

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**rdivide**(other[, level, fill_value, axis])

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**rfloordiv**(other[, level, fill_value, axis])

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**rmul**(other[, level, fill_value, axis])

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**round**(decimals, out)

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**rpow**(other[, level, fill_value, axis])

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**rsub**(other[, level, fill_value, axis])

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**rtruediv**(other[, level, fill_value, axis])

Return the median of the values for the requested axis
This method returns the minimum of the values in the object.

**sample**(n, frac, replace, weights, ...)

**searchsorted**(v[, side, sorter])

**select**(crit[, axis])

**percentile**(q)

**put**(args, **kwargs)

**quantile**(q)

**radd**(other[, level, fill_value, axis])

**rdiv**(other[, level, fill_value, axis])

**rdivmod**(other[, level, fill_value, axis])

return an object of same shape as self and whose corresponding entries are from
This method returns the maximum of the values in the object.
Return the mean of the values for the requested axis
Return the median of the values for the requested axis
This method returns the minimum of the values in the object.
Modulo of series and other, element-wise (binary operator mod).
Returns the mode(s) of the dataset.
Multiplication of series and other, element-wise (binary operator mul).
Multiplication of series and other, element-wise (binary operator mul).

Return the largest n elements.
Return the indices of the elements that are non-zero
Return a boolean same-sized object indicating if the values are
Return the smallest n elements.
Return number of unique elements in the object.
DEPRECATED: use Series.sort_values()
Percent change over given number of periods.
Apply func(self, *args, **kwargs)
alias of SeriesPlotMethods
Return item and drop from frame.

Exponential power of series and other, element-wise (binary operator pow).
Return the product of the values for the requested axis
Return the product of the values for the requested axis

return a ndarray with the values put
Return value at the given quantile, a la numpy.percentile.
Addition of series and other, element-wise (binary operator radd).
Compute data ranks (1 through n).
Return the flattened underlying data as an ndarray
Floating division of series and other, element-wise (binary operator rtruediv).
Conform Series to new index with optional filling logic, placing NA/NaN in loci
for compatibility with higher dims
return an object with matching indices to myself
Alter axes input function or functions.
Alter index and / or columns using input function or functions.
Return a new Series with the values repeated reps times
Replace values given in ‘to_replace’ with ‘value’. 

Convenience method for frequency conversion and resampling of regular time-series
Analogous to the pandas.DataFrame.reset_index() function, see doc
return an ndarray with the values shape
Integer division of series and other, element-wise (binary operator rdivmod).
Modulo of series and other, element-wise (binary operator rmod).
Multiplication of series and other, element-wise (binary operator rmul).
Return a with each element rounded to the given number of decimals.
Exponential power of series and other, element-wise (binary operator rpow).
Subtraction of series and other, element-wise (binary operator rsub).
Floating division of series and other, element-wise (binary operator rtruediv).
Returns a random sample of items from an axis of object.
Find indices where elements should be inserted to maintain order.
Return data corresponding to axis labels matching criteria
<table>
<thead>
<tr>
<th>Method</th>
<th>Functionality</th>
</tr>
</thead>
<tbody>
<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>public version of axis assignment</td>
</tr>
<tr>
<td><code>set_value</code></td>
<td>Quickly set single value at passed label.</td>
</tr>
<tr>
<td><code>shift</code></td>
<td>Shift index by desired number of periods with an optional time freq</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</code></td>
<td>DEPRECATED: use <code>Series.sort_values(inplace=True)</code> for INPLACE sorting</td>
</tr>
<tr>
<td><code>sort_index</code></td>
<td>Sort object by labels (along an axis)</td>
</tr>
<tr>
<td><code>sort_values</code></td>
<td>Sort by the values along either axis</td>
</tr>
<tr>
<td><code>sortlevel</code></td>
<td>Sort Series with MultiIndex by chosen level.</td>
</tr>
<tr>
<td><code>squeeze</code></td>
<td>squeeze length 1 dimensions</td>
</tr>
<tr>
<td><code>std</code></td>
<td>Return unbiased standard deviation over requested axis.</td>
</tr>
<tr>
<td><code>str</code></td>
<td>alias of <code>StringMethods</code></td>
</tr>
<tr>
<td><code>sub</code></td>
<td>Subtraction of series and other, element-wise (binary operator <code>sub</code>).</td>
</tr>
<tr>
<td><code>subtract</code></td>
<td>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 MultiIndex</td>
</tr>
<tr>
<td><code>tail</code></td>
<td>Returns last n rows</td>
</tr>
<tr>
<td><code>take</code></td>
<td>return Series corresponding to requested indices</td>
</tr>
<tr>
<td><code>to_clipboard</code></td>
<td>Attempt to write text representation of object to the system clipboard</td>
</tr>
<tr>
<td><code>to_csv</code></td>
<td>Write to a comma-separated values (csv) file</td>
</tr>
<tr>
<td><code>to_dense</code></td>
<td>Return dense representation of NDFrame (as opposed to sparse)</td>
</tr>
<tr>
<td><code>to_dict</code></td>
<td>Convert to {label -&gt; value} dict</td>
</tr>
<tr>
<td><code>to_frame</code></td>
<td>Convert to DataFrame</td>
</tr>
<tr>
<td><code>to_hdf</code></td>
<td>activate the HDFStore</td>
</tr>
<tr>
<td><code>to_json</code></td>
<td>Convert the object to a JSON string.</td>
</tr>
<tr>
<td><code>to_msgpack</code></td>
<td>msgpack (serialize) object to input file path</td>
</tr>
<tr>
<td><code>to_period</code></td>
<td>Convert from DatetimeIndex to PeriodIndex with desired</td>
</tr>
<tr>
<td><code>to_pickle</code></td>
<td>Pickle (serialize) object to input file path</td>
</tr>
<tr>
<td><code>to_sparse</code></td>
<td>Convert to SparseSeries</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 <code>beginning</code> of period</td>
</tr>
<tr>
<td><code>tolist</code></td>
<td>return the transpose, which is by definition self</td>
</tr>
<tr>
<td><code>truediv</code></td>
<td>Floating division of series and other, element-wise (binary operator <code>truediv</code>).</td>
</tr>
<tr>
<td><code>truncate</code></td>
<td>Truncates a sorted NDFrame before and/or after some particular dates.</td>
</tr>
<tr>
<td><code>tshift</code></td>
<td>Shift the time index, using the index’s frequency if available</td>
</tr>
<tr>
<td><code>tz_convert</code></td>
<td>Convert tz-aware axis to target time zone.</td>
</tr>
<tr>
<td><code>tz_localize</code></td>
<td>Localize tz-aware TimeSeries to target time zone</td>
</tr>
<tr>
<td><code>unique</code></td>
<td>Return array of unique values in the object.</td>
</tr>
<tr>
<td><code>unstack</code></td>
<td>Unstack, a.k.a.</td>
</tr>
<tr>
<td><code>valid</code></td>
<td>Modify Series in place using non-NA values from passed Series.</td>
</tr>
<tr>
<td><code>value_counts</code></td>
<td>Returns object containing counts of unique values.</td>
</tr>
<tr>
<td><code>var</code></td>
<td>Return unbiased variance over requested axis.</td>
</tr>
<tr>
<td><code>view</code></td>
<td>Return an object of same shape as self and whose corresponding entries are from <code>self</code>.</td>
</tr>
<tr>
<td><code>where</code></td>
<td>Returns a cross-section (row(s) or column(s)) from the Series/DataFrame.</td>
</tr>
<tr>
<td><code>xs</code></td>
<td></td>
</tr>
</tbody>
</table>
pandas.Series.abs

Series.abs()
Return an object with absolute value taken. Only applicable to objects that are all numeric

Returns abs: type of caller

pandas.Series.add

Series.add(other, level=None, fill_value=None, axis=0)
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 one of the inputs.

Parameters other: Series or scalar value

fill_value: None or float value, default None (NaN)
Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level: int or name
Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result: Series

See also:
Series.radd

pandas.Series.add_prefix

Series.add_prefix(prefix)
Concatenate prefix string with panel items names.

Parameters prefix: string

Returns with_prefix: type of caller

pandas.Series.add_suffix

Series.add_suffix(suffix)
Concatenate suffix string with panel items names

Parameters suffix: string

Returns with_suffix: type of caller

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 object on their axes with the specified join method 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: boolean, 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: str, default None

  
  limit: int, default None

  
  fill_axis: {0, ‘index’}, default 0
  
  Filling axis, method and limit

  
  broadcast_axis: {0, ‘index’}, default None
  
  Broadcast values along this axis, if aligning two objects of different dimensions
  
  New in version 0.17.0.

**Returns**  
(left, right): (Series, type of other)

  
  Aligned objects

---

**Series.all**

Series.all (axis=None, bool_only=None, skipna=None, level=None, **kwargs)  
Return whether all elements are True over requested axis

**Parameters**  
axis: [index (0)]

  
  skipna: boolean, 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

  
  bool_only: boolean, default None
  
  Include only boolean data. If None, will attempt to use everything, then use only boolean data

**Returns**  
all: scalar or Series (if level specified)
pandas.Series.any

Series.any(axis=None, bool_only=None, skipna=None, level=None, **kwargs)
Return whether any element is True over requested axis

Parameters axis : {index (0)}
skipna : boolean, 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
bool_only : boolean, default None
Include only boolean data. If None, will attempt to use everything, then use only
boolean data

Returns any : scalar or Series (if level specified)

pandas.Series.append

Series.append(to_append, verify_integrity=False)
Concatenate two or more Series.

Parameters to_append : Series or list/tuple of Series
verify_integrity : boolean, default False
If True, raise Exception on creating index with duplicates

Returns appended : Series

pandas.Series.apply

Series.apply(func, convert_dtype=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
convert_dtype : boolean, default True
Try to find better dtype for elementwise function results. If False, leave as dtype=object
args : tuple
Positional arguments to pass to function in addition to the value

Additional keyword arguments will be passed as keywords to the function

Returns y : Series or DataFrame if func returns a Series

See also:
Series.map For element-wise operations
Examples

Create a series with typical summer temperatures for each city.

```python
>>> import pandas as pd
>>> import numpy as np
>>> series = pd.Series([20, 21, 12], index=['London', 'New York', 'Helsinki'])
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
>>> series.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
>>> series.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
>>> series.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
>>> series.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.
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```python
>>> series.apply(np.log)
London    2.995732
New York  3.044522
Helsinki  2.484907
dtype: float64
```

**pandas.Series.argmax**

`Series.argmax(axis=None, out=None, skipna=True)`

Index of first occurrence of maximum of values.

- **Parameters**
  - `skipna` : boolean, default True
    - Exclude NA/null values

- **Returns**
  - `idxmax` : Index of maximum of values

**See also:**

- `DataFrame.idxmax`, `numpy.ndarray.argmax`

**Notes**

This method is the Series version of `ndarray.argmax`.

**pandas.Series.argmin**

`Series.argmin(axis=None, out=None, skipna=True)`

Index of first occurrence of minimum of values.

- **Parameters**
  - `skipna` : boolean, default True
    - Exclude NA/null values

- **Returns**
  - `idxmin` : Index of minimum of values

**See also:**

- `DataFrame.idxmin`, `numpy.ndarray.argmin`

**Notes**

This method is the Series version of `ndarray.argmin`.

**pandas.Series.argsort**

`Series.argsort(axis=0, kind='quicksort', order=None)`

Overrides `ndarray.argsort`. Argsorts the value, omitting NA/null values, and places the result in the same locations as the non-NA values.

- **Parameters**
  - `axis` : int (can only be zero)
    - `kind` : {‘mergesort’, ‘quicksort’, ‘heapsort’}, default ‘quicksort’
      - Choice of sorting algorithm. See `np.sort` for more information. ‘mergesort’ is the only stable algorithm
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order : ignored

Returns **argsorted** : Series, with -1 indicated where nan values are present

See also:

numpy.ndarray.argsort

**pandas.Series.as_blocks**

Series.as_blocks *(copy=True)*

Convert the frame to a dict of dtype -> Constructor Types that each has a homogeneous dtype.

**Parameters**

- **copy** : boolean, default True

**Returns**

- **values** : a dict of dtype -> Constructor Types

**pandas.Series.as_matrix**

Series.as_matrix *(columns=None)*

Convert the frame to its Numpy-array representation.

**Parameters**

- **columns** : list, optional, default:None
  
  If None, return all columns, otherwise, returns specified columns.

**Returns**

- **values** : ndarray
  
  If the caller is heterogeneous and contains booleans or objects, the result will be of dtype=object. See Notes.

See also:

pandas.DataFrame.values

**Notes**

Return is NOT a Numpy-matrix, rather, a Numpy-array.

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 upcase to int32.

This method is provided for backwards compatibility. Generally, it is recommended to use `.values`.

**pandas.Series.asfreq**

Series.asfreq *(freq, method=None, how=None, normalize=False)*

Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.
Parameters freq : DateOffset object, or string

- method : {'backfill', 'bfill', 'pad', 'ffill', 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

- how : {'start', 'end'}, default end

  For PeriodIndex only, see PeriodIndex.asfreq

- normalize : bool, default False

  Whether to reset output index to midnight

Returns converted : type of caller

pandas.Series.asof

Series.asof (where)

Return last good (non-NaN) value in Series if value is NaN for requested date.

If there is no good value, NaN is returned.

- Parameters where : date or array of dates

- Returns value or NaN

Notes

Dates are assumed to be sorted

pandas.Series.astype

Series.astype (dtype, copy=True, raise_on_error=True, **kwargs)

Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

- Parameters dtype : numpy.dtype or Python type

- raise_on_error : raise on invalid input

- kwargs : keyword arguments to pass on to the constructor

Returns casted : type of caller

pandas.Series.at_time

Series.at_time (time, asof=False)

Select values at particular time of day (e.g. 9:30AM)

- Parameters time : datetime.time or string

- Returns values_at_time : type of caller
pandas.Series.autocorr

Series.autocorr(lag=1)
Lag-N autocorrelation

Parameters lag : int, default 1
Number of lags to apply before performing autocorrelation.

Returns autocorr : float

pandas.Series.between

Series.between(left, right, inclusive=True)
Return boolean Series equivalent to left <= series <= right. NA values will be treated as False

Parameters left : scalar
Left boundary
right : scalar
Right boundary

Returns is_between : Series

pandas.Series.between_time

Series.between_time(start_time, end_time, include_start=True, include_end=True)
Select values between particular times of the day (e.g., 9:00-9:30 AM)

Parameters start_time : datetime.time or string
end_time : datetime.time or string
include_start : boolean, default True
include_end : boolean, default True

Returns values_between_time : type of caller

pandas.Series.bfill

Series.bfill(axis=None, inplace=False, limit=None, downcast=None)
Synonym for NDFrame.fillna(method='bfill')

pandas.Series.bool

Series.bool()
Return the bool of a single element PandasObject This must be a boolean scalar value, either True or False
Raise a ValueError if the PandasObject does not have exactly 1 element, or that element is not boolean
**pandas.Series.cat**

*Series.cat()*  
Accessor object for categorical properties of the Series values.

Be aware that assigning to *categories* is an in-place operation, while all methods return new categorical data per default (but can be called with *inplace=True*).

**Examples**

```python
>>> s.cat.categories
>>> s.cat.categories = list('abc')
>>> s.cat.rename_categories(list('cab'))
>>> s.cat.reorder_categories(list('cab'))
>>> s.cat.add_categories(['d', 'e'])
>>> s.cat.remove_categories(['d'])
>>> s.cat.remove_unused_categories()
>>> s.cat.set_categories(list('abcde'))
>>> s.cat.as_ordered()
>>> s.cat.as_unordered()
```

**pandas.Series.clip**

*Series.clip*(lower=None, upper=None, out=None, axis=None)  
Trim values at input threshold(s)

**Parameters**
- **lower**: float or array_like, default None
- **upper**: float or array_like, default None
- **axis**: int or string axis name, optional

Align object with lower and upper along the given axis.

**Returns**
- **clipped**: Series

**Examples**

```python
>>> df
  0    1
0  0.335232  -1.256177
1 -1.367855   0.746646
2  0.027753  -1.176076
3  0.230930  -0.679613
4  1.261967   0.570967
>>> df.clip(-1.0, 0.5)
  0    1
0  0.335232  -1.000000
1 -1.000000   0.500000
2  0.027753  -1.000000
3  0.230930  -0.679613
4  0.500000   0.500000
>>> t
  0   -0.3
  1  -0.2
```
2  -0.1
3   0.0
4   0.1
dtype: float64
>>> df.clip(t, t + 1, axis=0)
       0  1
0  0.335232 -0.300000
1 -0.200000  0.746646
2  0.027753 -0.100000
3  0.230930  0.000000
4  1.100000  0.570967

pandas.Series.clip_lower

Series.clip_lower(threshold, axis=None)
Return copy of the input with values below given value(s) truncated

Parameters threshold : float or array_like
    axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns clipped : same type as input

See also:
clip

pandas.Series.clip_upper

Series.clip_upper(threshold, axis=None)
Return copy of input with values above given value(s) truncated

Parameters threshold : float or array_like
    axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns clipped : same type as input

See also:
clip

pandas.Series.combine

Series.combine(other, func, fill_value=None)
Perform elementwise binary operation on two Series using given function with optional fill value when an
index is missing from one Series or the other

Parameters other : Series or scalar value
    func : function
    fill_value : scalar value

Returns result : Series

34.3. Series  1025
pandas.Series.combine_first

Series.combine_first(other)

Combine Series values, choosing the calling Series’s values first. Result index will be the union of the two indexes

Parameters other : Series

Returns y : Series

pandas.Series.compound

Series.compound(axis=None, skipna=None, level=None)

Return the compound percentage of the values for the requested axis

Parameters axis : {index (0)}

skipna : boolean, 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

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns compounded : scalar or Series (if level specified)

pandas.Series.compress

Series.compress(condition, axis=0, out=None, **kwargs)

Return selected slices of an array along given axis as a Series

See also:

numpy.ndarray.compress

pandas.Series.consolidate

Series.consolidate(inplace=False)

Compute NDFrame with “consolidated” internals (data of each dtype grouped together in a single ndarray). Mainly an internal API function, but available here to the savvy user

Parameters inplace : boolean, default False

If False return new object, otherwise modify existing object

Returns consolidated : type of caller
pandas.Series.convert_objects

Series.convert_objects(convert_dates=True, convert_numeric=False, convert_timedeltas=True, copy=True)

Attempt to infer better dtype for object columns

Parameters convert_dates : boolean, default True

If True, convert to date where possible. If ‘coerce’, force conversion, with unconvertible values becoming NaT.

convert_numeric : boolean, default False

If True, attempt to coerce to numbers (including strings), with unconvertible values becoming NaN.

convert_timedeltas : boolean, default True

If True, convert to timedelta where possible. If ‘coerce’, force conversion, with unconvertible values becoming NaT.

copy : boolean, default True

If True, return a copy even if no copy is necessary (e.g. no conversion was done). Note: This is meant for internal use, and should not be confused with inplace.

Returns converted : same as input object

pandas.Series.copy

Series.copy(deep=True)

Make a copy of this object

Parameters deep : boolean or string, default True

Make a deep copy, i.e. also copy data

Returns copy : type of caller

pandas.Series.corr

Series.corr(other, method='pearson', min_periods=None)

Compute correlation with other Series, excluding missing values

Parameters other : Series

method : {'pearson', 'kendall', 'spearman'}

- pearson : standard correlation coefficient
- kendall : Kendall Tau correlation coefficient
- spearman : Spearman rank correlation

min_periods : int, optional

Minimum number of observations needed to have a valid result

Returns correlation : float
**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**

- **nobs** : int or Series (if level specified)

**pandas.Series.cov**

`Series.cov(other, min_periods=None)`

Compute covariance with Series, excluding missing values

**Parameters**

- **other** : Series
- **min_periods** : int, optional
  
  Minimum number of observations needed to have a valid result

**Returns**

- **covariance** : float
  
  Normalized by N-1 (unbiased estimator).

**pandas.Series.cummax**

`Series.cummax(axis=None, dtype=None, out=None, skipna=True, **kwargs)`

Return cumulative max over requested axis.

**Parameters**

- **axis** : {index (0)}
- **skipna** : boolean, default True
  
  Exclude NA/null values. If an entire row/column is NA, the result will be NA

**Returns**

- **max** : scalar

**pandas.Series.cummin**

`Series.cummin(axis=None, dtype=None, out=None, skipna=True, **kwargs)`

Return cumulative min over requested axis.

**Parameters**

- **axis** : {index (0)}
- **skipna** : boolean, default True
  
  Exclude NA/null values. If an entire row/column is NA, the result will be NA

**Returns**

- **min** : scalar

**pandas.Series.cumprod**

`Series.cumprod(axis=None, dtype=None, out=None, skipna=True, **kwargs)`

Return cumulative prod over requested axis.
**Parameters**

- **axis**: {index (0)}
- **skipna**: boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**Returns**

- **prod**: scalar

---

**pandas.Series.cumsum**

```
Series.cumsum(axis=None, dtype=None, out=None, skipna=True, **kwargs)
```

Return cumulative sum over requested axis.

**Parameters**

- **axis**: {index (0)}
- **skipna**: boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**Returns**

- **sum**: scalar

---

**pandas.Series.describe**

```
Series.describe(percentiles=None, include=None, exclude=None)
```

Generate various summary statistics, excluding NaN values.

**Parameters**

- **percentiles**: array-like, optional
  - The percentiles to include in the output. Should all be in the interval [0, 1]. By default
  - **percentiles** is [.25, .5, .75], returning the 25th, 50th, and 75th percentiles.
  - **include**, **exclude**: list-like, ‘all’, or None (default)
  - Specify the form of the returned result. Either:
    - None to both (default). The result will include only numeric-typed columns or, if none are, only categorical columns.
    - A list of dtypes or strings to be included/excluded. To select all numeric types use numpy number. To select categorical objects use type object. See also the select_dtypes documentation. eg. df.describe(include=['O'])
    - If include is the string ‘all’, the output column-set will match the input one.

**Returns**

- **summary**: NDFrame of summary statistics

**See also:**

- **DataFrame.select_dtypes**

---

**Notes**

The output DataFrame index depends on the requested dtypes:

For numeric dtypes, it will include: count, mean, std, min, max, and lower, 50, and upper percentiles.

For object dtypes (e.g. timestamps or strings), the index will include the count, unique, most common, and frequency of the most common. Timestamps also include the first and last items.
For mixed dtypes, the index will be the union of the corresponding output types. Non-applicable entries will be filled with NaN. Note that mixed-dtype outputs can only be returned from mixed-dtype inputs and appropriate use of the include/exclude arguments.

If multiple values have the highest count, then the count and most common pair will be arbitrarily chosen from among those with the highest count.

The include, exclude arguments are ignored for Series.

**pandas.Series.diff**

`Series.diff(periods=1)`

1st discrete difference of object

**Parameters**
- **periods**: int, default 1
  - Periods to shift for forming difference

**Returns**
- **diffed**: Series

**pandas.Series.div**

`Series.div(other, level=None, fill_value=None, axis=0)`

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 one of the inputs.

**Parameters**
- **other**: Series or scalar value
- **fill_value**: None or float value, default None (NaN)
  - Fill missing (NaN) values with this value. If both Series are missing, the result will be missing
- **level**: int or name
  - Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**
- **result**: Series

**See also:**
- `Series.rtruediv`

**pandas.Series.divide**

`Series.divide(other, level=None, fill_value=None, axis=0)`

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 one of the inputs.

**Parameters**
- **other**: Series or scalar value
- **fill_value**: None or float value, default None (NaN)
  - Fill missing (NaN) values with this value. If both Series are missing, the result will be missing
- **level**: int or name
Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns** result : Series

See also:

Series.rtruediv

**pandas.Series.dot**

```python
Series.dot(other)
```

Matrix multiplication with DataFrame or inner-product with Series objects

**Parameters** other : Series or DataFrame

**Returns** dot_product : scalar or Series

**pandas.Series.drop**

```python
Series.drop(labels, axis=0, level=None, inplace=False, errors='raise')
```

Return new object with labels in requested axis removed

**Parameters** labels : single label or list-like

- axis : int or axis name
- level : int or level name, default None
  - For MultiIndex
- inplace : bool, default False
  - If True, do operation inplace and return None.
- errors : {‘ignore’, ‘raise’}, default ‘raise’
  - If ‘ignore’, suppress error and existing labels are dropped.

New in version 0.16.1.

**Returns** dropped : type of caller

**pandas.Series.drop_duplicates**

```python
Series.drop_duplicates(*args, **kwargs)
```

Return Series 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.

**take_last** : deprecated

- inplace : boolean, default False
  - If True, performs operation inplace and returns None.

**Returns** deduplicated : Series
**pandas.Series.dropna**

Series.dropna(axis=0, inplace=False, **kwargs)

Return Series without null values

Returns **valid** : Series

-inplace : boolean, default False

Do operation in place.

**pandas.Series.dt**

Series.dt()

Accessor object for datetimelike properties of the Series values.

**Examples**

```python
>>> s.dt.hour
>>> s.dt.second
>>> s.dt.quarter
```

Returns a Series indexed like the original Series. Raises TypeError if the Series does not contain datetimelike values.

**pandas.Series.duplicated**

Series.duplicated(*args, **kwargs)

Return boolean Series denoting duplicate values

Parameters **keep** : {'first', 'last', False}, default 'first'

- **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.

**take_last** : deprecated

Returns **duplicated** : Series

**pandas.Series.eq**

Series.eq(other, axis=None)

**pandas.Series.equals**

Series.equals(other)

Determines if two NDFrame objects contain the same elements. NaNs in the same location are considered equal.
**pandas.Series.factorize**

Series.factorize(sort=False, na_sentinel=-1)

Encode the object as an enumerated type or categorical variable

**Parameters**
- **sort**: boolean, default False
  Sort by values
- **na_sentinel**: int, default -1
  Value to mark “not found”

**Returns**
- **labels**: the indexer to the original array
- **uniques**: the unique Index

**pandas.Series.ffill**

Series.ffill(axis=None, inplace=False, limit=None, downcast=None)

Synonym for NDFrame.fillna(method='ffill')

**pandas.Series.fillna**

Series.fillna(value=None, method=None, axis=None, inplace=False, limit=None, downcast=None, **kwargs)

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, ‘index’}
- **inplace**: boolean, 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.
- **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**
- **filled**: Series
See also:

reindex, asfreq

pandas.Series.filter

Series.filter(items=None, like=None, regex=None, axis=None)
Restrict the info axis to set of items or wildcard

Parameters:
- **items**: list-like
  - List of info axis to restrict to (must not all be present)
- **like**: string
  - Keep info axis where “arg in col == True”
- **regex**: string (regular expression)
  - Keep info axis with re.search(regex, col) == True
- **axis**: int or None
  - The axis to filter on. By default this is the info axis. The “info axis” is the axis that is used when indexing with[]. For example, df = DataFrame(‘a’ : [1, 2, 3, 4]); df[‘a’]. So, the DataFrame columns are the info axis.

Notes

Arguments are mutually exclusive, but this is not checked for

pandas.Series.first

Series.first(offset)
Convenience method for subsetting initial periods of time series data based on a date offset

Parameters:
- **offset**: string, DateOffset, dateutil.relativedelta

Returns:
- **subset**: type of caller

Examples

ts.last(‘10D’) -> First 10 days

pandas.Series.first_valid_index

Series.first_valid_index()
Return label for first non-NA/null value
**pandas.Series.floordiv**

Series.floordiv(other, level=None, fill_value=None, axis=0)
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 one of the inputs.

**Parameters**
- **other**: Series or scalar value
  - `fill_value`: None or float scalar, default None (NaN)
    Fill missing (NaN) values with this value. If both Series are missing, the result will be missing.
  - `level`: int or name
    Broadcast across a level, matching Index values on the passed MultiIndex level.

**Returns**
- **result**: Series

**See also**:
- Series.rfloordiv

**pandas.Series.from_array**

classmethod Series.from_array(arr, index=None, name=None, dtype=None, copy=False, fast-path=False)

**pandas.Series.from_csv**

classmethod Series.from_csv(path, sep=',', parse_dates=True, header=None, index_col=0, encoding=None, infer_datetime_format=False)
Read CSV file (DISCOURAGED, please use pandas.read_csv() instead).

It is preferable to use the more powerful pandas.read_csv() for most general purposes, but from_csv makes for an easy roundtrip to and from a file (the exact counterpart of to_csv), especially with a time Series.

This method only differs from pandas.read_csv() in some defaults:

- `index_col` is 0 instead of None (take first column as index by default)
- `header` is None instead of 0 (the first row is not used as the column names)
- `parse_dates` is True instead of False (try parsing the index as datetime by default)

With pandas.read_csv(), the option squeeze=True can be used to return a Series like from_csv.

**Parameters**
- **path**: string file path or file handle / StringIO
  - `sep`: string, default ‘,’
    Field delimiter
  - `parse_dates`: boolean, default True
    Parse dates. Different default from read_table
  - `header`: int, default None
Row to use as header (skip prior rows)

**index_col**: int or sequence, default 0

Column to use for index. If a sequence is given, a MultiIndex is used. Different default from read_table

**encoding**: string, optional

A string representing the encoding to use if the contents are non-ascii, for python versions prior to 3

**infer_datetime_format**: boolean, default False

If True and `parse_dates` is True for a column, try to infer the datetime format based on the first datetime string. If the format can be inferred, there often will be a large parsing speed-up.

**Returns**: `y`: Series

See also:

pandas.read_csv

**pandas.Series.ge**

`Series.ge(other, axis=None)`

**pandas.Series.get**

`Series.get(key, default=None)`

Get item from object for given key (DataFrame column, Panel slice, etc.). Returns default value if not found

**Parameters**

- **key**: object

**Returns**

- **value**: type of items contained in object

**pandas.Series.get_dtype_counts**

`Series.get_dtype_counts()`

Return the counts of dtypes in this object

**pandas.Series.get_ftype_counts**

`Series.get_ftype_counts()`

Return the counts of ftypes in this object

**pandas.Series.get_value**

`Series.get_value(label, takeable=False)`

Quickly retrieve single value at passed index label

**Parameters**

- **index**: label

- **takeable**: interpret the index as indexers, default False
**pandas.Series.get_values**

Series.get_values()

same as values (but handles sparseness conversions); is a view

**pandas.Series.groupby**

Series.groupby(by=None, axis=0, level=None, as_index=True, sort=True, group_keys=True, squeeze=False)

Group series using mapper (dict or key function, apply given function to group, return result as series) or by a series of columns

**Parameters**

- **by**: mapping function / list of functions, dict, Series, or tuple / list of column names. Called on each element of the object index to determine the groups. If a dict or Series is passed, the Series or dict VALUES will be used to determine the groups
- **axis**: int, default 0
- **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**: boolean, 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**: boolean, 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**: boolean, default True
  When calling apply, add group keys to index to identify pieces
- **squeeze**: boolean, default False
  reduce the dimensionality of the return type if possible, otherwise return a consistent type

**Returns**

GroupBy object

**Examples**

**DataFrame results**

```python
>>> data.groupby(func, axis=0).mean()
>>> data.groupby(['col1', 'col2'])['col3'].mean()
```

**DataFrame with hierarchical index**

```python
>>> data.groupby(['col1', 'col2']).mean()
```
pandas.Series.gt

Series.gt (other, axis=None)

pandas.Series.head

Series.head (n=5)
  Returns first n rows

pandas.Series.hist

Series.hist (by=None, ax=None, grid=True, xlabelsize=None, xrot=None, ylabelsize=None, yrot=None, figsize=None, bins=10, **kwds)
  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 : boolean, 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 : integer, default 10
    Number of histogram bins to be used
  kwds : keywords
    To be passed to the actual plotting function

Notes

See matplotlib documentation online for more on this
pandas.Series.idxmax

Series.idxmax(axis=None, out=None, skipna=True)
Index of first occurrence of maximum of values.

Parameters

- skipna: boolean, default True
  Exclude NA/null values

Returns

- idxmax: Index of maximum of values

See also:

- DataFrame.idxmax
- numpy.ndarray.argmax

Notes

This method is the Series version of ndarray.argmax.

pandas.Series.idxmin

Series.idxmin(axis=None, out=None, skipna=True)
Index of first occurrence of minimum of values.

Parameters

- skipna: boolean, default True
  Exclude NA/null values

Returns

- idxmin: Index of minimum of values

See also:

- DataFrame.idxmin
- numpy.ndarray.argmin

Notes

This method is the Series version of ndarray.argmin.

pandas.Series.iget

Series.iget(i, axis=0)
DEPRECATED. Use .iloc[i] or .iat[i] instead

pandas.Series.iget_value

Series.iget_value(i, axis=0)
DEPRECATED. Use .iloc[i] or .iat[i] instead
Series.interpolate

Series.interpolate(func='linear', axis=0, limit=None, inplace=False, limit_direction='forward', downcast=None, **kwargs)

Interpolate values according to different methods.

Please note that only method='linear' is supported for DataFrames/Series with a MultiIndex.

Parameters

method : {'linear', 'time', 'index', 'values', 'nearest', 'zero', 'slinear', 'quadratic', 'cubic', 'barycentric', 'krogh', 'polynomial', 'spline', 'piecewise_polynomial', 'pchip'}
- 'linear': ignore the index and treat the values as equally spaced. This is the only method supported on MultiIndexes. default
- 'time': interpolation works on daily and higher resolution data to interpolate given length of interval
- 'index', 'values': use the actual numerical values of the index
- 'nearest', 'zero', 'slinear', 'quadratic', 'cubic', 'barycentric', 'polynomial' is passed to scipy.interpolate.interp1d. Both 'polynomial' and 'spline' require that you also specify an order (int), e.g. df.interpolate(method='polynomial', order=4). These use the actual numerical values of the index.
- 'krogh', 'piecewise_polynomial', 'spline', and 'pchip' are all wrappers around the scipy interpolation methods of similar names. These use the actual numerical values of the index. See the scipy documentation for more on their behavior here and here

axis : {0, 1}, default 0
- 0: fill column-by-column
- 1: fill row-by-row

limit : int, default None.
Maximum number of consecutive NaNs to fill.

limit_direction : {'forward', 'backward', 'both'}, defaults to 'forward'
If limit is specified, consecutive NaNs will be filled in this direction.
New in version 0.17.0.

inplace : bool, default False
Update the NDFrame in place if possible.

downcast : optional, ‘infer’ or None, defaults to None
Downcast dtypes if possible.

kwvars : keyword arguments to pass on to the interpolating function.

Returns

Series or DataFrame of same shape interpolated at the NaNs

See also:

reindex, replace, fillna
Examples

Filling in NaNs

```python
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s.interpolate()
0 0
1 1
2 2
3 3
dtype: float64
```

```python
pandas.Series.irow
```

Series.irow(i, axis=0)

DEPRECATED. Use .iloc[i] or .iat[i] instead

```python
pandas.Series.isin
```

Series.isin(values)

Return a boolean Series showing whether each element in the Series is exactly contained in the passed sequence of values.

Parameters values: 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 isin: Series (bool dtype)

Raises TypeError

• If values is a string

See also:

pandas.DataFrame.isin

Examples

```python
>>> s = pd.Series(list('abc'))
>>> s.isin(['a', 'c', 'e'])
0  True
1 False
2  True
dtype: bool
```

Passing a single string as s.isin('a') will raise an error. Use a list of one element instead:

```python
>>> s.isin(['a'])
0  True
1 False
2 False
dtype: bool
```
### pandas.Series.isnull

`Series.isnull()`

Return a boolean same-sized object indicating if the values are null

**See also:**

`notnull` boolean inverse of isnull

### pandas.Series.item

`Series.item()`

Return the first element of the underlying data as a python scalar

### pandas.Series.iteritems

`Series.iteritems()`

Lazily iterate over (index, value) tuples

### pandas.Series.iterkv

`Series.iterkv(*args, **kwargs)`

`iteritems` alias used to get around 2to3. Deprecated

### pandas.Series.keys

`Series.keys()`

Alias for index

### pandas.Series.kurt

`Series.kurt(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

**Parameters**

- **axis**: {index (0)}
- **skipna**: boolean, 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
- **numeric_only**: boolean, default None
  
  Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**

- **kurt**: scalar or Series (if level specified)
**pandas.Series.kurtosis**

Series.kurtosis(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)
Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

**Parameters**
axis : {index (0)}

skipna : boolean, 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

numeric_only : boolean, default None
Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**
kurt : scalar or Series (if level specified)

**pandas.Series.last**

Series.last(offset)
Convenience method for subsetting final periods of time series data based on a date offset

**Parameters**
offset : string, DateOffset, dateutil.relativedelta

**Returns**
subset : type of caller

**Examples**

ts.last('5M') -> Last 5 months

**pandas.Series.last_valid_index**

Series.last_valid_index()
Return label for last non-NA/null value

**pandas.Series.le**

Series.le(other, axis=None)

**pandas.Series.lt**

Series.lt(other, axis=None)
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)}
skipna : boolean, 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
numeric_only : boolean, default None
Include only float, int, boolean data. If None, will attempt to use everything, then use
only numeric data

Returns
mad : scalar or Series (if level specified)

pandas.Series.map

Series.map (arg, na_action=None)
Map values of Series using input correspondence (which can be a dict, Series, or function)

Parameters
arg : function, dict, or Series
na_action : {None, ‘ignore’}
If ‘ignore’, propagate NA values

Returns
y : Series
same index as caller

Examples

>>> x
one 1
two 2
three 3

>>> y
1  foo
2  bar
3  baz

>>> x.map(y)
one  foo
two  bar
three baz
**pandas.Series.mask**

```
Series.mask(cond, other=nan, inplace=False, axis=0, level=None, try_cast=False, raise_on_error=True)
```

Return an object of same shape as self and whose corresponding entries are from self where cond is False and otherwise are from other.

**Parameters**
- **cond**: boolean NDFrame or array
- **other**: scalar or NDFrame
- **inplace**: boolean, default False
  Whether to perform the operation in place on the data
- **axis**: alignment axis if needed, default None
- **level**: alignment level if needed, default None
- **try_cast**: boolean, default False
  try to cast the result back to the input type (if possible),
- **raise_on_error**: boolean, default True
  Whether to raise on invalid data types (e.g. trying to where on strings)

**Returns**
- **wh**: same type as caller

**pandas.Series.max**

```
Series.max(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)
```

This method returns the maximum of the values in the object. If you want the index of the maximum, use idxmax. This is the equivalent of the numpy.ndarray method argmax.

**Parameters**
- **axis**: {index (0)}
- **skipna**: boolean, 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
- **numeric_only**: boolean, default None
  Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**
- **max**: scalar or Series (if level specified)

**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)}
- **skipna**: boolean, default True
  Exclude NA/null values. If an entire row/column is NA, the result will be NA
**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)}

skipna : boolean, 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

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**

median : scalar or Series (if level specified)

**pandas.Series.min**

Series.min(\(axis=None, \) \(skipna=None, \) \(level=None, \) \(numeric\_only=None, \) **kwargs)

This method returns the minimum of the values in the object. If you want the index of the minimum, use idxmin. This is the equivalent of the numpy.ndarray method argmin.

**Parameters**

axis : {index (0)}

skipna : boolean, 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

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**

min : scalar or Series (if level specified)
pandas.Series.mod

Series.mod(other, level=None, fill_value=None, axis=0)
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 one of the inputs.

Parameters
other: Series or scalar value

fill_value: None or float value, default None (NaN)
Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level: int or name
Broadcast across a level, matching Index values on the passed MultiIndex level

Returns
result: Series

See also:
Series.rmod

pandas.Series.mode

Series.mode()
Returns the mode(s) of the dataset.
Empty if nothing occurs at least 2 times. Always returns Series even if only one value.

Parameters
sort: bool, default True
If True, will lexicographically sort values, if False skips sorting. Result ordering when sort=False is not defined.

Returns
modes: Series (sorted)

pandas.Series.mul

Series.mul(other, level=None, fill_value=None, axis=0)
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 one of the inputs.

Parameters
other: Series or scalar value

fill_value: None or float value, default None (NaN)
Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level: int or name
Broadcast across a level, matching Index values on the passed MultiIndex level

Returns
result: Series

See also:
Series.rmul
pandas.Series.multiply

Series.multiply (other, level=None, fill_value=None, axis=0)
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 one of the inputs.

Parameters other: Series or scalar value

fill_value : None or float value, default None (NaN)
Fill missing (NaN) values with this value. If both Series are missing, the result will be missing
level : int or name
Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

See also:
Series.rmul

pandas.Series.ne

Series.ne (other, axis=None)

pandas.Series.nlargest

Series.nlargest (*args, **kwargs)
Return the largest n elements.

Parameters n : int
Return this many descending sorted values
keep : {'first', 'last', False}, default ‘first’
Where there are duplicate values: - first : take the first occurrence. - last : take the last occurrence.
take_last : deprecated

Returns top_n : Series
The n largest values in the Series, in sorted order

See also:
Series.nsmallest

Notes

Faster than .sort_values(ascending=False).head(n) for small n relative to the size of the Series object.
Examples

```python
>>> import pandas as pd
>>> import numpy as np
>>> s = pd.Series(np.random.randn(1e6))
>>> s.nlargest(10)  # only sorts up to the N requested
```

**pandas.Series.nonzero**

Series.nonzero()

Return the indices of the elements that are non-zero

This method is equivalent to calling `numpy.nonzero` on the series data. For compatibility with NumPy, the return value is the same (a tuple with an array of indices for each dimension), but it will always be a one-item tuple because series only have one dimension.

See also:

`numpy.nonzero`

Examples

```python
>>> s = pd.Series([0, 3, 0, 4])
>>> s.nonzero()
(array([1, 3]),)
>>> s.ioc(s.nonzero()[0])
1 3
3 4
dtype: int64
```

**pandas.Series.notnull**

Series.notnull()

Return a boolean same-sized object indicating if the values are not null

See also:

`isnull` boolean inverse of notnull

**pandas.Series.nsmallest**

Series.nsmallest(*args, **kwargs)

Return the smallest n elements.

Parameters

- **n**: int
  - Return this many ascending sorted values
- **keep**: {'first', 'last', False}, default 'first'
  - Where there are duplicate values: - first : take the first occurrence. - last : take the last occurrence.
- take_last : deprecated


Returns `bottom_n` : Series

The n smallest values in the Series, in sorted order

See also:

`Series.nlargest`

Notes

Faster than `.sort_values().head(n)` for small n relative to the size of the Series object.

Examples

```python
>>> import pandas as pd
>>> import numpy as np

>>> s = pd.Series(np.random.randn(1e6))
>>> s.nsmallest(10)  # only sorts up to the N requested
```

`pandas.Series.nunique`

Series.nunique (dropna=True)

Return number of unique elements in the object.

Excludes NA values by default.

Parameters `dropna` : boolean, default True

Don’t include NaN in the count.

Returns `nunique` : int

`pandas.Series.order`

Series.order (na_last=None, ascending=True, kind='quicksort', na_position='last', inplace=False)

DEPRECATED: use `Series.sort_values()`

Sorts Series object, by value, maintaining index-value link. This will return a new Series by default. Series.sort is the equivalent but as an inplace method.

Parameters `na_last` : boolean (optional, default=True) (DEPRECATED; use na_position)

Put NaN’s at beginning or end

`ascending` : boolean, default True

Sort ascending. Passing False sorts descending

`kind` : {'mergesort', 'quicksort', 'heapsort'}, default ‘quicksort’

Choice of sorting algorithm. See np.sort for more information. ‘mergesort’ is the only stable algorithm

`na_position` : {'first', 'last'} (optional, default='last')

‘first’ puts NaNs at the beginning ‘last’ puts NaNs at the end

`inplace` : boolean, default False
Do operation in place.

**Returns** y : Series

*See also:*

Series.sort_values

### pandas.Series.pct_change

#### Series.pct_change(periods=1, fill_method='pad', limit=None, freq=None, **kwargs)

Percent change over given number of periods.

**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 offset alias string, optional
  - Increment to use from time series API (e.g. ‘M’ or BDay())

**Returns** chg : NDFrame

**Notes**

By default, the percentage change is calculated along the stat axis: 0, or Index, for DataFrame and 1, or minor for Panel. You can change this with the axis keyword argument.

### pandas.Series.pipe

#### Series.pipe(func, *args, **kwargs)

Apply func(self, *args, **kwargs)

New in version 0.16.2.

**Parameters**

- **func** : function
  - function to apply to the NDFrame. 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 NDFrame.
- **args** : positional arguments passed into func.
- **kwargs** : a dictionary of keyword arguments passed into func.

**Returns** object : the return type of func.

*See also:*

pandas.DataFrame.apply, pandas.DataFrame.applymap, pandas.Series.map
Notes

Use `.pipe` when chaining together functions that expect on Series or DataFrames. Instead of writing

```python
>>> f(g(h(df), arg1=a), arg2=b, arg3=c)
```

You can write

```python
>>> (df.pipe(h)
...   .pipe(g, arg1=a)
...   .pipe(f, 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((f, 'arg2'), arg1=a, arg3=c)
...)
```

**pandas.Series.plot**

Series.plot(kind='line', ax=None, figsize=None, use_index=True, title=None, grid=None, legend=False, style=None, logx=False, logy=False, loglog=False, xticks=None, yticks=None, xlim=None, ylim=None, rot=None, fontsize=None, colormap=None, table=False, yerr=None, xerr=None, label=None, secondary_y=False, **kwds)

Make plots of Series using matplotlib / pylab.

New in version 0.17.0: Each plot kind has a corresponding method on the Series.plot accessor: `s.plot(kind='line')` is equivalent to `s.plot.line()`.

Parameters

- **data** : Series
  - `kind` : str
    - '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
  - `ax` : matplotlib axes object
    - If not passed, uses gca()
  - `figsize` : a tuple (width, height) in inches
  - `use_index` : boolean, default True
    - Use index as ticks for x axis
**title**: string
Title to use for the plot

**grid**: boolean, default None (matlab style default)
Axis grid lines

**legend**: False/True/’reverse’
Place legend on axis subplots

**style**: list or dict
matplotlib line style per column

**logx**: boolean, default False
Use log scaling on x axis

**logy**: boolean, default False
Use log scaling on y axis

**loglog**: boolean, default False
Use log scaling on both x and y axes

**xticks**: sequence
Values to use for the xticks

**yticks**: sequence
Values to use for the yticks

**xlim** : 2-tuple/list

**ylim** : 2-tuple/list

**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**: boolean, 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)

**layout**: tuple (optional)
(rows, columns) for the layout of the plot

**table**: boolean, 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.
**pandas: powerful Python data analysis toolkit, Release 0.17.0**

- **yerr**: DataFrame, Series, array-like, dict and str  
  See *Plotting with Error Bars* for detail.

- **xerr**: same types as yerr.

- **label**: label argument to provide to plot

- **secondary_y**: boolean or sequence of ints, default False  
  If True then y-axis will be on the right

- **mark_right**: boolean, default True  
  When using a secondary_y axis, automatically mark the column labels with “(right)” in the legend

- **kwds**: keywords  
  Options to pass to matplotlib plotting method

**Returns axes**: matplotlib.AxesSubplot or np.array of them

---

**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 drop from frame. Raise KeyError if not found.

**pandas.Series.pow**

- **Series.pow(other, level=None, fill_value=None, axis=0)**  
  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 one of the inputs.

**Parameters other**: Series or scalar value

- **fill_value**: None or float value, default None (NaN)  
  Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

- **level**: int or name  
  Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns result**: Series

- See also:  
  **Series.rpow**
**pandas.Series.prod**

Series.prod(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

Return the product of the values for the requested axis

**Parameters**

- **axis**: {index (0)}
  - skipna: boolean, 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
  - numeric_only: boolean, default None
    - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**

- **prod**: scalar or Series (if level specified)

**pandas.Series.product**

Series.product(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

Return the product of the values for the requested axis

**Parameters**

- **axis**: {index (0)}
  - skipna: boolean, 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
  - numeric_only: boolean, default None
    - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**

- **prod**: scalar or Series (if level specified)

**pandas.Series.ptp**

Series.ptp(axis=None, out=None)

**pandas.Series.put**

Series.put(*args, **kwargs)

return a ndarray with the values put

See also:

numpy.ndarray.put
pandas.Series.quantile

Series.quantile(q=0.5)
Return value at the given quantile, a la numpy.percentile.

Parameters q : float or array-like, default 0.5 (50% quantile)
0 <= q <= 1, the quantile(s) to compute

Returns quantile : float or Series
if q is an array, a Series will be returned where the index is q and the values are the quantiles.

Examples

```python
>>> s = 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)
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 one of the inputs.

Parameters other: Series or scalar value
fill_value : None or float value, default None (NaN)
Fill missing (NaN) values with this value. If both Series are missing, the result will be missing
level : int or name
Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

See also:
Series.add

pandas.Series.rank

Series.rank(method='average', na_option='keep', ascending=True, pct=False)
Compute data ranks (1 through n). Equal values are assigned a rank that is the average of the ranks of those values

  • 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

na_option : {'keep'}
  keep: leave NA values where they are

ascending : boolean, default True
  False for ranks by high (1) to low (N)

pct : boolean, default False
  Computes percentage rank of data

**Returns**
ranks : Series

**pandas.Series.ravel**

Series.ravel(order='C')
  Return the flattened underlying data as an ndarray

  **See also:**
  numpy.ndarray.ravel

**pandas.Series.rdiv**

Series.rdiv(other, level=None, fill_value=None, axis=0)
  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 one of
  the inputs.

  **Parameters**
  other: Series or scalar value

  fill_value : None or float value, default None (NaN)
    Fill missing (NaN) values with this value. If both Series are missing, the result will be
    missing

  level : int or name
    Broadcast across a level, matching Index values on the passed MultiIndex level

  **Returns**
  result : Series

  **See also:**
  Series.truediv

**pandas.Series.reindex**

Series.reindex(index=None, **kwargs)
  Conform Series to new index with optional filling logic, placing 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 (can be specified in order, or as keywords) New labels / index to conform to. Preferably an Index object to avoid duplicating data

**method**: {None, 'backfill'/’bfill’, ‘pad’/’ffill’, ‘nearest’}, optional

Method to use for filling holes in reindexed DataFrame:

- 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**: boolean, 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 $\text{abs(index[indexer] - target)} <= \text{tolerance}$.

New in version 0.17.0.

**Returns** **reindexed**: Series

**Examples**

```python
>>> df.reindex(index=[date1, date2, date3], columns=['A', 'B', 'C'])
```

**pandas.Series.reindex_axis**

```
Series.reindex_axis(labels, axis=0, **kwargs)
```

for compatibility with higher dims

**pandas.Series.reindex_like**

```
Series.reindex_like(other, method=None, copy=True, limit=None, tolerance=None)
```

return an object with matching indices to myself

**Parameters** **other**: Object

- **method**: string or None
- **copy**: boolean, default True
limit : int, default None
    Maximum number of consecutive labels to fill for inexact matches.

tolerance : optional
    Maximum distance between labels of the other object and this object for inexact matches.
    New in version 0.17.0.

Returns reindexed : same as input

Notes

Like calling s.reindex(index=other.index, columns=other.columns, method=...)

pandas.Series.rename

Series.rename (index=None, **kwargs)
Alter axes input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters index : dict-like or function, optional
    Transformation to apply to that axis values

copy : boolean, default True
    Also copy underlying data

inplace : boolean, default False
    Whether to return a new Series. If True then value of copy is ignored.

Returns renamed : Series (new object)

pandas.Series.rename_axis

Series.rename_axis (mapper, axis=0, copy=True, inplace=False)
Alter index and / or columns using input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters mapper : dict-like or function, optional

axis : int or string, default 0

copy : boolean, default True
    Also copy underlying data

inplace : boolean, default False

Returns renamed : type of caller
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.

(axis: where to reorder levels

Returns type of caller (new object)

pandas.Series.repeat

Series.repeat(reps)
return a new Series with the values repeated reps times

See also:
	numpy.ndarray.repeat

pandas.Series.replace

Series.replace(to_replace=None, value=None, inplace=False, limit=None, regex=False, method='pad', axis=None)
Replace values given in ‘to_replace’ with ‘value’.

Parameters to_replace : str, regex, list, dict, Series, numeric, or None

• str or regex:
  – str: string exactly matching to_replace will be replaced with value
  – regex: regexes 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 regexes 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 and regex rules apply as above.

• dict:
  – Nested dictionaries, e.g., {'a': {'b': nan}}, are read as follows: look in column ‘a’ for the value ‘b’ and replace it with nan. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) cannot be regular expressions.
  – Keys map to column names and values map to substitution values. You can treat this as a special case of passing two lists except that you are specifying the column to search in.

• 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 use to fill holes (e.g. 0), alternately a dict of values specifying 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** : boolean, default False

If True, in place. Note: this will modify any other views on this object (e.g. a column form 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. Otherwise, `to_replace` must be `None` because this parameter will be interpreted as a regular expression or a list, dict, or array of regular expressions.

**method** : string, optional, {'pad', 'ffill', 'bfill'}

The method to use when for replacement, when `to_replace` is a list.

**Returns**

`filled` : NDFrame

**Raises**

**AssertionError**

- If `regex` is not a bool and `to_replace` is not `None`.

**TypeError**

- 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.

**ValueError**

- If `to_replace` and `value` are lists or ndarrays, but they are not the same length.

**See also**

NDFrame.reindex, NDFrame.asfreq, NDFrame.fillna

**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.

**pandas.Series.resample**

Series.resample*(rule, how=None, axis=0, fill_method=None, closed=None, label=None, convention='start', kind=None, loffset=None, limit=None, base=0)*  
Convenience method for frequency conversion and resampling of regular time-series data.

**Parameters**

- **rule**: string  
  the offset string or object representing target conversion

- **how**: string  
  method for down- or re-sampling, default to ‘mean’ for downsampling

- **axis**: int, optional, default 0

- **fill_method**: string, default None  
  fill_method for upsampling

- **closed**: {'right', 'left'}  
  Which side of bin interval is closed

- **label**: {'right', 'left'}  
  Which bin edge label to label bucket with

- **convention**: {'start', 'end', 's', 'e'}

- **kind**: “period”/“timestamp”

- **loffset**: timedelta
  Adjust the resampled time labels

- **limit**: int, default None  
  Maximum size gap to when reindexing with fill_method

- **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

**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
```

1062 Chapter 34. API Reference
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', how='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', how='sum', label='right')
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', how='sum', label='right', closed='right')
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')[0:5]  # select first 5 rows
2000-01-01 00:00:00    0
2000-01-01 00:00:30   NaN
2000-01-01 00:01:00    1
2000-01-01 00:01:30   NaN
2000-01-01 00:02:00    2
Freq: 30S, dtype: float64
```

Upsample the series into 30 second bins and fill the NaN values using the pad method.

```python
>>> series.resample('30S', fill_method='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', fill_method='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 to how.

```python
>>> def custom_resampler(array_like):
...     return np.sum(array_like)+5

>>> series.resample('3T', how=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
```

**pandas.Series.reset_index**

Series.reset_index (level=None, drop=False, name=None, inplace=False)

Analogous to the pandas.DataFrame.reset_index() function, see docstring there.

Parameters

- **level**: int, str, tuple, or list, default None
  Only remove the given levels from the index. Removes all levels by default
- **drop**: boolean, default False
  Do not try to insert index into dataframe columns
- **name**: object, default None
  The name of the column corresponding to the Series values
- **inplace**: boolean, default False
  Modify the Series in place (do not create a new object)

Returns

- **resetted**: DataFrame, or Series if drop == True

**pandas.Series.reshape**

Series.reshape(*args, **kwargs)

return an ndarray with the values shape if the specified shape matches exactly the current shape, then return self (for compat)

See also:

numpy.ndarray.take

**pandas.Series.rfloordiv**

Series.rfloordiv(other, level=None, fill_value=None, axis=0)

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 one of the inputs.

Parameters

- **other**: Series or scalar value
- **fill_value**: None or float value, default None (NaN)
Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

**level**: int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns** result : Series

**See also:**

Series.floordiv

**pandas.Series.rmod**

Series.rmod(other, level=None, fill_value=None, axis=0)

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 one of the inputs.

**Parameters**

*other*: Series or scalar value

*fill_value*: None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

*level*: int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns** result : Series

**See also:**

Series.mod

**pandas.Series.rmul**

Series.rmul(other, level=None, fill_value=None, axis=0)

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 one of the inputs.

**Parameters**

*other*: Series or scalar value

*fill_value*: None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

*level*: int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns** result : Series

**See also:**

Series.mul
**pandas.Series.round**

Series.{round} \((decimals=0, out=None)\)

Return a with each element rounded to the given number of decimals.

Refer to {numpy.around} for full documentation.

See also:

{numpy.around} equivalent function

**pandas.Series.rpow**

Series.\{rpow\} \((other, level=None, fill_value=None, axis=0)\)

Exponential power of series and other, element-wise (binary operator \{rpow\}).

Equivalent to \(other \^{*} \{\text{series}\}\), but with support to substitute a \{fill_value\} for missing data in one of the inputs.

**Parameters**

- \(\text{other}: \text{Series or scalar value}\)
  - \(\text{fill_value}\) : None or float value, default None (NaN)
    - Fill missing (NaN) values with this value. If both Series are missing, the result will be missing
  - \(\text{level}\) : int or name
    - Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**

- \(\text{result}: \text{Series}\)

See also:

{Series.pow}

**pandas.Series.rsub**

Series.\{rsub\} \((other, level=None, fill_value=None, axis=0)\)

Subtraction of series and other, element-wise (binary operator \{rsub\}).

Equivalent to \(\{\text{other}\} - \{\text{series}\}\), but with support to substitute a \{fill_value\} for missing data in one of the inputs.

**Parameters**

- \(\text{other}: \text{Series or scalar value}\)
  - \(\text{fill_value}\) : None or float value, default None (NaN)
    - Fill missing (NaN) values with this value. If both Series are missing, the result will be missing
  - \(\text{level}\) : int or name
    - Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**

- \(\text{result}: \text{Series}\)

See also:

{Series.sub}
pandas.Series.rtruediv

**Series.rtruediv**(other, level=None, fill_value=None, axis=0)

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 one of the inputs.

**Parameters**

- **other**: Series or scalar value
- **fill_value**: None or float value, default None (NaN)
  - Fill missing (NaN) values with this value. If both Series are missing, the result will be missing
- **level**: int or name
  - Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**

- **result**: Series

See also:

- Series.truediv

pandas.Series.sample

**Series.sample**(n=None, frac=None, replace=False, weights=None, random_state=None, axis=None)

Returns a random sample of items from an axis of object.

New in version 0.16.1.

**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**: boolean, optional
  - Sample with or without replacement. Default = False.
- **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. inf and -inf values not allowed.
- **random_state**: int or numpy.random.RandomState, optional
  - Seed for the random number generator (if int), or numpy RandomState object.
- **axis**: int or string, optional
Axis to sample. Accepts axis number or name. Default is stat axis for given data
type (0 for Series and DataFrames, 1 for Panels).

Returns A new object of same type as caller.

**pandas.Series.searchsorted**

`s` 

`series.searchsorted(v, 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 `v` were inserted before
the indices, the order of `self` would be preserved.

**Parameters**

- **v**: array_like
  - Values to insert into `a`.
- **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 `a`).
- **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**

- **indices**: array of ints
  - Array of insertion points with the same shape as `v`.

**See also:**

- `Series.sort_values`, `numpy.searchsorted`

**Notes**

Binary search is used to find the required insertion points.

**Examples**

```python
>>> x = pd.Series([1, 2, 3])
```

```python
>>> x
0 1
1 2
2 3
```

```python
dtype: int64
```

```python
>>> x.searchsorted(4)
array([3])
```

```python
>>> x.searchsorted([0, 4])
array([0, 3])
```

```python
>>> x.searchsorted([1, 3], side='left')
array([0, 2])
```

```python
>>> x.searchsorted([1, 3], side='right')
array([1, 3])
```

```python
>>> x.searchsorted([1, 2], side='right', sorter=[0, 2, 1])
array([1, 3])
```
pandas.Series.select

Series.select(crit, axis=0)
Return data corresponding to axis labels matching criteria

Parameters
- crit : function
  To be called on each index (label). Should return True or False
- axis : int

Returns
- selection : type of caller

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 : boolean, 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
- numeric_only : boolean, default None
  Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns
- sem : scalar or Series (if level specified)

pandas.Series.set_axis

Series.set_axis(axis, labels)
public version of axis assignment

pandas.Series.set_value

Series.set_value(label, value, takeable=False)
Quickly set single value at passed label. If label is not contained, a new object is created with the label placed at the end of the result index

Parameters
- label : object
  Partial indexing with MultiIndex not allowed
- value : object
  Scalar value
- takeable : interpret the index as indexers, default False

Returns
- series : Series
If label is contained, will be reference to calling Series, otherwise a new object

**pandas.Series.shift**

`Series.shift(periods=1, freq=None, axis=0)`
Shift index by desired number of periods with an optional time freq

- **Parameters**
  - `periods`: int
    Number of periods to move, can be positive or negative
  - `freq`: DateOffset, timedelta, or time rule string, optional
    Increment to use from datetools module or time rule (e.g. ‘EOM’). See Notes.
  - `axis`: {0, ‘index’}

- **Returns**
  - `shifted`: Series

**Notes**
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.

**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)}
  - `skipna`: boolean, 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
  - `numeric_only`: boolean, default None
    Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

- **Returns**
  - `skew`: 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**

Series.sort (axis=0, ascending=True, kind='quicksort', na_position='last', inplace=True)

DEPRECATED: use Series.sort_values(inplace=True)() for INPLACE sorting

Sort values and index labels by value. This is an inplace sort by default. Series.order is the equivalent but returns a new Series.

**Parameters**

- axis : int (can only be zero)
- ascending : boolean, default True
  - Sort ascending. Passing False sorts descending
- kind : {'mergesort', 'quicksort', 'heapsort'}, default 'quicksort'
  - Choice of sorting algorithm. See np.sort for more information. 'mergesort' is the only stable algorithm
- na_position : {'first', 'last'} (optional, default='last')
  - 'first' puts NaNs at the beginning 'last' puts NaNs at the end
- inplace : boolean, default True
  - Do operation in place.

**See also:**

Series.sort_values

**pandas.Series.sort_index**

Series.sort_index (axis=0, level=None, ascending=True, inplace=False, sort_remaining=True)

Sort object by labels (along an axis)

**Parameters**

- axis : index to direct sorting
- 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 : boolean, default True
  - Sort ascending vs. descending
- inplace : bool
  - if True, perform operation in-place
- kind : {quicksort, mergesort, heapsort}
  - 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'}
  - first puts NaNs at the beginning, last puts NaNs at the end
sort_remaining : bool
    if true and sorting by level and index is multilevel, sort by other levels too (in order) after sorting by specified level

Returns sorted_obj : Series

pandas.Series.sort_values

Series.sort_values(axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last')
Sort by the values along either axis
New in version 0.17.0.

Parameters by : string name or list of names which refer to the axis items
    axis : index to direct sorting
    ascending : bool or list of bool
        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
        if True, perform operation in-place
    kind : {quicksort, mergesort, heapsort}
        Choice of sorting algorithm. See also ndarray.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'}
        first puts NaNs at the beginning, last puts NaNs at the end

Returns sorted_obj : Series

pandas.Series.sortlevel

Series.sortlevel(level=0, ascending=True, sort_remaining=True)
Sort Series with MultiIndex by chosen level. Data will be lexicographically sorted by the chosen level followed by the other levels (in order)

Parameters level : int or level name, default None
    ascending : bool, default True

Returns sorted : Series

See also:
    Series.sort_index

pandas.Series.squeeze

Series.squeeze()
squeeze length 1 dimensions
pandas.Series.std

Series.std(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)
Return unbiased standard deviation over requested axis.
Normalized by N-1 by default. This can be changed using the ddof argument

Parameters
axis : {index (0)}
skipna : boolean, 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
numeric_only : boolean, default None
Include only float, int, boolean data. If None, will attempt to use everything, then
use only numeric data

Returns
std : scalar or Series (if level specified)

pandas.Series.str

Series.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

>>> s.str.split('_')
>>> s.str.replace('_', '')

pandas.Series.sub

Series.sub(other, level=None, fill_value=None, axis=0)
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 one of
the inputs.

Parameters
other: Series or scalar value
fill_value : None or float value, default None (NaN)
Fill missing (NaN) values with this value. If both Series are missing, the result
will be missing
level : int or name
Broadcast across a level, matching Index values on the passed MultiIndex level

Returns
result : Series

See also:
Series.rsub
### pandas.Series.subtract

**Series.subtract** (other, level=None, fill_value=None, axis=0)

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 one of the inputs.

**Parameters**

- **other**: Series or scalar value
  - **fill_value**: None or float value, default None (NaN)
    Fill missing (NaN) values with this value. If both Series are missing, the result will be missing
  - **level**: int or name
    Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**

- **result**: Series

**See also**

- `Series.rsub`

### pandas.Series.sum

**Series.sum** (axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

Return the sum of the values for the requested axis

**Parameters**

- **axis**: {index (0)}
  - **skipna**: boolean, 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
  - **numeric_only**: boolean, default None
    Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**

- **sum**: scalar or Series (if level specified)

### 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, j, copy=True)

Swap levels i and j in a MultiIndex
Parameters i, j : int, string (can be mixed)

Level of index to be swapped. Can pass level name as string.

Returns swapped : Series

pandas.Series.tail

Series.tail(n=5)

Returns last n rows

pandas.Series.take

Series.take(indices, axis=0, convert=True, is_copy=False)

return Series corresponding to requested indices

Parameters indices : list / array of ints

convert : translate negative to positive indices (default)

Returns taken : Series

See also:
numpy.ndarray.take

pandas.Series.to_clipboard

Series.to_clipboard(excel=None, sep=None, **kwargs)

Attempt to write text representation of object to the system clipboard This can be pasted into Excel, for example.

Parameters excel : boolean, defaults to True

if True, use the provided separator, writing in a csv format for allowing easy pasting into excel. if False, write a string representation of the object to the clipboard

sep : optional, defaults to tab

other keywords are passed to to_csv

Notes

Requirements for your platform

• Linux: xclip, or xsel (with gtk or PyQt4 modules)

• Windows: none

• OS X: none

pandas.Series.to_csv

Series.to_csv(path, index=True, sep=', ', na_rep='\'', float_format=None, header=False, index_label=None, mode='w', nanRep=None, encoding=None, date_format=None, decimal='\'')

Write Series to a comma-separated values (csv) file
**Parameters**

- **path**: string file path or file handle / StringIO. If None is provided, the result is returned as a string.
- **na_rep**: string, default "". Missing data representation.
- **float_format**: string, default None. Format string for floating point numbers.
- **header**: boolean, default False. Write out series name.
- **index**: boolean, default True. Write row names (index).
- **index_label**: string or sequence, 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 DataFrame uses MultiIndex.
- **mode**: Python write mode, default ‘w’.
- **sep**: character, default ",". Field delimiter for the output file.
- **encoding**: string, optional. A string representing the encoding to use if the contents are non-ascii, for python versions prior to 3.
- **date_format**: string, default None. Format string for datetime objects.
- **decimal**: string, default ".". Character recognized as decimal separator. E.g. use ‘,’ for European data.

**pandas.Series.to_dense**

Series.to_dense()  
Return dense representation of NDFrame (as opposed to sparse)

**pandas.Series.to_dict**

Series.to_dict()  
Convert Series to {label -> value} dict  
Returns **value_dict** : dict

**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**

**data_frame**: DataFrame

---

**pandas.Series.to_hdf**

```python
Series.to_hdf(path_or_buf, key, **kwargs)
```

Activate the HDFStore

**Parameters**

**path_or_buf**: the path (string) or HDFStore object

**key**: string

Identifier for the group in the store

**mode**: optional, {'a', 'w', 'r', 'r+'}, default 'a'

- 'r': Read-only; no data can be modified.
- '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+': It is similar to 'a', but the file must already exist.

**format**: ‘fixed(f)table(t)’, default is ‘fixed’

- **fixed(f)**: [Fixed format] Fast writing/reading. Not-appendable, nor searchable
- **table(t)**: [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**: boolean, default False

For Table formats, append the input data to the existing

**complevel**: int, 1-9, default 0

If a complib is specified compression will be applied where possible

**complib**: {'zlib', 'bz2', 'lzma', 'blosc', None}, default None

If complevel is > 0 apply compression to objects written in the store wherever possible

**fletcher32**: bool, default False

If applying compression use the fletcher32 checksum

**dropna**: boolean, default False.

If true, ALL nan rows will not be written to store.

---

**pandas.Series.to_json**

```python
Series.to_json(path_or_buf=None, orient=None, date_format='epoch', double_precision=10,
force_ascii=True, date_unit='ms', default_handler=None)
```

Convert the object to a JSON string.
pandas: powerful Python data analysis toolkit, Release 0.17.0

Note NaN’s and None will be converted to null and datetime objects will be converted to UNIX timestamps.

**Parameters** `path_or_buf` : the path or buffer to write the result string

if this is None, return a StringIO of the converted string

**orient** : string

- Series
  - default is ‘index’
  - allowed values are: {'split','records','index’}
- DataFrame
  - default is ‘columns’
  - allowed values are: {'split','records','index’,'columns','values’}
- 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 -> {index -> value}}
  - values : just the values array

**date_format** : {'epoch’, ‘iso’}

Type of date conversion. *epoch* = epoch milliseconds, *iso* = ISO8601, default is epoch.

**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** : string, 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.

**Returns** same type as input object with filtered info axis

**pandas.Series.to_msgpack**

`Series.to_msgpack` *(path_or_buf=*, **kwargs)*

msgpack (serialize) object to input file path

THIS IS AN EXPERIMENTAL LIBRARY and the storage format may not be stable until a future release.

**Parameters** `path` : string File path, buffer-like, or None
if None, return generated string

**append** : boolean whether to append to an existing msgpack
(default is False)

**compress** : type of compressor (zlib or blosc), default to None (no compression)

---

**pandas.Series.to_period**

```
Series.to_period(freq=None, copy=True)
```

Convert Series from DatetimeIndex to PeriodIndex with desired frequency (inferred from index if not passed)

**Parameters**
- `freq` : string, default
- `copy` : boolean, default

**Returns**
- `ts` : Series with PeriodIndex

---

**pandas.Series.to_pickle**

```
Series.to_pickle(path)
```

Pickle (serialize) object to input file path

**Parameters**
- `path` : string

---

**pandas.Series.to_sparse**

```
Series.to_sparse(kind='block', fill_value=None)
```

Convert Series to SparseSeries

**Parameters**
- `kind` : {'block', 'integer'}
- `fill_value` : float, defaults to NaN (missing)

**Returns**
- `sp` : SparseSeries

---

**pandas.Series.to_sql**

```
Series.to_sql(name, con, flavor='sqlite', schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None)
```

Write records stored in a DataFrame to a SQL database.

**Parameters**
- `name` : string
  - Name of SQL table
- `con` : SQLAlchemy engine or DBAPI2 connection (legacy mode)
  - Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.
- `flavor` : {'sqlite', 'mysql'}, default 'sqlite'
The flavor of SQL to use. Ignored when using SQLAlchemy engine. ‘mysql’ is deprecated and will be removed in future versions, but it will be further supported through SQLAlchemy engines.

**schema**: string, default None

Specify the schema (if database flavor supports this). If None, use default schema.

**if_exists**: {'fail', 'replace', 'append'}, default ‘fail’

- fail: If table exists, do nothing.
- replace: If table exists, drop it, recreate it, and insert data.
- append: If table exists, insert data. Create if does not exist.

**index**: boolean, default True

Write DataFrame index as a column.

**index_label**: string 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, default None

If not None, then rows will be written in batches of this size at a time. If None, all rows will be written at once.

**dtype**: dict of column name to SQL type, default None

Optional specifying the datatype for columns. The SQL type should be a SQLAlchemy type, or a string for sqlite3 fallback connection.

---

**pandas.Series.to_string**

Series.to_string(buf=None, na_rep='NaN', float_format=None, header=True, length=False, dtype=False, name=False, max_rows=None)

Render a string representation of the Series

**Parameters**

- **buf**: StringIO-like, optional
  buffer to write to

- **na_rep**: string, optional
  string representation of NaN to use, default ‘NaN’

- **float_format**: one-parameter function, optional
  formatter function to apply to columns’ elements if they are floats default None

- **header**: boolean, default True
  Add the Series header (index name)

- **length**: boolean, default False
  Add the Series length

- **dtype**: boolean, default False
  Add the Series dtype

- **name**: boolean, 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.

**Returns** **formatted**: string (if not buffer passed)

**pandas.Series.to_timestamp**

**Series.to_timestamp**(freq=None, how='start', copy=True)

Cast to datetimeindex of timestamps, at beginning of period

**Parameters**  
**freq**: string, default frequency of PeriodIndex

Desired frequency

**how**: {'s', 'e', 'start', 'end'}

Convention for converting period to timestamp; start of period vs. end

**Returns**  
**ts**: Series with DatetimeIndex

**pandas.Series.tolist**

**Series.tolist()**

Convert Series to a nested list

**pandas.Series.transpose**

**Series.transpose()**

return the transpose, which is by definition self

**pandas.Series.truediv**

**Series.truediv**(other, level=None, fill_value=None, axis=0)

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 one of the inputs.

**Parameters**  
**other**: Series or scalar value

**fill_value**: None or float scalar, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

**level**: int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**  
**result**: Series

**See also**:

Series.rtruediv
**pandas.Series.truncate**

Series.truncate (before=None, after=None, axis=None, copy=True)  
Truncates a sorted NDFrame before and/or after some particular dates.

**Parameters**

- **before**: date  
  Truncate before date
- **after**: date  
  Truncate after date
- **axis**: the truncation axis, defaults to the stat axis
- **copy**: boolean, default is True,  
  return a copy of the truncated section

**Returns**

- **truncated**: type of caller

**pandas.Series.tshift**

Series.tshift (periods=1, freq=None, axis=0)  
Shift the time index, using the index’s frequency if available

**Parameters**

- **periods**: int  
  Number of periods to move, can be positive or negative
- **freq**: DateOffset, timedelta, or time rule string, default None  
  Increment to use from datetools module or time rule (e.g. ‘EOM’)
- **axis**: int or basestring  
  Corresponds to the axis that contains the Index

**Returns**

- **shifted**: NDFrame

**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**: string or pytz.timezone object
- **axis**: the axis to convert
- **level**: int, str, default None  
  If axis ia a MultiIndex, convert a specific level. Otherwise must be None
- **copy**: boolean, default True  
  Also make a copy of the underlying data
Raises `TypeError`  
If the axis is tz-naive.

**pandas.Series.tz_localize**

`Series.tz_localize(*args, **kwargs)`  
Localize tz-naive TimeSeries to target time zone

**Parameters**  
- `tz`: string or pytz.timezone object  
- `axis`: the axis to localize  
- `level`: int, str, default None  
  - If axis ia a MultiIndex, localize a specific level. Otherwise must be None  
- `copy`: boolean, default True  
  - Also make a copy of the underlying data  
- `ambiguous`: ‘infer’, bool-ndarray, ‘NaT’, default ‘raise’  
  - ‘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  
- `infer_dst`: boolean, default False (DEPRECATED)  
  - Attempt to infer fall dst-transition hours based on order  

Raises `TypeError`  
If the TimeSeries is tz-aware and tz is not None.

**pandas.Series.unique**

`Series.unique()`  
Return array of unique values in the object. Significantly faster than numpy.unique. Includes NA values.  

**Returns**  
uniques : ndarray

**pandas.Series.unstack**

`Series.unstack(level=-1)`  
Unstack, a.k.a. pivot, Series with MultiIndex to produce DataFrame. The level involved will automatically get sorted.  

**Parameters**  
- `level`: int, string, or list of these, default last level  
  - Level(s) to unstack, can pass level name  

**Returns**  
unstacked : DataFrame
Examples

```python
>>> s
one a 1.
one b 2.
two a 3.
two b 4.

>>> s.unstack(level=-1)
a  b
one 1. 2.
two 3. 4.

>>> s.unstack(level=0)
one two
  a 1. 2.
b 3. 4.
```

**pandas.Series.update**

Series.update(other)
Modify Series in place using non-NA values from passed Series. Aligns on index

**Parameters**
other : Series

**pandas.Series.valid**

Series.valid(inplace=False, **kwargs)

**pandas.Series.value_counts**

Series.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)
Returns object 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 : boolean, default False
If True then the object returned will contain the relative frequencies of the unique values.

sort : boolean, default True
Sort by values

ascending : boolean, default False
Sort in ascending order

bins : integer, optional
Rather than count values, group them into half-open bins, a convenience for pd.cut, only works with numeric data

dropna : boolean, default True
Don’t include counts of NaN.

**Returns**  
`counts : Series`

### pandas.Series.var

**Series.var**  
`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 : boolean, 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
  - `numeric_only : boolean, default None`  
    - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

- **Returns**  
  - `var : scalar or Series (if level specified)`

### pandas.Series.view

**Series.view**  
`Series.view(dtype=None)`

### pandas.Series.where

**Series.where**  
`Series.where(cond, other=nan, inplace=False, axis=None, level=None, try_cast=False, raise_on_error=True)`  
Return an object of same shape as self and whose corresponding entries are from self where cond is True and otherwise are from other.

- **Parameters**  
  - `cond : boolean NDFrame or array`
  - `other : scalar or NDFrame`
  - `inplace : boolean, default False`  
    - Whether to perform the operation in place on the data
  - `axis : alignment axis if needed, default None`
  - `level : alignment level if needed, default None`
  - `try_cast : boolean, default False`  
    - try to cast the result back to the input type (if possible),
  - `raise_on_error : boolean, default True`  
    - Whether to raise on invalid data types (e.g. trying to where on strings)

- **Returns**  
  - `wh : same type as caller`
pandas.Series.xs

Series.xs(key, axis=0, level=None, copy=None, drop_level=True)

Returns a cross-section (row(s) or column(s)) from the Series/DataFrame. Defaults to cross-section on the rows (axis=0).

Parameters

key : object
Some label contained in the index, or partially in a MultiIndex

axis : int, 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.

copy : boolean [deprecated]
Whether to make a copy of the data

drop_level : boolean, default True
If False, returns object with same levels as self.

Returns

xs : Series or DataFrame

Notes

xs is only for getting, not setting 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
>>> df
   A  B  C
a  4  5  2
b  4  0  9
c  9  7  3
>>> df.xs('a')
   A  B  C
a  4  5  2
>>> df.xs('C', axis=1)
   A  B  C
a  2
b  9
Name: C
```

```python
>>> df
   A  B  C  D   
first second third
bar one  1  4  1  8  9
  two  1  7  5  5  0
```
### 34.3.2 Attributes

**Axes**

- **index**: axis labels

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.values</td>
<td>Return Series as ndarray or ndarray-like</td>
</tr>
<tr>
<td>Series.dtype</td>
<td>return the dtype object of the underlying data</td>
</tr>
<tr>
<td>Series.dtype</td>
<td>return if the data is sparse</td>
</tr>
<tr>
<td>Series.shape</td>
<td>return a tuple of the shape of the underlying data</td>
</tr>
<tr>
<td>Series.nbytes</td>
<td>return the number of bytes in the underlying data</td>
</tr>
<tr>
<td>Series.ndim</td>
<td>return the number of dimensions of the underlying data, by definition 1</td>
</tr>
<tr>
<td>Series.size</td>
<td>return the number of elements in the underlying data</td>
</tr>
<tr>
<td>Series.strides</td>
<td>return the strides of the underlying data</td>
</tr>
<tr>
<td>Series.itemsize</td>
<td>return the size of the dtype of the item of the underlying data</td>
</tr>
<tr>
<td>Series.base</td>
<td>return the base object if the memory of the underlying data is shared</td>
</tr>
<tr>
<td>Series.T</td>
<td>return the transpose, which is by definition self</td>
</tr>
</tbody>
</table>

**pandas.Series.values**

Series.values

Return Series as ndarray or ndarray-like depending on the dtype

- **Returns** `arr`: numpy.ndarray or ndarray-like

#### 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
dtype('category')
Categories (3, object): [a, b, c]
```

Timezone aware datetime data is converted to UTC:
>>> pd.Series(pd.date_range('20130101', periods=3, tz='US/Eastern')).values
array(['2013-01-01T00:00:00.000000000-0500',
       '2013-01-02T00:00:00.000000000-0500',
       '2013-01-03T00:00:00.000000000-0500'], dtype='datetime64[ns]')

**pandas.Series.dtype**

Series.

return the dtype object of the underlying data

**pandas.Series.ftype**

Series.

return if the data is sparseldense

**pandas.Series.shape**

Series.

return a tuple of the shape of the underlying data

**pandas.Series.nbytes**

Series.

return the number of bytes in the underlying data

**pandas.Series.ndim**

Series.

return the number of dimensions of the underlying data, by definition 1

**pandas.Series.size**

Series.

return the number of elements in the underlying data

**pandas.Series.strides**

Series.

return the strides of the underlying data

**pandas.Series.itemsize**

Series.

return the size of the dtype of the item of the underlying data
pandas.Series.base

Series.base
return the base object if the memory of the underlying data is shared

pandas.Series.T

Series.T
return the transpose, which is by definition self

34.3.3 Conversion

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.astype(dtype[, copy, raise_on_error])</td>
<td>Cast object to input numpy.dtype</td>
</tr>
<tr>
<td>Series.copy([deep])</td>
<td>Make a copy of this object</td>
</tr>
<tr>
<td>Series.isnull()</td>
<td>Return a boolean same-sized object indicating if the values are null</td>
</tr>
<tr>
<td>Series.notnull()</td>
<td>Return a boolean same-sized object indicating if the values are not null</td>
</tr>
</tbody>
</table>

pandas.Series.astype

Series.astype(dtype, copy=True, raise_on_error=True, **kwargs)
Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

Parameters
dtype : numpy.dtype or Python type
raise_on_error : raise on invalid input
kwargs : keyword arguments to pass on to the constructor

Returns
casted : type of caller

pandas.Series.copy

Series.copy(deep=True)
Make a copy of this object

Parameters
depth : boolean or string, default True
Make a deep copy, i.e. also copy data

Returns
copy : type of caller

pandas.Series.isnull

Series.isnull()
Return a boolean same-sized object indicating if the values are null

See also:
notnull boolean inverse of isnull
pandas.Series.notnull

Series.notnull()

Return a boolean same-sized object indicating if the values are not null

See also:

isnull  boolean inverse of notnull

34.3.4 Indexing, iteration

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.get(key[, default])</td>
<td>Get item from object for given key (DataFrame column, Panel slice, etc.). Returns default value if not found</td>
</tr>
<tr>
<td>Series.at</td>
<td>Fast label-based scalar accessor</td>
</tr>
<tr>
<td>Series.iat</td>
<td>Fast integer location scalar accessor.</td>
</tr>
<tr>
<td>Series.ix</td>
<td>A primarily label-location based indexer, with integer position fallback.</td>
</tr>
<tr>
<td>Series.loc</td>
<td>Purely label-location based indexer for selection by label.</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>provide iteration over the values of the Series</td>
</tr>
<tr>
<td>Series.iteritems()</td>
<td>Lazily iterate over (index, value) tuples</td>
</tr>
</tbody>
</table>

pandas.Series.get

Series.get(key, default=None)

Get item from object for given key (DataFrame column, Panel slice, etc.). Returns default value if not found

Parameters

key : object

Returns

value : type of items contained in object

pandas.Series.at

Series.at

Fast label-based scalar accessor

Similarly to loc, at provides label based scalar lookups. You can also set using these indexers.

pandas.Series.iat

Series.iat

Fast integer location scalar accessor.

Similarly to iloc, iat provides integer based lookups. You can also set using these indexers.

pandas.Series.ix

Series.ix

A primarily label-location based indexer, with integer position fallback.

.ix[] supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type.
.ix is the most general indexer and will support any of the inputs in .loc and .iloc. .ix also supports floating point label schemes. .ix is exceptionally useful when dealing with mixed positional and label based hierarchical indexes.

However, when an axis is integer based, ONLY label based access and not positional access is supported. Thus, in such cases, it’s usually better to be explicit and use .iloc or .loc.

See more at Advanced Indexing.

**pandas.Series.loc**

Series.loc

Purely label-location based indexer for selection by label.

.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’ (note that contrary to usual python slices, both the start and the stop are included!).
- A boolean array.

.loc will raise a KeyError when the items are not found.

See more at Selection by Label

**pandas.Series.iloc**

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.

.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

**pandas.Series.__iter__**

Series.__iter__()

provide iteration over the values of the Series box values if necessary
pandas.Series.iteritems

Series.iteritems()
   Lazily iterate over (index, value) tuples

For more information on .at, .iat, .ix, .loc, and .iloc, see the indexing documentation.

34.3.5 Binary operator functions

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.add</td>
<td>Addition of series and other, element-wise (binary operator add).</td>
</tr>
<tr>
<td>Series.sub</td>
<td>Subtraction of series and other, element-wise (binary operator sub).</td>
</tr>
<tr>
<td>Series.mul</td>
<td>Multiplication of series and other, element-wise (binary operator mul).</td>
</tr>
<tr>
<td>Series.div</td>
<td>Floating division of series and other, element-wise (binary operator truediv).</td>
</tr>
<tr>
<td>Series.truediv</td>
<td>Floating division of series and other, element-wise (binary operator truediv).</td>
</tr>
<tr>
<td>Series.floordiv</td>
<td>Integer division of series and other, element-wise (binary operator floordiv).</td>
</tr>
<tr>
<td>Series.mod</td>
<td>Modulo of series and other, element-wise (binary operator mod).</td>
</tr>
<tr>
<td>Series.pow</td>
<td>Exponential power of series and other, element-wise (binary operator pow).</td>
</tr>
<tr>
<td>Series.radd</td>
<td>Addition of series and other, element-wise (binary operator radd).</td>
</tr>
<tr>
<td>Series.rsub</td>
<td>Subtraction of series and other, element-wise (binary operator rsub).</td>
</tr>
<tr>
<td>Series.rmul</td>
<td>Multiplication of series and other, element-wise (binary operator rmul).</td>
</tr>
<tr>
<td>Series.rdiv</td>
<td>Floating division of series and other, element-wise (binary operator rtruediv).</td>
</tr>
<tr>
<td>Series.rfloordiv</td>
<td>Floating division of series and other, element-wise (binary operator rfloordiv).</td>
</tr>
<tr>
<td>Series.rmod</td>
<td>Modulo of series and other, element-wise (binary operator rmod).</td>
</tr>
<tr>
<td>Series.rpow</td>
<td>Exponential power of series and other, element-wise (binary operator rpow).</td>
</tr>
<tr>
<td>Series.combine</td>
<td>Perform elementwise binary operation on two Series using given function.</td>
</tr>
<tr>
<td>Series.combine_first</td>
<td>Combine Series values, choosing the calling Series’s values first.</td>
</tr>
<tr>
<td>Series.round</td>
<td>Return a with each element rounded to the given number of decimals.</td>
</tr>
<tr>
<td>Series.gt</td>
<td>Greater than (binary operator gt).</td>
</tr>
<tr>
<td>Series.le</td>
<td>Less than or equal to (binary operator le).</td>
</tr>
<tr>
<td>Series.ge</td>
<td>Greater than or equal to (binary operator ge).</td>
</tr>
<tr>
<td>Series.ne</td>
<td>Not equal to (binary operator ne).</td>
</tr>
<tr>
<td>Series.eq</td>
<td>Equal to (binary operator eq).</td>
</tr>
</tbody>
</table>

pandas.Series.add

Series.add(other[, level=None, fill_value=None, axis=0])
   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 one of the inputs.

Parameters

* other: Series or scalar value
  * fill_value: None or float value, default None (NaN)

  Fill missing (NaN) values with this value. If both Series are missing, the result will be missing.
  * level: int or name

  Broadcast across a level, matching Index values on the passed MultiIndex level

Returns

* result: Series
See also:
Series.radd

**pandas.Series.sub**

Series.sub(other, level=None, fill_value=None, axis=0)
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 one of the inputs.

**Parameters**
- **other**: Series or scalar value
  - **fill_value**: None or float value, default None (NaN)
    - Fill missing (NaN) values with this value. If both Series are missing, the result will be missing
  - **level**: int or name
    - Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**
- **result**: Series

See also:
Series.rsub

**pandas.Series.mul**

Series.mul(other, level=None, fill_value=None, axis=0)
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 one of the inputs.

**Parameters**
- **other**: Series or scalar value
  - **fill_value**: None or float value, default None (NaN)
    - Fill missing (NaN) values with this value. If both Series are missing, the result will be missing
  - **level**: int or name
    - Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**
- **result**: Series

See also:
Series.rmul

**pandas.Series.div**

Series.div(other, level=None, fill_value=None, axis=0)
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 one of the inputs.
Parameters other: Series or scalar value

**fill_value**: None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

**level**: int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result: Series

See also:

Series.rtruediv

### pandas.Series.truediv

Series.truediv(other, level=None, fill_value=None, axis=0)

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 one of the inputs.

Parameters other: Series or scalar value

**fill_value**: None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

**level**: int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result: Series

See also:

Series.rtruediv

### pandas.Series.floordiv

Series.floordiv(other, level=None, fill_value=None, axis=0)

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 one of the inputs.

Parameters other: Series or scalar value

**fill_value**: None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

**level**: int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result: Series
See also:
Series.rfloordiv

**pandas.Series.mod**

Series.mod(other, level=None, fill_value=None, axis=0)

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 one of the inputs.

**Parameters**

other: Series or scalar value

fill_value: None or float value, default None (NaN)
  Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level: int or name
  Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**

result: Series

See also:
Series.rmod

**pandas.Series.pow**

Series.pow(other, level=None, fill_value=None, axis=0)

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 one of the inputs.

**Parameters**

other: Series or scalar value

fill_value: None or float value, default None (NaN)
  Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level: int or name
  Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**

result: Series

See also:
Series.rpow

**pandas.Series.radd**

Series.radd(other, level=None, fill_value=None, axis=0)

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 one of the inputs.
pandas: powerful Python data analysis toolkit, Release 0.17.0

**Parameters**

other: Series or scalar value

- **fill_value**: None or float value, default None (NaN)
  
  Fill missing (NaN) values with this value. If both Series are missing, the result will be missing.

- **level**: int or name
  
  Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**

result: Series

See also:

Series.add

---

**pandas.Series.rsub**

Series.rsub(other, level=None, fill_value=None, axis=0)

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 one of the inputs.

**Parameters**

other: Series or scalar value

- **fill_value**: None or float value, default None (NaN)
  
  Fill missing (NaN) values with this value. If both Series are missing, the result will be missing.

- **level**: int or name
  
  Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**

result: Series

See also:

Series.sub

---

**pandas.Series.rmul**

Series.rmul(other, level=None, fill_value=None, axis=0)

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 one of the inputs.

**Parameters**

other: Series or scalar value

- **fill_value**: None or float value, default None (NaN)
  
  Fill missing (NaN) values with this value. If both Series are missing, the result will be missing.

- **level**: int or name
  
  Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**

result: Series
See also:

Series.mul

**pandas.Series.rdiv**

Series.rdiv(other, level=None, fill_value=None, axis=0)
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 one of the inputs.

**Parameters**
other: Series or scalar value

fill_value: None or float value, default None (NaN)
  Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level: int or name
  Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**
result: Series

See also:
Series.truediv

**pandas.Series.rtruediv**

Series.rtruediv(other, level=None, fill_value=None, axis=0)
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 one of the inputs.

**Parameters**
other: Series or scalar value

fill_value: None or float value, default None (NaN)
  Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level: int or name
  Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**
result: Series

See also:
Series.truediv

**pandas.Series.rfloordiv**

Series.rfloordiv(other, level=None, fill_value=None, axis=0)
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 one of the inputs.
Parameters `other`: Series or scalar value

- **fill_value**: None or float value, default None (NaN)
  
  Fill missing (NaN) values with this value. If both Series are missing, the result will be missing.

- **level**: int or name
  
  Broadcast across a level, matching Index values on the passed MultiIndex level

Returns `result`: Series

See also:

- `Series.floordiv`

### pandas.Series.rmod

**Series.rmod**(other, level=None, fill_value=None, axis=0)

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 one of the inputs.

Parameters `other`: Series or scalar value

- **fill_value**: None or float value, default None (NaN)
  
  Fill missing (NaN) values with this value. If both Series are missing, the result will be missing.

- **level**: int or name
  
  Broadcast across a level, matching Index values on the passed MultiIndex level

Returns `result`: Series

See also:

- `Series.mod`

### pandas.Series.rpow

**Series.rpow**(other, level=None, fill_value=None, axis=0)

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 one of the inputs.

Parameters `other`: Series or scalar value

- **fill_value**: None or float value, default None (NaN)
  
  Fill missing (NaN) values with this value. If both Series are missing, the result will be missing.

- **level**: int or name
  
  Broadcast across a level, matching Index values on the passed MultiIndex level

Returns `result`: Series
See also:
Series.pow

pandas.Series.combine

Series.combine(other, func, fill_value=nan)
Perform elementwise binary operation on two Series using given function with optional fill value when an index
is missing from one Series or the other

Parameters
other : Series or scalar value
func : function
fill_value : scalar value

Returns
result : Series

pandas.Series.combine_first

Series.combine_first(other)
Combine Series values, choosing the calling Series’s values first. Result index will be the union of the two
indexes

Parameters
other : Series

Returns
y : Series

pandas.Series.round

Series.round(decimals=0, out=None)
Return a with each element rounded to the given number of decimals.
Refer to numpy.around for full documentation.
See also:

numpy.around equivalent function

pandas.Series.lt

Series.lt(other, axis=None)

pandas.Series.gt

Series.gt(other, axis=None)

pandas.Series.le

Series.le(other, axis=None)

pandas.Series.ge

Series.ge(other, axis=None)
pandas.Series.ne

Series.ne(other, axis=None)

pandas.Series.eq

Series.eq(other, axis=None)

### 34.3.6 Function application, GroupBy

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.apply(func[, convert_dtype, args])</td>
<td>Invoke function on values of Series.</td>
</tr>
<tr>
<td>Series.map(arg[, na_action])</td>
<td>Map values of Series using input correspondence (which can be</td>
</tr>
<tr>
<td>Series.groupby([by, axis, level, as_index, ...])</td>
<td>Group series using mapper (dict or key function, apply given function</td>
</tr>
</tbody>
</table>

**pandas.Series.apply**

Series.apply(func, convert_dtype=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
- **convert_dtype**: boolean, default True
  - Try to find better dtype for elementwise function results. If False, leave as dtype=object
- **args**: tuple
  - Positional arguments to pass to function in addition to the value

**Additional keyword arguments will be passed as keywords to the function**

**Returns**

- **y**: Series or DataFrame if func returns a Series

**See also:**

- **Series.map** For element-wise operations

**Examples**

Create a series with typical summer temperatures for each city.

```python
>>> import pandas as pd
>>> import numpy as np
>>> series = pd.Series([20, 21, 12], index=['London', 'New York', 'Helsinki'])
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
...series.apply(square)
London    400
New York  441
Helsinki  144
dtype: int64
```
>>> def square(x):
...     return x**2
>>> series.apply(square)
London 400
New York 441
Helsinki 144
dtype: int64

Square the values by passing an anonymous function as an argument to apply().

>>> series.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.

>>> def subtract_custom_value(x, custom_value):
...     return x-custom_value

>>> series.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.

>>> def add_custom_values(x, **kwargs):
...     for month in kwargs:
...         x+=kwargs[month]
...     return x

>>> series.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.

>>> series.apply(np.log)
London 2.995732
New York 3.044522
Helsinki 2.484907
dtype: float64

**pandas.Series.map**

Series.map(arg, na_action=None)

Map values of Series using input correspondence (which can be a dict, Series, or function)

- **Parameters arg**: function, dict, or Series
- **na_action**: {None, ‘ignore’}
  - If ‘ignore’, propagate NA values
Returns y : Series

same index as caller

Examples

>>> x
one 1
two 2
three 3

>>> y
1 foo
2 bar
3 baz

>>> x.map(y)
one foo
two bar
three baz

pandas.Series.groupby

Series.<br>groupby(by=None, axis=0, level=None, as_index=True, sort=True, group_keys=True, squeeze=False)<br>
Group series using mapper (dict or key function, apply given function to group, return result as series) or by a series of columns

Parameters by : mapping function / list of functions, dict, Series, or tuple /

list of column names. Called on each element of the object index to determine the groups. If a dict or Series is passed, the Series or dict VALUES will be used to determine the groups

axis : int, default 0

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 : boolean, 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 : boolean, 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 : boolean, default True

When calling apply, add group keys to index to identify pieces

squeeze : boolean, default False

reduce the dimensionality of the return type if possible, otherwise return a consistent type

Returns GroupBy object
Examples

DataFrame results

```python
>>> data.groupby(func, axis=0).mean()
>>> data.groupby(['col1', 'col2'])['col3'].mean()
```

DataFrame with hierarchical index

```python
>>> data.groupby(['col1', 'col2']).mean()
```

34.3.7 Computations / Descriptive Stats

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Series.abs()</code></td>
<td>Return an object with absolute value taken.</td>
</tr>
<tr>
<td><code>Series.all([axis, bool_only, skipna, level])</code></td>
<td>Return whether all elements are True over requested axis</td>
</tr>
<tr>
<td><code>Series.any([axis, bool_only, skipna, level])</code></td>
<td>Return whether any element is True over requested axis</td>
</tr>
<tr>
<td><code>Series.autocorr([lag])</code></td>
<td>Lag-N autocorrelation</td>
</tr>
<tr>
<td><code>Series.between(left, right[, inclusive])</code></td>
<td>Return boolean Series equivalent to left &lt;= series &lt;= right.</td>
</tr>
<tr>
<td><code>Series.clip([lower, upper, out, axis])</code></td>
<td>Trim values at input threshold(s)</td>
</tr>
<tr>
<td><code>Series.clip_lower(threshold[, axis])</code></td>
<td>Return copy of the input with values below given value(s) truncated</td>
</tr>
<tr>
<td><code>Series.clip_upper(threshold[, axis])</code></td>
<td>Return copy of input with values above given value(s) truncated</td>
</tr>
<tr>
<td><code>Series.corr(other[, method, min_periods])</code></td>
<td>Compute correlation with <code>other</code> Series, excluding missing values</td>
</tr>
<tr>
<td><code>Series.count([level])</code></td>
<td>Return number of non-NA/null observations in the Series</td>
</tr>
<tr>
<td><code>Series.cov(other[, method, min_periods])</code></td>
<td>Compute covariance with Series, excluding missing values</td>
</tr>
<tr>
<td><code>Series.cummak([axis, dtype, out, skipna])</code></td>
<td>Return cumulative max over requested axis.</td>
</tr>
<tr>
<td><code>Series.cummak([axis, dtype, out, skipna])</code></td>
<td>Return cumulative min over requested axis.</td>
</tr>
<tr>
<td><code>Series.cumprod([axis, dtype, out, skipna])</code></td>
<td>Return cumulative product over requested axis.</td>
</tr>
<tr>
<td><code>Series.cumsum([axis, dtype, out, skipna])</code></td>
<td>Return cumulative sum over requested axis.</td>
</tr>
<tr>
<td><code>Series.describe([percentiles, include, exclude])</code></td>
<td>Generate various summary statistics, excluding NaN values.</td>
</tr>
<tr>
<td><code>Series.diff([periods])</code></td>
<td>1st discrete difference of object</td>
</tr>
<tr>
<td><code>Series.factorize([sort, na_sentinel])</code></td>
<td>Encode the object as an enumerated type or categorical variable</td>
</tr>
<tr>
<td><code>Series.kurt([axis, skipna, level, numeric_only])</code></td>
<td>Return unbiased kurtosis over requested axis using Fishers definition of kurtosis</td>
</tr>
<tr>
<td><code>Series.max([axis, skipna, level, numeric_only])</code></td>
<td>Return the mean absolute deviation of the values for the requested axis</td>
</tr>
<tr>
<td><code>Series.mean([axis, skipna, level, numeric_only])</code></td>
<td>This method returns the maximum of the values in the object.</td>
</tr>
<tr>
<td><code>Series.median([axis, skipna, level, ...])</code></td>
<td>Return the mean of the values for the requested axis</td>
</tr>
<tr>
<td><code>Series.min([axis, skipna, level, numeric_only])</code></td>
<td>Return the median of the values for the requested axis</td>
</tr>
<tr>
<td><code>Series.mode()</code></td>
<td>This method returns the minimum of the values in the object.</td>
</tr>
<tr>
<td><code>Series.nlargest(*args, **kwargs)</code></td>
<td>Returns the mode(s) of the dataset.</td>
</tr>
<tr>
<td><code>Series.nsmallest(*args, **kwargs)</code></td>
<td>Return the largest n elements.</td>
</tr>
<tr>
<td><code>Series.percent_change([periods, fill_method, ...])</code></td>
<td>Return the smallest n elements.</td>
</tr>
<tr>
<td><code>Series.prod([axis, skipna, level, numeric_only])</code></td>
<td>Percent change over given number of periods.</td>
</tr>
<tr>
<td><code>Series.quantile([q])</code></td>
<td>Return the product of the values for the requested axis.</td>
</tr>
<tr>
<td><code>Series.rank([method, na_option, ascending, pct])</code></td>
<td>Return value at the given quantile, a la numpy.percentile.</td>
</tr>
<tr>
<td><code>Series.sem([axis, skipna, level, ddof, ...])</code></td>
<td>Compute data ranks (1 through n).</td>
</tr>
<tr>
<td><code>Series.skew([axis, skipna, level, numeric_only])</code></td>
<td>Return unbiased standard error of the mean over requested axis</td>
</tr>
<tr>
<td><code>Series.std([axis, skipna, level, ddof, ...])</code></td>
<td>Return unbiased skew over requested axis.</td>
</tr>
<tr>
<td><code>Series.sum([axis, skipna, level, numeric_only])</code></td>
<td>Return unbiased standard deviation over requested axis.</td>
</tr>
<tr>
<td><code>Series.var([axis, skipna, level, ddof, ...])</code></td>
<td>Return the sum of the values for the requested axis</td>
</tr>
<tr>
<td><code>Series.unique()</code></td>
<td>Return unbiased variance over requested axis.</td>
</tr>
<tr>
<td><code>Series.unique([dropna])</code></td>
<td>Return array of unique values in the object.</td>
</tr>
<tr>
<td><code>Series.value_counts([normalize, sort, ...])</code></td>
<td>Return number of unique elements in the object.</td>
</tr>
<tr>
<td><code>Series.nunique([dropna])</code></td>
<td>Returns object containing counts of unique values.</td>
</tr>
</tbody>
</table>
pandas.Series.abs

Series.abs()
Return an object with absolute value taken. Only applicable to objects that are all numeric

Returns abs: type of caller

pandas.Series.all

Series.all (axis=None, bool_only=None, skipna=None, level=None, **kwargs)
Return whether all elements are True over requested axis

Parameters axis : {index (0)}
   skipna : boolean, 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
   bool_only : boolean, default None
      Include only boolean data. If None, will attempt to use everything, then use only
      boolean data

Returns all: scalar or Series (if level specified)

pandas.Series.any

Series.any (axis=None, bool_only=None, skipna=None, level=None, **kwargs)
Return whether any element is True over requested axis

Parameters axis : {index (0)}
   skipna : boolean, 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
   bool_only : boolean, default None
      Include only boolean data. If None, will attempt to use everything, then use only
      boolean data

Returns any: scalar or Series (if level specified)

pandas.Series.autocorr

Series.autocorr (lag=1)
Lag-N autocorrelation

Parameters lag : int, default 1
   Number of lags to apply before performing autocorrelation.
Returns autocorr : float

pandas.Series.between

Series.between (left, right, inclusive=True)  
Return boolean Series equivalent to left <= series <= right. NA values will be treated as False  

Parameters left : scalar  
    Left boundary  
right : scalar  
    Right boundary  

Returns is_between : Series

pandas.Series.clip

Series.clip (lower=None, upper=None, out=None, axis=None)  
Trim values at input threshold(s)  

Parameters lower : float or array_like, default None  
    upper : float or array_like, default None  
    axis : int or string axis name, optional  
    Align object with lower and upper along the given axis.  

Returns clipped : Series

Examples

>>> df
  0  1
0 0.335232 -1.256177
1 -1.367855  0.746646
2 0.230930 -0.679613
3 1.261967  0.570967
>>> df.clip(-1.0, 0.5)
  0  1
0 0.335232 -1.000000
1 -1.000000  0.500000
2 0.027753 -1.000000
3 0.230930 -0.679613
4 0.500000  0.500000

>>> t
  0  -0.3
  1  -0.2
  2  -0.1
  3   0.0
  4   0.1
  dtype: float64
>>> df.clip(t, t + 1, axis=0)
  0  1
0 0.335232 -0.300000
pandas.Series.clip_lower

Series.clip_lower(threshold, axis=None)
Return copy of the input with values below given value(s) truncated

Parameters
threshold : float or array_like
axis : int or string axis name, optional
    Align object with threshold along the given axis.

Returns
clipped : same type as input

See also:
clip

pandas.Series.clip_upper

Series.clip_upper(threshold, axis=None)
Return copy of input with values above given value(s) truncated

Parameters
threshold : float or array_like
axis : int or string axis name, optional
    Align object with threshold along the given axis.

Returns
clipped : same type as input

See also:
clip

pandas.Series.corr

Series.corr(other, method='pearson', min_periods=None)
Compute correlation with other Series, excluding missing values

Parameters
other : Series
method : {'pearson', 'kendall', 'spearman'}
    • pearson : standard correlation coefficient
    • kendall : Kendall Tau correlation coefficient
    • spearman : Spearman rank correlation

min_periods : int, optional
    Minimum number of observations needed to have a valid result

Returns
correlation : float
**pandas.Series.count**

Series.\texttt{count} (\texttt{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 nobs** : int or Series (if level specified)

**pandas.Series.cov**

Series.\texttt{cov} (\texttt{other}, \texttt{min_periods=None})

Compute covariance with Series, excluding missing values

- **Parameters other** : Series
  - **min_periods** : int, optional
    - Minimum number of observations needed to have a valid result

- **Returns covariance** : float
  - Normalized by N-1 (unbiased estimator).

**pandas.Series.cummax**

Series.\texttt{cummax} (\texttt{axis=None}, \texttt{dtype=None}, \texttt{out=None}, \texttt{skipna=True}, **\texttt{kwargs})

Return cumulative max over requested axis.

- **Parameters axis** : {index (0)}
  - **skipna** : boolean, default True
    - Exclude NA/null values. If an entire row/column is NA, the result will be NA

- **Returns max** : scalar

**pandas.Series.cummin**

Series.\texttt{cummin} (\texttt{axis=None}, \texttt{dtype=None}, \texttt{out=None}, \texttt{skipna=True}, **\texttt{kwargs})

Return cumulative min over requested axis.

- **Parameters axis** : {index (0)}
  - **skipna** : boolean, default True
    - Exclude NA/null values. If an entire row/column is NA, the result will be NA

- **Returns min** : scalar

**pandas.Series.cumprod**

Series.\texttt{cumprod} (\texttt{axis=None}, \texttt{dtype=None}, \texttt{out=None}, \texttt{skipna=True}, **\texttt{kwargs})

Return cumulative prod over requested axis.
**Parameters**  
`axis`: {index (0)}

`skipna`: boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**Returns**  
`prod`: scalar

---

**pandas.Series.cumsum**

Series.cumsum(\naxis=None, dtype=None, out=None, skipna=True, **kwargs)\n
Return cumulative sum over requested axis.

**Parameters**  
`axis`: {index (0)}

`skipna`: boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**Returns**  
`sum`: scalar

---

**pandas.Series.describe**

Series.describe(percentiles=None, include=None, exclude=None)\n
Generate various summary statistics, excluding NaN values.

**Parameters**  
`percentiles`: array-like, optional

The percentiles to include in the output. Should all be in the interval [0, 1]. By default percentiles is [.25, .5, .75], returning the 25th, 50th, and 75th percentiles.

`include, exclude`: list-like, ‘all’, or None (default)

Specify the form of the returned result. Either:

- None to both (default). The result will include only numeric-typed columns or, if none are, only categorical columns.
- A list of dtypes or strings to be included/excluded. To select all numeric types use numpy numpy.number. To select categorical objects use type object. See also the select_dtypes documentation. eg. df.describe(include=['O'])
- If include is the string ‘all’, the output column-set will match the input one.

**Returns**  
`summary`: NDFrame of summary statistics

**See also:**

`DataFrame.select_dtypes`

**Notes**

The output DataFrame index depends on the requested dtypes:

For numeric dtypes, it will include: count, mean, std, min, max, and lower, 50, and upper percentiles.

For object dtypes (e.g. timestamps or strings), the index will include the count, unique, most common, and frequency of the most common. Timestamps also include the first and last items.

For mixed dtypes, the index will be the union of the corresponding output types. Non-applicable entries will be filled with NaN. Note that mixed-dtype outputs can only be returned from mixed-dtype inputs and appropriate use of the include/exclude arguments.
If multiple values have the highest count, then the *count* and *most common* pair will be arbitrarily chosen from among those with the highest count.

The include, exclude arguments are ignored for Series.

### pandas.Series.diff

**Series.diff** *(periods=1)*

1st discrete difference of object

**Parameters**

- **periods**: int, default 1
  - Periods to shift for forming difference

**Returns**

- **difff**: Series

### pandas.Series.factorize

**Series.factorize** *(sort=False, na_sentinel=-1)*

Encode the object as an enumerated type or categorical variable

**Parameters**

- **sort**: boolean, default False
  - Sort by values

- **na_sentinel**: int, default -1
  - Value to mark “not found”

**Returns**

- **labels**: the indexer to the original array
- **uniques**: the unique Index

### pandas.Series.kurt

**Series.kurt** *(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)*

Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

**Parameters**

- **axis**: {index (0)}

- **skipna**: boolean, 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

- **numeric_only**: boolean, default None
  - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**

- **kurt**: scalar or Series (if level specified)
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)}
    skipna: boolean, 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
    numeric_only: boolean, default None
        Include only float, int, boolean data. If None, will attempt to use everything, then
        use only numeric data

Returns mad: scalar or Series (if level specified)

pandas.Series.max

Series.max (axis=None, skipna=None, level=None, numeric_only=None, **kwargs)
This method returns the maximum of the values in the object. If you want the index of the maximum, use
idxmax. This is the equivalent of the numpy.ndarray method argmax.

Parameters axis: {index (0)}
    skipna: boolean, 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
    numeric_only: boolean, default None
        Include only float, int, boolean data. If None, will attempt to use everything, then
        use only numeric data

Returns max: scalar or Series (if level specified)

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)}
    skipna: boolean, 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
numeric_only : boolean, default None

   Include only float, int, boolean data. If None, will attempt to use everything, then
   use only numeric data

Returns mean : 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)}

skipna : boolean, 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

numeric_only : boolean, default None

   Include only float, int, boolean data. If None, will attempt to use everything, then
   use only numeric data

Returns median : scalar or Series (if level specified)

pandas.Series.min

Series.min(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

This method returns the minimum of the values in the object. If you want the index of the minimum, use
idxmin. This is the equivalent of the numpy.ndarray method argmin.

Parameters axis : {index (0)}

skipna : boolean, 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

numeric_only : boolean, default None

   Include only float, int, boolean data. If None, will attempt to use everything, then
   use only numeric data

Returns min : scalar or Series (if level specified)

pandas.Series.mode

Series.mode()

Returns the mode(s) of the dataset.

   Empty if nothing occurs at least 2 times. Always returns Series even if only one value.

Parameters sort : bool, default True
If True, will lexicographically sort values, if False skips sorting. Result ordering when `sort=False` is not defined.

**Returns**

- modes : Series (sorted)

---

**pandas.Series.nlargest**

`Series.nlargest(*args, **kwargs)`

Return the largest `n` elements.

**Parameters**

- `n` : int
  
  Return this many descending sorted values

  - `keep` : {'first', 'last', False}, default ‘first’
    
    Where there are duplicate values: - `first` : take the first occurrence. - `last` : take the last occurrence.

- `take_last` : deprecated

**Returns**

- `top_n` : Series
  
  The `n` largest values in the Series, in sorted order

**See also:**

`Series.nsmallest`

**Notes**

Faster than `.sort_values(ascending=False).head(n)` for small `n` relative to the size of the Series object.

**Examples**

```python
>>> import pandas as pd
>>> import numpy as np

>>> s = pd.Series(np.random.randn(1e6))
>>> s.nlargest(10)  # only sorts up to the N requested
```

---

**pandas.Series.nsmallest**

`Series.nsmallest(*args, **kwargs)`

Return the smallest `n` elements.

**Parameters**

- `n` : int
  
  Return this many ascending sorted values

  - `keep` : {'first', 'last', False}, default ‘first’
    
    Where there are duplicate values: - `first` : take the first occurrence. - `last` : take the last occurrence.

- `take_last` : deprecated

**Returns**

- `bottom_n` : Series
The n smallest values in the Series, in sorted order

See also:

Series.nlargest

Notes

Faster than .sort_values().head(n) for small n relative to the size of the Series object.

Examples

```python
>>> import pandas as pd
>>> import numpy as np

>>> s = pd.Series(np.random.randn(1e6))
>>> s.nsmallest(10)  # only sorts up to the N requested
```

**pandas.Series.pct_change**

`Series.pct_change(periods=1, fill_method='pad', limit=None, freq=None, **kwargs)`

Percent change over given number of periods.

**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 offset alias string, optional
  - Increment to use from time series API (e.g. ‘M’ or BDay())

**Returns**

- **chg**: NDFrame

**Notes**

By default, the percentage change is calculated along the stat axis: 0, or `Index`, for `DataFrame` and 1, or `minor` for `Panel`. You can change this with the `axis` keyword argument.

**pandas.Series.prod**

`Series.prod(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return the product of the values for the requested axis.

**Parameters**

- **axis**: {index (0)}
  - Excludes NA/null values. If an entire row/column is NA, the result will be NA
- **skipna**: boolean, default True
  - Excludes 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

**numeric_only** : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**

**prod** : scalar or Series (if level specified)

### pandas.Series.quantile

**Series.quantile**(q=0.5)

Return value at the given quantile, a la numpy.percentile.

**Parameters**

- **q** : float or array-like, default 0.5 (50% quantile)
  
  $0 \leq q \leq 1$, the quantile(s) to compute

**Returns**

**quantile** : float or Series

if $q$ is an array, a Series will be returned where the index is $q$ and the values are the quantiles.

**Examples**

```python
>>> s = 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.rank

**Series.rank**(method='average', na_option='keep', ascending=True, pct=False)

Compute data ranks (1 through n). Equal values are assigned a rank that is the average of the ranks of those values

**Parameters**

- **method** : {'average', 'min', 'max', 'first', 'dense'}

  - 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

- **na_option** : {'keep'}

  keep: leave NA values where they are

- **ascending** : boolean, default True

  False for ranks by high (1) to low (N)
pandas: powerful Python data analysis toolkit, Release 0.17.0

pandas.Series.pct

pct : boolean, default False
Computes percentage rank of data

Returns ranks : Series

pandas.Series.sem

Series.sem(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwags)
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 : boolean, 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
numeric_only : boolean, default None
Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns sem : scalar or Series (if level specified)

pandas.Series.skew

Series.skew(axis=None, skipna=None, level=None, numeric_only=None, **kwags)
Return unbiased skew over requested axis Normalized by N-1

Parameters axis : {index (0)}
skipna : boolean, 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
numeric_only : boolean, default None
Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns skew : scalar or Series (if level specified)

pandas.Series.std

Series.std(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwags)
Return unbiased standard deviation over requested axis.
Normalized by N-1 by default. This can be changed using the ddof argument
Parameters  
axis : {index (0)}

    skipna : boolean, 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
    numeric_only : boolean, default None
    Include only float, int, boolean data. If None, will attempt to use everything, then
    use only numeric data

Returns  
std : scalar or Series (if level specified)

pandas.Series.sum

Series.sum(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

Return the sum of the values for the requested axis

Parameters  
axis : {index (0)}

    skipna : boolean, 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
    numeric_only : boolean, default None
    Include only float, int, boolean data. If None, will attempt to use everything, then
    use only numeric data

Returns  
sum : scalar or Series (if level specified)

pandas.Series.var

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 : boolean, 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
    numeric_only : boolean, default None
    Include only float, int, boolean data. If None, will attempt to use everything, then
    use only numeric data
**pandas.Series.unique**

Series.unique()

Return array of unique values in the object. Significantly faster than numpy.unique. Includes NA values.

**Returns uniques**: ndarray

**pandas.Series.nunique**

Series.nunique(dropna=True)

Return number of unique elements in the object.

Excludes NA values by default.

**Parameters dropna**: boolean, default True

Don’t include NaN in the count.

**Returns nunique**: int

**pandas.Series.value_counts**

Series.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)

Returns object 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**: boolean, default False

If True then the object returned will contain the relative frequencies of the unique values.

**sort**: boolean, default True

Sort by values

**ascending**: boolean, default False

Sort in ascending order

**bins**: integer, optional

Rather than count values, group them into half-open bins, a convenience for pd.cut, only works with numeric data

**dropna**: boolean, default True

Don’t include counts of NaN.

**Returns counts**: Series

### 34.3.8 Reindexing / Selection / Label manipulation

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.align(other[, join, axis, level, ...])</td>
<td>Align two object on their axes with the</td>
</tr>
<tr>
<td>Series.drop(labels[, axis, level, inplace, ...])</td>
<td>Return new object with labels in requested axis removed</td>
</tr>
<tr>
<td>Method</td>
<td>Description</td>
</tr>
<tr>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Series.drop_duplicates(*args, **kwargs)</td>
<td>Return Series with duplicate values removed</td>
</tr>
<tr>
<td>Series.duplicated(*args, **kwargs)</td>
<td>Return boolean Series denoting duplicate values</td>
</tr>
<tr>
<td>Series.equals(other)</td>
<td>Determines if two NDFrame objects contain the same elements.</td>
</tr>
<tr>
<td>Series.first(offset)</td>
<td>Convenience method for subsetting initial periods of time series data</td>
</tr>
<tr>
<td>Series.head(n)</td>
<td>Returns first n rows</td>
</tr>
<tr>
<td>Series.idxmax((axis, out, skipna))</td>
<td>Index of first occurrence of maximum of values.</td>
</tr>
<tr>
<td>Series.idxmin((axis, out, skipna))</td>
<td>Index of first occurrence of minimum of values.</td>
</tr>
<tr>
<td>Series.isin(values)</td>
<td>Return a boolean Series showing whether each element in the Series is in the passed values.</td>
</tr>
<tr>
<td>Series.last(offset)</td>
<td>Convenience method for subsetting final periods of time series data</td>
</tr>
<tr>
<td>Series.reindex((index))</td>
<td>Conform Series to new index with optional filling logic, placing NA/Nan in locations having no value in the previous index.</td>
</tr>
<tr>
<td>Series.rename((level, drop, name, inplace))</td>
<td>Analogous to the pandas.DataFrame.reset_index() function, see docstring there.</td>
</tr>
<tr>
<td>Series.sample((n, frac, replace, weights, ...))</td>
<td>Return a random sample of items from an axis of object.</td>
</tr>
<tr>
<td>Series.select(crit[, axis])</td>
<td>Return data corresponding to axis labels matching criteria</td>
</tr>
<tr>
<td>Series.take(indices[, axis, convert, is_copy])</td>
<td>Return Series corresponding to requested indices</td>
</tr>
<tr>
<td>Series.tail(n)</td>
<td>Returns last n rows</td>
</tr>
<tr>
<td>Series.truncate((before, after, axis, copy))</td>
<td>Truncates a sorted NDFrame before and/or after some particular dates.</td>
</tr>
<tr>
<td>Series.where(cond[, other, inplace, axis, ...])</td>
<td>Return an object of same shape as self and whose corresponding entries are from other.</td>
</tr>
<tr>
<td>Series.mask(cond[, other, inplace, axis, ...])</td>
<td>Return an object of same shape as self and whose corresponding entries are from other.</td>
</tr>
</tbody>
</table>

**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 object on their axes with the specified join method 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
- `level`: int or level name, default None
- `copy`: boolean, default True
- `fill_value`: scalar, default np.NaN
- `method`: str, default None
- `limit`: int, default None
- `fill_axis`: {0, ‘index’}, default 0
- `broadcast_axis`: {0, ‘index’}, default None

Value to use for missing values. Defaults to NaN, but can be any “compatible” value

Always returns new objects. If copy=False and no reindexing is required then original objects are returned.

New in version 0.17.0.
**pandas.Series.drop**

Series.drop(labels, axis=0, level=None, inplace=False, errors='raise')

Return new object with labels in requested axis removed

**Parameters**
- **labels**: single label or list-like
- **axis**: int or axis name
- **level**: int or level name, default None
  - For MultiIndex
- **inplace**: bool, default False
  - If True, do operation inplace and return None.
- **errors**: {'ignore', 'raise'}, default 'raise'
  - If ‘ignore’, suppress error and existing labels are dropped.

**New in version 0.16.1.**

**Returns**
- **dropped**: type of caller

**pandas.Series.drop_duplicates**

Series.drop_duplicates(*args, **kwargs)

Return Series 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.
- **take_last**: deprecated
- **inplace**: boolean, default False
  - If True, performs operation inplace and returns None.

**Returns**
- **deduplicated**: Series

**pandas.Series.duplicated**

Series.duplicated(*args, **kwargs)

Return boolean Series denoting duplicate values

**Parameters**
- **keep**: {'first', 'last', False}, default 'first'
  - 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.
- **take_last**: deprecated
Returns duplicated: Series

**pandas.Series.equals**

Series.equals(other)
Determines if two NDFrame objects contain the same elements. NaNs in the same location are considered equal.

**pandas.Series.first**

Series.first(offset)
Convenience method for subsetting initial periods of time series data based on a date offset

- **Parameters**
  - offset: string, DateOffset, dateutil.relativedelta
- **Returns**
  - subset: type of caller

**Examples**

ts.last('10D') -> First 10 days

**pandas.Series.head**

Series.head(n=5)
Returns first n rows

**pandas.Series.idxmax**

Series.idxmax(axis=None, out=None, skipna=True)
Index of first occurrence of maximum of values.

- **Parameters**
  - skipna: boolean, default True
    - Exclude NA/null values
- **Returns**
  - idxmax: Index of maximum of values

**See also:**

DataFrame.idxmax, numpy.ndarray.argmax

**Notes**

This method is the Series version of ndarray.argmax.

**pandas.Series.idxmin**

Series.idxmin(axis=None, out=None, skipna=True)
Index of first occurrence of minimum of values.

- **Parameters**
  - skipna: boolean, default True
    - Exclude NA/null values
- **Returns**
  - idxmin: Index of minimum of values
See also:

DataFrame.idxmin, numpy.ndarray.argmin

Notes

This method is the Series version of ndarray.argmin.

pandas.Series.isin

Series.isin(values)
Return a boolean Series showing whether each element in the Series is exactly contained in the passed sequence of values.

Parameters values : 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 isin : Series (bool dtype)

 Raises TypeError
• If values is a string

See also:
pandas.DataFrame.isin

Examples

```python
>>> s = pd.Series(list('abc'))
>>> s.isin(['a', 'c', 'e'])
0   True
1  False
2   True
dtype: bool
```

Passing a single string as s.isin('a') will raise an error. Use a list of one element instead:

```python
>>> s.isin(['a'])
0   True
1  False
2  False
dtype: bool
```

pandas.Series.last

Series.last(offset)
Convenience method for subsetting final periods of time series data based on a date offset

Parameters offset : string, DateOffset, dateutil.relativedelta

Returns subset : type of caller
Examples

ts.last('5M') -> Last 5 months

pandas.Series.reindex

Series.reindex(index=None, **kwargs)
Conform Series to new index with optional filling logic, placing 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 (can be specified in order, or as keywords) New labels / index to conform to. Preferably an Index object to avoid duplicating data
- **method**: {None, ‘backfill’/’bfill’, ‘pad’/’ffill’, ‘nearest’}, optional
  Method to use for filling holes in reindexed DataFrame:
  - 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**: boolean, 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.
  New in version 0.17.0.

Returns

- **reindexed**: Series

Examples

```python
>>> df.reindex(index=[date1, date2, date3], columns=['A', 'B', 'C'])
```
**pandas.Series.reindex_like**

Series.reindex_like (other, method=None, copy=True, limit=None, tolerance=None)

return an object with matching indices to myself

**Parameters**
- **other**: Object
  - **method**: string or None
  - **copy**: boolean, default True
  - **limit**: int, default None
    - Maximum number of consecutive labels to fill for inexact matches.
  - **tolerance**: optional
    - Maximum distance between labels of the other object and this object for inexact matches.
  - **New in version 0.17.0.**

**Returns**
- **reindexed**: same as input

**Notes**

Like calling s.reindex(index=other.index, columns=other.columns, method=...)

**pandas.Series.rename**

Series.rename (index=None, **kwargs)

Alter axes input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

**Parameters**
- **index**: dict-like or function, optional
  - Transformation to apply to that axis values
- **copy**: boolean, default True
  - Also copy underlying data
- **inplace**: boolean, default False
  - Whether to return a new Series. If True then value of copy is ignored.

**Returns**
- **renamed**: Series (new object)

**pandas.Series.reset_index**

Series.reset_index (level=None, drop=False, name=None, inplace=False)

Analogous to the pandas.DataFrame.reset_index() function, see docstring there.

**Parameters**
- **level**: int, str, tuple, or list, default None
  - Only remove the given levels from the index. Removes all levels by default
- **drop**: boolean, default False
  - Do not try to insert index into dataframe columns
- **name**: object, default None
The name of the column corresponding to the Series values

**inplace**: boolean, default False
Modify the Series in place (do not create a new object)

**Returns** resetted: DataFrame, or Series if drop == True

**pandas.Series.sample**

Series. sample (n=None, frac=None, replace=False, weights=None, random_state=None, axis=None)

Returns a random sample of items from an axis of object.

New in version 0.16.1.

**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**: boolean, optional
  Sample with or without replacement. Default = False.

- **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. inf and -inf values not allowed.

- **random_state**: int or numpy.random.RandomState, optional
  Seed for the random number generator (if int), or numpy RandomState object.

- **axis**: int or string, optional
  Axis to sample. Accepts axis number or name. Default is stat axis for given data type (0 for Series and DataFrames, 1 for Panels).

**Returns** A new object of same type as caller.

**pandas.Series.select**

Series. select (crit, axis=0)

Return data corresponding to axis labels matching criteria

**Parameters**

- **crit**: function
  To be called on each index (label). Should return True or False

- **axis**: int

**Returns** selection : type of caller
### pandas.Series.take

`Series.take(indices, axis=0, convert=True, is_copy=False)`

Return Series corresponding to requested indices

**Parameters**
- `indices` : list / array of ints
  - `convert` : translate negative to positive indices (default)

**Returns**
- `taken` : Series

See also:
- `numpy.ndarray.take`

### pandas.Series.tail

`Series.tail(n=5)`

Returns last n rows

### pandas.Series.truncate

`Series.truncate(before=None, after=None, axis=None, copy=True)`

Truncates a sorted NDFrame before and/or after some particular dates.

**Parameters**
- `before` : date
  - Truncate before date
- `after` : date
  - Truncate after date
- `axis` : the truncation axis, defaults to the stat axis
- `copy` : boolean, default is True,
  - return a copy of the truncated section

**Returns**
- `truncated` : type of caller

### pandas.Series.where

`Series.where(cond, other=nan, inplace=False, axis=None, level=None, try_cast=False, raise_on_error=True)`

Return an object of same shape as self and whose corresponding entries are from self where cond is True and otherwise are from other.

**Parameters**
- `cond` : boolean NDFrame or array
- `other` : scalar or NDFrame
- `inplace` : boolean, default False
  - Whether to perform the operation in place on the data
- `axis` : alignment axis if needed, default None
- `level` : alignment level if needed, default None
- `try_cast` : boolean, default False
  - try to cast the result back to the input type (if possible),
raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns wh : same type as caller

pandas.Series.mask

Series.mask (cond, other=nan, inplace=False, axis=None, level=None, try_cast=False, raise_on_error=True)

Return an object of same shape as self and whose corresponding entries are from self where cond is False and otherwise are from other.

Parameters cond : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible).

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns wh : same type as caller

34.3.9 Missing data handling

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.dropna</td>
<td>Return Series without null values</td>
</tr>
<tr>
<td>Series.fillna</td>
<td>Fill NA/NaN values using the specified method</td>
</tr>
<tr>
<td>Series.interpolate</td>
<td>Interpolate values according to different methods.</td>
</tr>
</tbody>
</table>

pandas.Series.dropna

Series.dropna (axis=0, inplace=False, **kwargs)

Return Series without null values

Returns valid : Series

inplace : boolean, default False

Do operation in place.

pandas.Series.fillna

Series.fillna (value=None, method=None, axis=None, inplace=False, limit=None, downcast=None, **kwargs)

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, 'index'}

**inplace**: boolean, 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.

**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 filled : Series

See also:
reindex, asfreq

### pandas.Series.interpolate

**Series.interpolate**(method='linear', axis=0, limit=None, inplace=False, limit_direction='forward', downcast=None, **kwargs)

Interpolate values according to different methods.

Please note that only method='linear' is supported for DataFrames/Series with a MultiIndex.


- ‘linear’: ignore the index and treat the values as equally spaced. This is the only method supported on MultiIndexes. default
- ‘time’: interpolation works on daily and higher resolution data to interpolate given length of interval
- ‘index’: use the actual numerical values of the index
- ‘values’: use the actual numerical values of the index
- ‘nearest’, ‘zero’, ‘slinear’, ‘quadratic’, ‘cubic’, ‘barycentric’, ‘polynomial’ is passed to scipy.interpolate.interp1d. Both ‘polynomial’ and ‘spline’ require that you also specify an order (int), e.g. df.interpolate(method='polynomial', order=4). These use the actual numerical values of the index.
• ‘krogh’, ‘piecewise_polynomial’, ‘spline’, and ‘pchip’ are all wrappers around
  the scipy interpolation methods of similar names. These use the actual numerical
  values of the index. See the scipy documentation for more on their behavior here
  and here

axis : {0, 1}, default 0
  • 0: fill column-by-column
  • 1: fill row-by-row

limit : int, default None.
  Maximum number of consecutive NaNs to fill.

limit_direction : {‘forward’, ‘backward’, ‘both’}, defaults to ‘forward’
  If limit is specified, consecutive NaNs will be filled in this direction.
  New in version 0.17.0.

inplace : bool, default False
  Update the NDFrame in place if possible.

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 of same shape interpolated at the NaNs

See also:
  reindex, replace, fillna

Examples

Filling in NaNs

>>> s = pd.Series([0, 1, np.nan, 3])
>>> s.interpolate()
   0 0
   1 1
   2 2
   3 3
dtype: float64

34.3.10 Reshaping, sorting

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.argsort([axis, kind, order])</td>
<td>Overrides ndarray.argsort.</td>
</tr>
<tr>
<td>Series.reorder_levels(order)</td>
<td>Rearranges index levels using input order.</td>
</tr>
<tr>
<td>Series.sort_values([axis, ascending, ...])</td>
<td>Sort by the values along either axis.</td>
</tr>
<tr>
<td>Series.sort_index([axis, level, ascending, ...])</td>
<td>Sort object by labels (along an axis).</td>
</tr>
<tr>
<td>Series.sortlevel([level])</td>
<td>Sort Series with MultiIndex by chosen level.</td>
</tr>
<tr>
<td>Series.swapslevel(i, j, copy)</td>
<td>Swap levels i and j in a MultiIndex.</td>
</tr>
<tr>
<td>Series.unstack([level])</td>
<td>Unstack, a.k.a.</td>
</tr>
<tr>
<td>Series.searchsorted(v[, side, sorter])</td>
<td>Find indices where elements should be inserted to maintain order.</td>
</tr>
</tbody>
</table>
pandas.Series.argsort

Series.argsort(axis=0, kind='quicksort', order=None)

Overrides ndarray.argsort. Argsorts the value, omitting NA/null values, and places the result in the same locations as the non-NA values

Parameters
axis : int (can only be zero)
kind : {'mergesort', 'quicksort', 'heapsort'}, default 'quicksort'
order : ignored

Returns argsorted : Series, with -1 indicated where nan values are present

See also:
numpy.ndarray.argsort

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.
(axis by number or key)

axis : where to reorder levels

Returns type of caller (new object)

pandas.Series.sort_values

Series.sort_values(axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last')
Sort by the values along either axis

New in version 0.17.0.

Parameters
by : string name or list of names which refer to the axis items
axis : index to direct sorting
ascending : bool or list of bool
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
if True, perform operation in-place
kind : {'quicksort', 'mergesort', 'heapsort'}
Choice of sorting algorithm. See also ndarray.np.sort for more information. merge-
sort is the only stable algorithm. For DataFrames, this option is only applied when
sorting on a single column or label.
na_position : {'first', 'last'}
first puts NaNs at the beginning, last puts NaNs at the end
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Returns  sorted_obj : Series

pandas.Series.sort_index

Series.sort_index (axis=0, level=None, ascending=True, inplace=False, sort_remaining=True)
Sort object by labels (along an axis)

Parameters  
axis : index to direct sorting
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 : boolean, default True
Sort ascending vs. descending
inplace : bool
if True, perform operation in-place
kind : {'quicksort', 'mergesort', 'heapsort'}
Choice of sorting algorithm. See also ndarray.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'}
first puts NaNs at the beginning, last puts NaNs at the end

sort_remaining : bool
if true and sorting by level and index is multilevel, sort by other levels too (in order) after sorting by specified level

Returns  sorted_obj : Series

pandas.Series.sortlevel

Series.sortlevel (level=0, ascending=True, sort_remaining=True)
Sort Series with MultiIndex by chosen level. Data will be lexicographically sorted by the chosen level followed by the other levels (in order)

Parameters  
level : int or level name, default None
ascending : bool, default True

Returns  sorted : Series

See also:
Series.sort_index

pandas.Series.swaplevel

Series.swaplevel (i, j, copy=True)
Swap levels i and j in a MultiIndex

Parameters  
i, j : int, string (can be mixed)
Level of index to be swapped. Can pass level name as string.
pandas.Series.unstack

Series.unstack(level=-1)
Unstack, a.k.a. pivot, Series with MultiIndex to produce DataFrame. The level involved will automatically get sorted.

Parameters level : int, string, or list of these, default last level
Level(s) to unstack, can pass level name

Returns unstacked : DataFrame

Examples

>>> s
one a 1.
two b 2.
one a 3.
two b 4.

>>> s.unstack(level=-1)
a b
one 1. 2.
two 3. 4.

>>> s.unstack(level=0)
one two
a 1. 2.
b 3. 4.

pandas.Series.searchsorted

Series.searchsorted(v, 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 v were inserted before the indices, the order of self would be preserved.

Parameters v : array_like
Values to insert into a.
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 a).

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 indices : array of ints
Array of insertion points with the same shape as v.
See also:

Series.sort_values, numpy.searchsorted

Notes

Binary search is used to find the required insertion points.

Examples

```python
>>> x = pd.Series([1, 2, 3])
>>> x
0 1
1 2
2 3
dtype: int64
>>> x.searchsorted(4)
array([3])
>>> x.searchsorted([0, 4])
array([0, 3])
>>> x.searchsorted([1, 3], side='left')
array([0, 2])
>>> x.searchsorted([1, 3], side='right')
array([1, 3])
>>> x.searchsorted([1, 2], side='right', sorter=[0, 2, 1])
array([1, 3])
```

34.3.11 Combining / joining / merging

Series.append(to_append[, verify_integrity]) Concatenate two or more Series.
Series.replace(to_replace, value, inplace, ...) Replace values given in 'to_replace' with 'value'.
Series.update(other) Modify Series in place using non-NA values from passed Series.

pandas.Series.append

Series.append(to_append[, verify_integrity=False]) Concatenate two or more Series.

Parameters to_append : Series or list/tuple of Series
verify_integrity : boolean, default False

    If True, raise Exception on creating index with duplicates

Returns appended : Series

pandas.Series.replace

Series.replace(to_replace=None, value=None, inplace=False, limit=None, regex=False, method='pad', axis=None) Replace values given in 'to_replace' with 'value'.

Parameters to_replace : str, regex, list, dict, Series, numeric, or None
• str or regex:
  – str: string exactly matching to_replace will be replaced with value
  – regex: regexes 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 regexes 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 and regex rules apply as above.
• dict:
  – Nested dictionaries, e.g., {'a': {'b': nan}}, are read as follows: look in column 'a' for the value 'b' and replace it with nan. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) cannot be regular expressions.
  – Keys map to column names and values map to substitution values. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
• 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 use to fill holes (e.g. 0), alternately a dict of values specifying 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 : boolean, default False

If True, in place. Note: this will modify any other views on this object (e.g. a column form 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. Otherwise, to_replace must be None because this parameter will be interpreted as a regular expression or a list, dict, or array of regular expressions.

method : string, optional, {'pad', ‘fill’, ‘bfill’}

The method to use when for replacement, when to_replace is a list.

Returns filled : NDFrame

Raises AssertionError

• If regex is not a bool and to_replace is not None.
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TypeError

- 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.

ValueError

- If `to_replace` and `value` are lists or ndarrays, but they are not the same length.

See also:

NDFrame.reindex, NDFrame.asfreq, NDFrame.fillna

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.

pandas.Series.update

Series.update(other)

Modify Series in place using non-NA values from passed Series. Aligns on index

Parameters other : Series

34.3.12 Time series-related

Series.asfreq(freq[, method, how, normalize]) Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

Series.asof(where) Return last good (non-NaN) value in Series if value is NaN for requested date.

Series.shift([periods, freq, axis]) Shift index by desired number of periods with an optional time freq

Series.first_valid_index() Return label for first non-NA/null value

Series.last_valid_index() Return label for last non-NA/null value

Series.resample(rule[, how, axis, ...]) Convenience method for frequency conversion and resampling of regular time-series data.

Series.tz_convert(tz[, axis, level, copy]) Convert tz-aware axis to target time zone.

Series.tz_localize(*args, **kwargs) Localize tz-naive TimeSeries to target time zone

pandas.Series.asfreq

Series.asfreq(freq, method=None, how=None, normalize=False)

Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

Parameters freq : DateOffset object, or string

method : {'backfill', 'bfill', 'pad', 'ffill', 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 method

**how**: {'start', 'end'}, default end

For PeriodIndex only, see PeriodIndex.asfreq

**normalize**: bool, default False

Whether to reset output index to midnight

**Returns** converted: type of caller

### pandas.Series.asof

**Series.asof**(where)

Return last good (non-NaN) value in Series if value is NaN for requested date.

If there is no good value, NaN is returned.

**Parameters** where: date or array of dates

**Returns** value or NaN

**Notes**

Dates are assumed to be sorted

### pandas.Series.shift

**Series.shift**(periods=1, freq=None, axis=0)

Shift index by desired number of periods with an optional time freq

**Parameters** periods: int

Number of periods to move, can be positive or negative

freq: DateOffset, timedelta, or time rule string, optional

Increment to use from datetools module or time rule (e.g. ‘EOM’). See Notes.

axis: {0, ‘index’}

**Returns** shifted: Series

**Notes**

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.

### pandas.Series.first_valid_index

**Series.first_valid_index**()

Return label for first non-NA/null value
pandas.Series.last_valid_index

Series.

last_valid_index()

Return label for last non-NA/null value

pandas.Series.resample

Series.

resample(

rule, how=None, axis=0, fill_method=None, closed=None, label=None, convention='start', kind=None, loffset=None,

limit=None, base=0)

Convenience method for frequency conversion and resampling of regular time-series data.

Parameters

rule : string

the offset string or object representing target conversion

how : string

method for down- or re-sampling, default to ‘mean’ for downsampling

axis : int, optional, default 0

fill_method : string, default None

fill_method for upsampling

closed : {‘right’, ‘left’}

Which side of bin interval is closed

label : {‘right’, ‘left’}

Which bin edge label to label bucket with

convention : {‘start’, ‘end’, ‘s’, ‘e’}

kind : “period”/”timestamp”

loffset : timedelta

Adjust the resampled time labels

limit : int, default None

Maximum size gap to when reindexing with fill_method

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

Examples

Start by creating a series with 9 one minute timestamps.

>>> 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', how='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', how='sum', label='right')
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', how='sum', label='right', closed='right')
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')[0:5] #select first 5 rows
2000-01-01 00:00:00 0
2000-01-01 00:00:30 NaN
2000-01-01 00:01:00 1
2000-01-01 00:01:30 NaN
2000-01-01 00:02:00 2
Freq: 30S, dtype: float64
```

Upsample the series into 30 second bins and fill the NaN values using the pad method.

```python
>>> series.resample('30S', fill_method='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', fill_method='bfill')[0:5]
2000-01-01 00:00:00 0
2000-01-01 00:00:30 1
```

34.3. Series
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 to how.

```python
>>> def custom_resampler(array_like):
...     return np.sum(array_like)+5
```
```
>>> series.resample('3T', how=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
```

**pandas.Series.tz_convert**

Series.tz_convert (tz, axis=0, level=None, copy=True)

Convert tz-aware axis to target time zone.

- **Parameters**
  - tz : string or pytz.timezone object
  - axis : the axis to convert
  - level : int, str, default None
    - If axis ia a MultiIndex, convert a specific level. Otherwise must be None
  - copy : boolean, default True
    - Also make a copy of the underlying data

- **Raises**
  - TypeError
    - If the axis is tz-naive.

**pandas.Series.tz_localize**

Series.tz_localize(*args, **kwargs)

Localize tz-naive TimeSeries to target time zone

- **Parameters**
  - tz : string or pytz.timezone object
  - axis : the axis to localize
  - level : int, str, default None
    - If axis ia a MultiIndex, localize a specific level. Otherwise must be None
  - copy : boolean, default True
    - Also make a copy of the underlying data

- **ambiguos** : ‘infer’, bool-ndarray, ‘NaT’, default ‘raise’
  - ‘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

```
infer_dst : boolean, default False (DEPRECATED)
```

Attempt to infer fall dst-transition hours based on order

**Raises** **TypeError**

If the TimeSeries is tz-aware and tz is not None.

### 34.3.13 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>`.

**Datet ime 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 datetime.date.</td>
</tr>
<tr>
<td><code>Series.dt.time</code></td>
<td>Returns numpy array of datetime.time.</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 days 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>The week ordinal of the year</td>
</tr>
<tr>
<td><code>Series.dt.weekofyear</code></td>
<td>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>Logical indicating if first day of month (defined by frequency)</td>
</tr>
<tr>
<td><code>Series.dt.is_month_end</code></td>
<td>Logical indicating if last day of month (defined by frequency)</td>
</tr>
<tr>
<td><code>Series.dt.is_quarter_start</code></td>
<td>Logical indicating if first day of quarter (defined by frequency)</td>
</tr>
<tr>
<td><code>Series.dt.is_quarter_end</code></td>
<td>Logical indicating if last day of quarter (defined by frequency)</td>
</tr>
<tr>
<td><code>Series.dt.is_year_start</code></td>
<td>Logical indicating if first day of year (defined by frequency)</td>
</tr>
<tr>
<td><code>Series.dt.is_year_end</code></td>
<td>Logical indicating if last day of year (defined by frequency)</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.days_in_month</code></td>
<td>The number of days in the month</td>
</tr>
<tr>
<td><code>Series.dt.tz</code></td>
<td>get/set the frequency of the Index</td>
</tr>
</tbody>
</table>

**pandas.Series.dt.date**

```
Series.dt.date
```

Returns numpy array of datetime.date. The date part of the Timestamps.

**pandas.Series.dt.time**

```
Series.dt.time
```

Returns numpy array of datetime.time. The time part of the Timestamps.
pandas.Series.dt.year

Series.dt.year
   The year of the datetime

pandas.Series.dt.month

Series.dt.month
   The month as January=1, December=12

pandas.Series.dt.day

Series.dt.day
   The days of the datetime

pandas.Series.dt.hour

Series.dt.hour
   The hours of the datetime

pandas.Series.dt.minute

Series.dt.minute
   The minutes of the datetime

pandas.Series.dt.second

Series.dt.second
   The seconds of the datetime

pandas.Series.dt.microsecond

Series.dt.microsecond
   The microseconds of the datetime

pandas.Series.dt.nanosecond

Series.dt.nanosecond
   The nanoseconds of the datetime

pandas.Series.dt.week

Series.dt.week
   The week ordinal of the year
pandas.Series.dt.weekofyear

Series.dt.weekofyear
The week ordinal of the year

pandas.Series.dt.dayofweek

Series.dt.dayofweek
The day of the week with Monday=0, Sunday=6

pandas.Series.dt.weekday

Series.dt.weekday
The day of the week with Monday=0, Sunday=6

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
Logical indicating if first day of month (defined by frequency)

pandas.Series.dt.is_month_end

Series.dt.is_month_end
Logical indicating if last day of month (defined by frequency)

pandas.Series.dt.is_quarter_start

Series.dt.is_quarter_start
Logical indicating if first day of quarter (defined by frequency)

pandas.Series.dt.is_quarter_end

Series.dt.is_quarter_end
Logical indicating if last day of quarter (defined by frequency)
pandas.Series.dt.is_year_start

Series.dt.\texttt{is\_year\_start}
Logical indicating if first day of year (defined by frequency)

pandas.Series.dt.is_year_end

Series.dt.\texttt{is\_year\_end}
Logical indicating if last day of year (defined by frequency)

pandas.Series.dt.daysinmonth

Series.dt.\texttt{daysinmonth}
The number of days in the month
New in version 0.16.0.

pandas.Series.dt.days_in_month

Series.dt.\texttt{days\_in\_month}
The number of days in the month
New in version 0.16.0.

pandas.Series.dt.tz

Series.dt.\texttt{tz}

pandas.Series.dt.freq

Series.dt.\texttt{freq}
get/set the frequency of the Index

\textbf{Datetime Methods}

\begin{tabular}{ll}
\texttt{Series.dt.to\_period} & Cast to PeriodIndex at a particular frequency \\
\texttt{Series.dt.to\_pydatetime} & \\
\texttt{Series.dt.tz\_localize} & Localize tz-naive DatetimeIndex to given time zone (using pytz/dateutil),
\texttt{Series.dt.tz\_convert} & Convert tz-aware DatetimeIndex from one time zone to another (using pytz/dateutil),
\texttt{Series.dt.normalize} & Return DatetimeIndex with times to midnight,
\texttt{Series.dt.strftime} & Return an array of formatted strings specified by date\_format, which supports the
\end{tabular}

pandas.Series.dt.to_period

Series.dt.\texttt{to\_period} (\texttt{*args, **kwargs})
Cast to PeriodIndex at a particular frequency

pandas.Series.dt.to_pydatetime

Series.dt.\texttt{to\_pydatetime} ()
pandas.Series.dt.tz_localize

Series.dt.tz_localize(*args, **kwargs)
Localize tz-naive DatetimeIndex to given time zone (using pytz/dateutil), or remove timezone from tz-aware DatetimeIndex

Parameters
- **tz** : string, pytz.timezone, dateutil.tz.tzfile or None
  Time zone for time. Corresponding timestamps would be converted to time zone of the TimeSeries. None will remove timezone holding local time.
- **ambiguous** : ‘infer’, bool-ndarray, ‘NaT’, default ‘raise’
  - ‘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
- **infer_dst** : boolean, default False (DEPRECATED)
  Attempt to infer fall dst-transition hours based on order

Returns
- **localized** : DatetimeIndex

Raises
- **TypeError**
  If the DatetimeIndex is tz-aware and tz is not None.

pandas.Series.dt.tz_convert

Series.dt.tz_convert(*args, **kwargs)
Convert tz-aware DatetimeIndex from one time zone to another (using pytz/dateutil)

Parameters
- **tz** : string, pytz.timezone, dateutil.tz.tzfile or None
  Time zone for time. Corresponding timestamps would be converted to time zone of the TimeSeries. None will remove timezone holding UTC time.

Returns
- **normalized** : DatetimeIndex

Raises
- **TypeError**
  If DatetimeIndex is tz-naive.

pandas.Series.dt.normalize

Series.dt.normalize(*args, **kwargs)
Return DatetimeIndex with times to midnight. Length is unaltered

Returns
- **normalized** : DatetimeIndex

pandas.Series.dt.strftime

Series.dt.strftime(*args, **kwargs)
Return an array 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 the python string format doc
New in version 0.17.0.

**Parameters**

- **date_format**: str
  
  date format string (e.g. “%Y-%m-%d”)

**Returns**

ndarray of formatted strings

### Timedelta Properties

<table>
<thead>
<tr>
<th>Property</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 (days, hours, minutes, seconds, milliseconds, microseconds) of the Timedeltas.</td>
</tr>
</tbody>
</table>

### Timedelta Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.dt.to_pytimedelta()</td>
<td></td>
</tr>
<tr>
<td>Series.dt.total_seconds(*args, **kwargs)</td>
<td>Total duration of each element expressed in seconds.</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 (days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds) of the Timedeltas.

**Returns**

a DataFrame
### 34.3.14 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>`.

- `Series.str.capitalize()`: Convert strings in the Series/Index to be capitalized.
- `Series.str.cat((others, sep, na_rep))`: Concatenate strings in the Series/Index with given separator.
- `Series.str.center(width[, fillchar])`: Filling left and right side of strings in the Series/Index with an additional character.
- `Series.str.contains(pat[, case, flags, na, ...])`: Return boolean Series/array whether given pattern/regex is contained in each string.
- `Series.str.count(pat[, flags])`: Count occurrences of pattern in each string of the Series/Index.
- `Series.str.decode(encoding[, errors])`: Decode character string in the Series/Index to unicode using indicated encoding.
- `Series.str.encode(encoding[, errors])`: Encode character string in the Series/Index to some other encoding using indicated encoding.
- `Series.str.endswith(array, pat[, case, flags, na, ...])`: Return boolean Series indicating whether each string in the Series/Index ends with passed pattern.
- `Series.str.extract(pat[, to_strip])`: Find groups in each string in the Series using passed regular expression.
- `Series.str.find(sub[, start, end])`: Find lowest indexes in each strings in the Series/Index where the substring is fully contained between [start:end].
- `Series.str.get(i)`: Find all occurrences of pattern or regular expression in the Series/Index.
- `Series.str.index(array, sub[, start, end])`: Find lowest indexes in each strings where the substring is fully contained by it.
- `Series.str.join(sep)`: Join lists contained as elements in the Series/Index with passed delimiter.
- `Series.str.ljust(width[, fillchar])`: Filling left side of strings in the Series/Index with an additional character.
- `Series.str.lower()`: Convert strings in the Series/Index to lowercase.
- `Series.str.lstrip((to_strip))`: Strip whitespace (including newlines) from each string in the Series/Index from left.
- `Series.str.match(pat[, case, flags, na, ...])`: Deprecated: Find groups in each string in the Series/Index using passed regular expression.
- `Series.str.normalize(form)`: Find all occurrences of pattern or regular expression in the Series/Index.
- `Series.str.padr(width[, side, fillchar])`: Pad strings in the Series/Index with an additional character to specified side.
- `Series.str.partition((pat, expand))`: Split the string at the first occurrence of `sep`, and return 3 elements containing:
- Duplicate each string in the Series/Index by indicated number of times.
- Replace occurrences of pattern/regex in the Series/Index with some other string.
- Return highest indexes in each strings in the Series/Index where the substring is fully contained by it.
- Filling left side of strings in the Series/Index with an additional character.
- Split the string at the last occurrence of `sep`, and return 3 elements containing:
- Replace a slice of each string in the Series/Index with another string.
- Split each string (a la re.split) in the Series/Index by given pattern, propagating NA values.
- Split each string in the Series/Index by the given delimiter string, starting at the first occurrence.
- Return boolean Series/array indicating whether each string in the Series/Index ends with passed pattern.
- Strip whitespace (including newlines) from each string in the Series/Index from right.
- Convert strings in the Series/Index to be swapcased.
- Convert strings in the Series/Index to titlecase.
- Map all characters in the string through the given mapping table.
- Convert strings in the Series/Index to uppercase.
- Wrap long strings in the Series/Index to be formatted in paragraphs with leading `"`. 

```python
pandas.Series.dt.total_seconds
```

### Example

```python
# Series.dt.total_seconds (*args, **kwargs)
Total duration of each element expressed in seconds.

New in version 0.17.0.
```
Series.str.isalnum()  
Check whether all characters in each string in the Series/Index are alphanumeric.

Series.str.isalpha()  
Check whether all characters in each string in the Series/Index are alphabetic.

Series.str.isdigit()  
Check whether all characters in each string in the Series/Index are digits.

Series.str.isspace()  
Check whether all characters in each string in the Series/Index are whitespace.

Series.str.islower()  
Check whether all characters in each string in the Series/Index are lowercase.

Series.str.isupper()  
Check whether all characters in each string in the Series/Index are uppercase.

Series.str.istitle()  
Check whether all characters in each string in the Series/Index are titlecase.

Series.str.isnumeric()  
Check whether all characters in each string in the Series/Index are numeric.

Series.str.isdecimal()  
Check whether all characters in each string in the Series/Index are decimal.

Series.str.get_dummies([sep])  
Split each string in the Series by sep and return a frame of dummy/indicator variables.

pandas.Series.str.capitalize

Series.str.capitalize()  
Convert strings in the Series/Index to be capitalized. Equivalent to str.capitalize().

Returns converted : Series/Index of objects

pandas.Series.str.cat

Series.str.cat (others=None, sep=None, na_rep=None)  
Concatenate strings in the Series/Index with given separator.

Parameters others : list-like, or list of list-likes
If None, returns str concatenating strings of the Series

sep : string or None, default None

na_rep : string or None, default None
If None, an NA in any array will propagate

Returns concat : Series/Index of objects or str

Examples

If others is specified, corresponding values are concatenated with the separator. Result will be a Series of strings.

```python
>>> Series(['a', 'b', 'c']).str.cat(['A', 'B', 'C'], sep=',')
0    a,A
1    b,B
2    c,C
dtype: object
```

Otherwise, strings in the Series are concatenated. Result will be a string.

```python
>>> Series(['a', 'b', 'c']).str.cat(sep=',')
'a,b,c'
```

Also, you can pass a list of list-likes.
```
>>> Series(['a', 'b']).str.cat([['x', 'y'], ['1', '2']], sep=',')
0   a,x,1
1   b,y,2
dtype: object
```

**pandas.Series.str.center**

Series.str.center(*width*, *fillchar=' '*)

Filling left and right side of strings in the Series/Index with an additional character. 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(*pat*, *case=True*, *flags=0*, *na=nan*, *regex=True*)

Return boolean Series/array whether given pattern/regex is contained in each string in the Series/Index.

- **Parameters**
  - *pat*: string
    - Character sequence or regular expression
  - *case*: boolean, default True
    - If True, case sensitive
  - *flags*: int, default 0 (no flags)
    - re module flags, e.g. re.IGNORECASE
  - *na*: default NaN, fill value for missing values.
  - *regex*: bool, default True
    - If True use re.search, otherwise use Python in operator

- **Returns**
  - *contained*: Series/array of boolean values

See also:

- `match` analogous, but stricter, relying on re.match instead of re.search

**pandas.Series.str.count**

Series.str.count(*pat*, *flags=0*, **kwargs)

Count occurrences of pattern in each string of the Series/Index.

- **Parameters**
  - *pat*: string, valid regular expression
  - *flags*: int, default 0 (no flags)
    - re module flags, e.g. re.IGNORECASE

---

34.3. Series
pandas: powerful Python data analysis toolkit, Release 0.17.0

Returns counts: Series/Index of integer values

pandas.Series.str.decode

Series.str.decode(encoding, errors='strict')
Decode character string in the Series/Index to unicode using indicated encoding. Equivalent to str.decode().

Parameters encoding: string
errors: string

Returns decoded: Series/Index of objects

pandas.Series.str.encode

Series.str.encode(encoding, errors='strict')
Encode character string in the Series/Index to some other encoding using indicated encoding. Equivalent to str.encode().

Parameters encoding: string
errors: string

Returns encoded: Series/Index of objects

pandas.Series.str.endswith

Series.str.endswith(pat, na=nan)
Return boolean Series indicating whether each string in the Series/Index ends with passed pattern. Equivalent to str.endswith().

Parameters pat: string
Character sequence
na: bool, default NaN

Returns endswith: Series/array of boolean values

pandas.Series.str.extract

Series.str.extract(pat, flags=0)
Find groups in each string in the Series using passed regular expression.

Parameters pat: string
Pattern or regular expression
flags: int, default 0 (no flags)
re module flags, e.g. re.IGNORECASE

Returns extracted groups: Series (one group) or DataFrame (multiple groups)
Note that dtype of the result is always object, even when no match is found and the result is a Series or DataFrame containing only NaN values.
Examples

A pattern with one group will return a Series. Non-matches will be NaN.

```python
>>> Series(['a1', 'b2', 'c3']).str.extract('[ab](\d)')
0    1
1    2
2   NaN
dtype: object
```

A pattern with more than one group will return a DataFrame.

```python
>>> Series(['a1', 'b2', 'c3']).str.extract('([ab])(\d)')
    0   1
0   a  1
1   b  2
2  NaN NaN
```

A pattern may contain optional groups.

```python
>>> Series(['a1', 'b2', 'c3']).str.extract('([ab])?(\d)')
    0   1
0   a  1
1   b  2
2  NaN  3
```

Named groups will become column names in the result.

```python
>>> Series(['a1', 'b2', 'c3']).str.extract('(?P<letter>[ab])(?P<digit>(\d))')
  letter digit
0    a    1
1    b    2
2   NaN  NaN
```

**pandas.Series.str.find**

```
Series.str.find(sub, start=0, end=None)
```

Return lowest indexes in each strings in the Series/Index 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**

- **found**: Series/Index of integer values

See also:

- `rfind` Return highest indexes in each strings
**pandas.Series.str.findall**

Series.str.findall(pat, flags=0, **kwargs)

Find all occurrences of pattern or regular expression in the Series/Index. Equivalent to re.findall().

- **Parameters**
  - `pat` : string
    - Pattern or regular expression
  - `flags` : int, default 0 (no flags)
    - re module flags, e.g. re.IGNORECASE

- **Returns**
  - `matches` : Series/Index of lists

**pandas.Series.str.get**

Series.str.get(i)

Extract element from lists, tuples, or strings in each element in the Series/Index.

- **Parameters**
  - `i` : int
    - Integer index (location)

- **Returns**
  - `items` : Series/Index of objects

**pandas.Series.str.index**

Series.str.index(sub, start=0, end=None)

Return lowest indexes in each strings 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**
  - `found` : Series/Index of objects

**See also:**

- `rindex` Return highest indexes in each strings

**pandas.Series.str.join**

Series.str.join(sep)

Join lists contained as elements in the Series/Index with passed delimiter. Equivalent to str.join().

- **Parameters**
  - `sep` : string
    - Delimiter

- **Returns**
  - `joined` : Series/Index of objects
**pandas.Series.str.len**

```python
Series.str.len()
```

Computes length of each string in the Series/Index.

**Returns**

- `lengths`: Series/Index of integer values

**pandas.Series.str.ljust**

```python
Series.str.ljust(width, fillchar=')
```

Fills right side of strings in the Series/Index with an additional character. 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**

- `filled`: Series/Index of objects

**pandas.Series.str.lower**

```python
Series.str.lower()
```

Converts strings in the Series/Index to lowercase. Equivalent to `str.lower()`.

**Returns**

- `converted`: Series/Index of objects

**pandas.Series.str.lstrip**

```python
Series.str.lstrip(to_strip=None)
```

Strip whitespace (including newlines) from each string in the Series/Index from left side. Equivalent to `str.lstrip()`.

**Returns**

- `stripped`: Series/Index of objects

**pandas.Series.str.match**

```python
Series.str.match(pat, case=True, flags=0, na=nan, as_indexer=False)
```

Deprecated: Find groups in each string in the Series/Index using passed regular expression. If `as_indexer=True`, determine if each string matches a regular expression.

**Parameters**

- `pat`: string
  - Character sequence or regular expression
- `case`: boolean, default True
  - If True, case sensitive
- `flags`: int, default 0 (no flags)
  - `re` module flags, e.g. `re.IGNORECASE`
- `na`: default NaN, fill value for missing values
- `as_indexer`: False, by default, gives deprecated behavior better achieved
using str_extract. True return boolean indexer.

**Returns** Series/array of boolean values
- if `as_indexer=True`
  - Series/Index of tuples
- if `as_indexer=False`, default but deprecated

**See also:**
- `contains` analogous, but less strict, relying on `re.search` instead of `re.match`
- `extract` now preferred to the deprecated usage of `match` (`as_indexer=False`)

**Notes**

To extract matched groups, which is the deprecated behavior of `match`, use `str.extract`.

**pandas.Series.str.normalize**

Series.str.normalize(form)

Return the Unicode normal form for the strings in the Series/Index. For more information on the forms, see the `unicodedata.normalize()`.

**Parameters**
- `form`: {'NFC', 'NFKC', 'NFD', 'NFKD'}
  - Unicode form

**Returns** normalised: Series/Index of objects

**pandas.Series.str.pad**

Series.str.pad(width, side='left', fillchar=' ')

Pad strings in the Series/Index with an additional character to specified side.

**Parameters**
- `width`: int
  - Minimum width of resulting string; additional characters will be filled with spaces
- `side`: {'left', 'right', 'both'}, default 'left'
- `fillchar`: str
  - Additional character for filling, default is whitespace

**Returns** padded: Series/Index of objects

**pandas.Series.str.partition**

Series.str.partition(pat=' ', expand=True)

Split the string at the first occurrence of `sep`, and return 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**
- `pat`: string, default whitespace
  - String to split on.
**expand** : bool, default True

- If True, return DataFrame/MultiIndex expanding dimensionality.
- If False, return Series/Index.

**Returns** split : DataFrame/MultiIndex or Series/Index of objects

See also:

**rpartition** Split the string at the last occurrence of *sep*

**Examples**

```python
g>>> s = Series(['A_B_C', 'D_E_F', 'X'])
g 0    A_B_C
g 1    D_E_F
g 2      X
g dtype: object

g>>> s.str.partition('_')
g       0   1   2
0  A  _  B_C
g 1  D  _  E_F
g 2      X

g>>> s.str.rpartition('_')
       0   1   2
0  A_B  _  C
1  D_E  _  F
2      X
```

**pandas.Series.str.repeat**

Series.str.repeat(repeats)

Duplicate each string in the Series/Index by indicated number of times.

**Parameters** repeats : int or array

- Same value for all (int) or different value per (array)

**Returns** repeated : Series/Index of objects

**pandas.Series.str.replace**

Series.str.replace(pat, repl, n=-1, case=True, flags=0)

Replace occurrences of pattern/regex in the Series/Index with some other string. Equivalent to **str.replace()** or **re.sub()**.

**Parameters** pat : string

- Character sequence or regular expression

repl : string

- Replacement sequence

n : int, default -1 (all)
Number of replacements to make from start

case : boolean, default True
    If True, case sensitive
flags : int, default 0 (no flags)
    re module flags, e.g. re.IGNORECASE

Returns replaced : Series/Index of objects

pandas.Series.str.rfind

Series.str.rfind(sub, start=0, end=None)
    Return highest indexes in each strings in the Series/Index 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 found : Series/Index of integer values

See also:

find  Return lowest indexes in each strings

pandas.Series.str.rindex

Series.str.rindex(sub, start=0, end=None)
    Return highest indexes in each strings 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 found : Series/Index of objects

See also:

index   Return lowest indexes in each strings
**pandas.Series.str.rjust**

Series.str.rjust(width, fillchar=\'\')

Filling left side of strings in the Series/Index with an additional character. 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(pat=' ', expand=True)

Split the string at the last occurrence of sep, and return 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**

- **pat**: string, default whitespace
  - String to split on.

- **expand**: bool, default True
  - • If True, return DataFrame/MultiIndex expanding dimensionality.
  - • If False, return Series/Index.

**Returns**

split : DataFrame/MultiIndex or Series/Index of objects

See also:

partition Split the string at the first occurrence of sep

---

**Examples**

```python
>>> s = Series(['A_B_C', 'D_E_F', 'X'])
0   A_B_C
1   D_E_F
2    X
dtype: object

>>> s.str.partition('_')
0 1 2
0 A _ B_C
1 D _ E_F
2 X

>>> s.str.rpartition('_')
0 1 2
0 A_B _ C
1 D_E _ F
2 X
```
**pandas.Series.str.rstrip**

Series.str.rstrip(to_strip=None)
Strip whitespace (including newlines) from each string in the Series/Index from right side. Equivalent to str.rstrip().

Returns stripped : Series/Index of objects

**pandas.Series.str.slice**

Series.str.slice(start=None, stop=None, step=None)
Slice substrings from each element in the Series/Index

Parameters start : int or None
stop : int or None
step : int or None

Returns sliced : Series/Index of objects

**pandas.Series.str.slice_replace**

Series.str.slice_replace(start=None, stop=None, repl=None)
Replace a slice of each string in the Series/Index with another string.

Parameters start : int or None
stop : int or None
repl : str or None
String for replacement

Returns replaced : Series/Index of objects

**pandas.Series.str.split**

Series.str.split(*args, **kwargs)
Split each string (a la re.split) in the Series/Index by given pattern, propagating NA values. Equivalent to str.split().

Parameters pat : string, default None
String or regular expression to split on. If None, splits on whitespace
n : int, default -1 (all)
None, 0 and -1 will be interpreted as return all splits
expand : bool, default False
• If True, return DataFrame/MultiIndex expanding dimensionality.
• If False, return Series/Index.
New in version 0.16.1.

Returns split : Series/Index or DataFrame/MultiIndex of objects
pandas.Series.str.rsplit

Series.str.rsplit (pat=None, n=-1, expand=False)
Split each string in the Series/Index by the given delimiter string, starting at the end of the string and working to the front. Equivalent to str.rsplit().

New in version 0.16.2.

Parameters  
- **pat** : string, default None
  - Separator to split on. If None, splits on whitespace
- **n** : int, default -1 (all)
  - None, 0 and -1 will be interpreted as return all splits
- **expand** : bool, default False
  - If True, return DataFrame/MultiIndex expanding dimensionality.
  - If False, return Series/Index.

Returns split : Series/Index or DataFrame/MultiIndex of objects

pandas.Series.str.startswith

Series.str.startswith (pat, na=nan)
Return boolean Series/array indicating whether each string in the Series/Index starts with passed pattern. Equivalent to str.startswith().

Parameters  
- **pat** : string
  - Character sequence
- **na** : bool, default NaN

Returns startswith : Series/array of boolean values

pandas.Series.str.strip

Series.str.strip (to_strip=None)
Strip whitespace (including newlines) from each string in the Series/Index from left and right sides. Equivalent to str.strip().

Returns stripped : Series/Index of objects

pandas.Series.str.swapcase

Series.str.swapcase ()
Convert strings in the Series/Index to be swapcased. Equivalent to str.swapcase().

Returns converted : Series/Index of objects

pandas.Series.str.title

Series.str.title ()
Convert strings in the Series/Index to titlecase. Equivalent to str.title().

Returns converted : Series/Index of objects
**pandas.Series.str.translate**

Series.str.translate(table, deletechars=None)

Map all characters in the string through the given mapping table. Equivalent to standard str.translate(). Note that the optional argument deletechars is only valid if you are using python 2. For python 3, character deletion should be specified via the table argument.

**Parameters**
- **table**: dict (python 3), str or None (python 2)
  - In python 3, 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.
  - In python 2, table is either a string of length 256 or None. If the table argument is None, no translation is applied and the operation simply removes the characters in deletechars. string.maketrans() is a helper function for making translation tables.
- **deletechars**: str, optional (python 2)
  - A string of characters to delete. This argument is only valid in python 2.

**Returns**
- **translated**: Series/Index of objects

**pandas.Series.str.upper**

Series.str.upper()

Convert strings in the Series/Index to uppercase. Equivalent to str.upper().

**Returns**
- **converted**: Series/Index of objects

**pandas.Series.str.wrap**

Series.str.wrap(width, **kwargs)

Wrap long strings in the Series/Index to be formatted in paragraphs with length less than a given 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** wrapped: Series/Index of objects

**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\nto be\n  wrapped
```

**pandas.Series.str.zfill**

Series.str.zfill(width)

"Filling left side of strings in the Series/Index with 0. Equivalent to `str.zfill()`.

**Parameters** width : int

Minimum width of resulting string; additional characters will be filled with 0

**Returns** filled: Series/Index of objects

**pandas.Series.str.isalnum**

Series.str.isalnum()

Check whether all characters in each string in the Series/Index are alphanumeric. Equivalent to `str.isalnum()`.

**Returns** is: Series/array of boolean values

**pandas.Series.str.isalpha**

Series.str.isalpha()

Check whether all characters in each string in the Series/Index are alphabetic. Equivalent to `str.isalpha()`.

**Returns** is: Series/array of boolean values
**pandas.Series.str.isdigit**

Series.str.isdigit()  
Check whether all characters in each string in the Series/Index are digits. Equivalent to str.isdigit().  
Returns is : Series/array of boolean values

**pandas.Series.str.isspace**

Series.str.isspace()  
Check whether all characters in each string in the Series/Index are whitespace. Equivalent to str.isspace().  
Returns is : Series/array of boolean values

**pandas.Series.str.islower**

Series.str.islower()  
Check whether all characters in each string in the Series/Index are lowercase. Equivalent to str.islower().  
Returns is : Series/array of boolean values

**pandas.Series.str.isupper**

Series.str.isupper()  
Check whether all characters in each string in the Series/Index are uppercase. Equivalent to str.isupper().  
Returns is : Series/array of boolean values

**pandas.Series.str.istitle**

Series.str.istitle()  
Check whether all characters in each string in the Series/Index are titlecase. Equivalent to str.istitle().  
Returns is : Series/array of boolean values

**pandas.Series.str.isnumeric**

Series.str.isnumeric()  
Check whether all characters in each string in the Series/Index are numeric. Equivalent to str.isnumeric().  
Returns is : Series/array of boolean values

**pandas.Series.str.isdecimal**

Series.str.isdecimal()  
Check whether all characters in each string in the Series/Index are decimal. Equivalent to str.isdecimal().  
Returns is : Series/array of boolean values
pandas.Series.str.get_dummies

Series.str.get_dummies(sep='|')

Split each string in the Series by sep and return a frame of dummy/indicator variables.

**Parameters**

- **sep**: string, default “|”
  
  String to split on.

**Returns**

- **dummies**: DataFrame

**See also:**

- pandas.get_dummies

**Examples**

```python
>>> Series(['a|b', 'a', 'a|c']).str.get_dummies()
   a  b  c
0  1  1  0
1  1  0  0
2  1  0  1
```

```python
>>> 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
```

### 34.3.15 Categorical

If the Series is of dtype category, Series.cat can be used to change the the categorical data. This accessor is similar to the Series.dt or Series.str and has the following usable methods and properties:

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.cat.categories</td>
<td>The categories of this categorical.</td>
</tr>
<tr>
<td>Series.cat.ordered</td>
<td>Gets the ordered attribute</td>
</tr>
<tr>
<td>Series.cat.codes</td>
<td></td>
</tr>
</tbody>
</table>

**pandas.Series.cat.categories**

- **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, reorder_categories, add_categories, remove_categories, remove_unused_categories, set_categories

pandas.Series.cat.ordered

Series.cat.ordered
Gets the ordered attribute

pandas.Series.cat.codes

Series.cat.codes

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.cat.rename_categories(*args, **kwargs)</td>
<td>Renames categories.</td>
</tr>
<tr>
<td>Series.cat.reorder_categories(*args, **kwargs)</td>
<td>Reorders categories as specified in new_categories.</td>
</tr>
<tr>
<td>Series.cat.add_categories(*args, **kwargs)</td>
<td>Add new categories.</td>
</tr>
<tr>
<td>Series.cat.remove_categories(*args, **kwargs)</td>
<td>Removes the specified categories.</td>
</tr>
<tr>
<td>Series.cat.remove_unused_categories(*args, ...)</td>
<td>Removes categories which are not used.</td>
</tr>
<tr>
<td>Series.cat.set_categories(*args, **kwargs)</td>
<td>Sets the categories to the specified new_categories.</td>
</tr>
<tr>
<td>Series.cat.as_ordered(*args, **kwargs)</td>
<td>Sets the Categorical to be ordered</td>
</tr>
<tr>
<td>Series.cat.as_unordered(*args, **kwargs)</td>
<td>Sets the Categorical to be unordered</td>
</tr>
</tbody>
</table>

pandas.Series.cat.rename_categories

Series.cat.rename_categories(*args, **kwargs)
Renames categories.

The new categories 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.

**Parameters**

- **new_categories** : Index-like
  
  The renamed categories.

- **inplace** : boolean (default: False)
  
  Whether or not to rename the categories inplace or return a copy of this categorical with renamed categories.

**Returns**

- **cat** : Categorical with renamed categories added or None if inplace.

**Raises**

- **ValueError**
  
  If the new categories do not have the same number of items than the current categories or do not validate as categories

  **See also:**

  reorder_categories, add_categories, remove_categories, remove_unused_categories, set_categories

pandas.Series.cat.reorder_categories

Series.cat.reorder_categories(*args, **kwargs)
Reorders 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 : boolean, optional

Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

inplace : boolean (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, add_categories, remove_categories, remove_unused_categories, set_categories

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 : boolean (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, reorder_categories, remove_categories, remove_unused_categories, set_categories

pandas.Series.cat.remove_categories

Series.cat.remove_categories(*args, **kwargs)

Removes 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.
**pandas**: powerful Python data analysis toolkit, Release 0.17.0

**inplace**: boolean (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, reorder_categories, add_categories, remove_unused_categories, set_categories

**pandas.Series.cat.remove_unused_categories**

Series.cat.remove_unused_categories(*args, **kwargs)

Removes categories which are not used.

**Parameters** inplace: boolean (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, reorder_categories, add_categories, remove_categories, set_categories

**pandas.Series.cat.set_categories**

Series.cat.set_categories(*args, **kwargs)

Sets the categories to the specified new_categories.

new_categories can include new categories (which will result in unused categories) or 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 on python3, 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: boolean, (default: False)

Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

rename: boolean (default: False)

Whether or not the new_categories should be considered as a rename of the old categories or as reordered categories.
inplace : boolean (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 new_categories does not validate as categories

See also:

rename_categories, reorder_categories, add_categories, remove_categories, remove_unused_categories

pandas.Series.cat.as_ordered

Series.cat.as_ordered(*args, **kwargs)

Sets the Categorical to be ordered

Parameters inplace : boolean (default: False)

Whether or not to set the ordered attribute inplace or return a copy of this categorical with ordered set to True

pandas.Series.cat.as_unordered

Series.cat.as_unordered(*args, **kwargs)

Sets the Categorical to be unordered

Parameters inplace : boolean (default: False)

Whether or not to set the ordered attribute inplace or return a copy of this categorical with ordered set to False

To create a Series of dtype category, use cat = s.astype("category").

The following two Categorical constructors are considered API but should only be used when adding ordering information or special categories is need at creation time of the categorical data:

Categorical(values[, categories, ordered, ...]) Represents a categorical variable in classic R / S-plus fashion

pandas.Categorical

class pandas.Categorical (values, categories=None, ordered=False, name=None, fastpath=False, levels=None)

Represents 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.

**ordered** : boolean, (default False)

Whether or not this categorical is treated as a ordered categorical. If not given, the resulting categorical will not be ordered.

**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.

---

**Examples**

```python
>>> from pandas import Categorical
>>> Categorical([1, 2, 3, 1, 2, 3])
[1, 2, 3, 1, 2, 3]
Categories (3, int64): [1 < 2 < 3]

>>> Categorical(['a', 'b', 'c', 'a', 'b', 'c'])
[a, b, c, a, b, c]
Categories (3, object): [a < b < c]

>>> a = Categorical(['a','b','c','a','b','c'], ['c', 'b', 'a'], ordered=True)

>>> a.min()
'c'
```

**Categorical.from_codes**(codes, categories[, ...])  Make a Categorical type from codes and categories arrays.

**pandas.Categorical.from_codes**

**classmethod** **pandas.Categorical.from_codes**(codes, categories[, ordered=False, name=None])

Make a Categorical type from codes and categories arrays.

This constructor is useful if you already have codes and categories 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, integers

An integer array, where each integer points to a category in categories or -1 for NaN

**categories** : index-like

The categories for the categorical. Items need to be unique.

**ordered** : boolean, (default False)

Whether or not this categorical is treated as a ordered categorical. If not given, the resulting categorical will be unordered.

**np.asarray**(categorical) works by implementing the array interface. Be aware, that this converts the Categorical back to a numpy array, so levels and order information is not preserved!
Categorical.__array__((dtype))  The numpy array interface.

pandas.Categorical.__array__

Categorical.__array__(dtype=None)

The numpy array interface.

Returns values : numpy array

A numpy array of either the specified dtype or, if dtype==None (default), the same
dtype as categorical.categories.dtype

34.3.16 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

pandas.Series.plot

Series.plot(kind='line', ax=None, figsize=None, use_index=True, title=None, grid=None, legend=False, style=None, logx=False, logy=False, loglog=False, xticks=None, yticks=None, xlim=None, ylim=None, rot=None, fontsize=None, colormap=None, table=False, yerr=None, xerr=None, label=None, secondary_y=False, **kwds)

Make plots of Series using matplotlib / pylab.

New in version 0.17.0: Each plot kind has a corresponding method on the Series.plot accessor:
s.plot(kind='line') is equivalent to s.plot.line().

Parameters data : Series

kind : str
  • ‘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
ax : matplotlib axes object
  If not passed, uses gca()
figsize : a tuple (width, height) in inches
use_index : boolean, default True
Use index as ticks for x axis

title : string
    Title to use for the plot

grid : boolean, default None (matlab style default)
    Axis grid lines

legend : False/True/‘reverse’
    Place legend on axis subplots

style : list or dict
    matplotlib line style per column

logx : boolean, default False
    Use log scaling on x axis

logy : boolean, default False
    Use log scaling on y axis

loglog : boolean, default False
    Use log scaling on both x and y axes

xticks : sequence
    Values to use for the xticks

yticks : sequence
    Values to use for the yticks

xlim : 2-tuple/list

ylim : 2-tuple/list

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 : boolean, 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)

layout : tuple (optional)
    (rows, columns) for the layout of the plot

table : boolean, 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** : same types as yerr.

**label** : label argument to provide to plot

**secondary_y** : boolean or sequence of ints, default False

If True then y-axis will be on the right

**mark_right** : boolean, default True

When using a secondary_y axis, automatically mark the column labels with “(right)” in the legend

**kwds** : keywords

Options to pass to matplotlib plotting method

Returns axes : matplotlib.AxesSubplot or np.array of them

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)

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series.plot.area(<strong>kwds)</strong></td>
<td>Area plot</td>
</tr>
<tr>
<td>Series.plot.bar(<strong>kwds)</strong></td>
<td>Vertical bar plot</td>
</tr>
<tr>
<td>Series.plot.barh(<strong>kwds)</strong></td>
<td>Horizontal bar plot</td>
</tr>
<tr>
<td>Series.plot.box(<strong>kwds)</strong></td>
<td>Boxplot</td>
</tr>
<tr>
<td>Series.plot.density(<strong>kwds)</strong></td>
<td>Kernel Density Estimate plot</td>
</tr>
<tr>
<td>Series.plot.hist([bins])</td>
<td>Histogram</td>
</tr>
<tr>
<td>Series.plot.kde(<strong>kwds)</strong></td>
<td>Kernel Density Estimate plot</td>
</tr>
<tr>
<td>Series.plot.line(<strong>kwds)</strong></td>
<td>Line plot</td>
</tr>
<tr>
<td>Series.plot.pie(<strong>kwds)</strong></td>
<td>Pie chart</td>
</tr>
</tbody>
</table>

### pandas.Series.plot.area

**Series.plot.area(**kwds)**

Area plot

New in version 0.17.0.

Parameters **kwds** : optional

Keyword arguments to pass on to pandas.Series.plot().

Returns axes : matplotlib.AxesSubplot or np.array of them
pandas.Series.plot.bar

Series.plot.bar(**kwds)
    Vertical bar plot

    New in version 0.17.0.

    Parameters **kwds : optional
        Keyword arguments to pass on to pandas.Series.plot().

    Returns axes : matplotlib.AxesSubplot or np.array of them

pandas.Series.plot.barh

Series.plot.barh(**kwds)
    Horizontal bar plot

    New in version 0.17.0.

    Parameters **kwds : optional
        Keyword arguments to pass on to pandas.Series.plot().

    Returns axes : matplotlib.AxesSubplot or np.array of them

pandas.Series.plot.box

Series.plot.box(**kwds)
    Boxplot

    New in version 0.17.0.

    Parameters **kwds : optional
        Keyword arguments to pass on to pandas.Series.plot().

    Returns axes : matplotlib.AxesSubplot or np.array of them

pandas.Series.plot.density

Series.plot.density(**kwds)
    Kernel Density Estimate plot

    New in version 0.17.0.

    Parameters **kwds : optional
        Keyword arguments to pass on to pandas.Series.plot().

    Returns axes : matplotlib.AxesSubplot or np.array of them

pandas.Series.plot.hist

Series.plot.hist(bins=10, **kwds)
    Histogram

    New in version 0.17.0.

    Parameters bins : integer, default 10
Number of histogram bins to be used

**kwds**: optional

Keyword arguments to pass on to `pandas.Series.plot()`.

**Returns** axes : matplotlib.AxesSubplot or np.array of them

### pandas.Series.plot.kde

`Series.plot.kde(**kwds)`

Kernel Density Estimate plot

New in version 0.17.0.

**Parameters** **kwds**: optional

Keyword arguments to pass on to `pandas.Series.plot()`.

**Returns** axes : matplotlib.AxesSubplot or np.array of them

### pandas.Series.plot.line

`Series.plot.line(**kwds)`

Line plot

New in version 0.17.0.

**Parameters** **kwds**: optional

Keyword arguments to pass on to `pandas.Series.plot()`.

**Returns** axes : matplotlib.AxesSubplot or np.array of them

### pandas.Series.plot.pie

`Series.plot.pie(**kwds)`

Pie chart

New in version 0.17.0.

**Parameters** **kwds**: optional

Keyword arguments to pass on to `pandas.Series.plot()`.

**Returns** axes : matplotlib.AxesSubplot or np.array of them

**Series.hist(by, ax, grid, xlabelsize, ...)**  
Draw histogram of the input series using matplotlib

### pandas.Series.hist

`Series.hist(by=None, ax=None, grid=True, xlabelsize=None, xrot=None, ylabelsize=None, yrot=None, figsize=None, bins=10, **kwds)`

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 : boolean, 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: integer, default 10
    Number of histogram bins to be used

kwds : keywords
    To be passed to the actual plotting function

Notes

See matplotlib documentation online for more on this

34.3.17 Serialization / IO / Conversion

Series.from_csv(path[, sep, parse_dates, ...])
    Read CSV file (DISCOURAGED, please use pandas.read_csv() instead)

Series.to_pickle(path)
    Pickle (serialize) object to input file path

Series.to_csv(path[, index, sep, na_rep, ...])
    Write Series to a comma-separated values (csv) file

Series.to_dict()
    Convert Series to {label -> value} dict

Series.to_frame([name])
    Convert Series to DataFrame

Series.to_hdf(path_or_buf, key, **kwargs)
    activate the HDFStore

Series.to_sql(name, con[, flavor, schema, ...])
    Write records stored in a DataFrame to a SQL database.

Series.to_msgpack([path_or_buf])
    msgpack (serialize) object to input file path

Series.to_json([path_or_buf, orient, ...])
    Convert the object to a JSON string.

Series.to_sparse([kind, fill_value])
    Convert Series to SparseSeries

Series.to_dense()
    Return dense representation of NDFrame (as opposed to sparse)

Series.to_string([buf, na_rep, ...])
    Render a string representation of the Series

Series.to_clipboard([excel, sep])
    Attempt to write text representation of object to the system clipboard This can be

pandas.Series.from_csv

classmethod Series.from_csv(path, sep=' ', parse_dates=True, header=None, index_col=0, encoding=None, infer_datetime_format=False)
    Read CSV file (DISCOURAGED, please use pandas.read_csv() instead).
It is preferable to use the more powerful `pandas.read_csv()` for most general purposes, but `from_csv` makes for an easy roundtrip to and from a file (the exact counterpart of `to_csv`), especially with a time Series.

This method only differs from `pandas.read_csv()` in some defaults:

- `index_col` is 0 instead of None (take first column as index by default)
- `header` is None instead of 0 (the first row is not used as the column names)
- `parse_dates` is True instead of False (try parsing the index as datetime by default)

With `pandas.read_csv()`, the option `squeeze=True` can be used to return a Series like `from_csv`.

**Parameters**

- **path**: string file path or file handle / StringIO
  - `sep`: string, default ','
    - Field delimiter
  - `parse_dates`: boolean, default True
    - Parse dates. Different default from read_table
  - `header`: int, default None
    - Row to use as header (skip prior rows)
  - `index_col`: int or sequence, default 0
    - Column to use for index. If a sequence is given, a MultiIndex is used. Different default from read_table
  - `encoding`: string, optional
    - a string representing the encoding to use if the contents are non-ascii, for python versions prior to 3
  - `infer_datetime_format`: boolean, default False
    - If True and `parse_dates` is True for a column, try to infer the datetime format based on the first datetime string. If the format can be inferred, there often will be a large parsing speed-up.

**Returns**

- `y`: Series

**See also:**

- `pandas.read_csv`

### pandas.Series.to_pickle

**Series.to_pickle**(path)

Pickle (serialize) object to input file path

**Parameters**

- **path**: string
  - File path

### pandas.Series.to_csv

**Series.to_csv**(path, index=True, sep=’,’, na_rep=’,’, float_format=None, header=False, index_label=None, mode='w', nanRep=None, encoding=None, date_format=None, decimal=’,’)

Write Series to a comma-separated values (csv) file
**Parameters**  
*path*: string file path or file handle / `StringIO`. If None is provided, the result is returned as a string.
  
*na_rep*: string, default ‘’
  
*float_format*: string, default None
  
*header*: boolean, default False
  
*index*: boolean, default True
  
*index_label*: string or sequence, default None
  
*mode*: Python write mode, default ‘w’
  
*sep*: character, default ‘,”’
  
*encoding*: string, optional
  
*date_format*: string, default None
  
*decimal*: string, default ‘.’
  
---

**pandas.Series.to_dict**

Series.to_dict()  
Convert Series to {label -> value} dict  
  
**Returns**  
*value_dict*: dict

**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**  
*data_frame*: DataFrame
**pandas.Series.to_hdf**

`Series.to_hdf(path_or_buf, key, **kwargs)`

activate the HDFStore

**Parameters**

- **path_or_buf**: the path (string) or HDFStore object
- **key**: string
  - identifier for the group in the store
- **mode**: optional, {'a', 'w', 'r', 'r+'}, default ‘a’
  - ‘r’ Read-only; no data can be modified.
  - ‘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+’ It is similar to ‘a’, but the file must already exist.
- **format**: ‘fixed(f)|table(t)’, default is ‘fixed’
  - fixed(f) [Fixed format] Fast writing/reading. Not-appendable, nor searchable
  - table(t) [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**: boolean, default False
  - For Table formats, append the input data to the existing
- **complevel**: int, 1-9, default 0
  - If a complib is specified compression will be applied where possible
- **complib**: {'zlib', 'bzip2', 'lzma', 'blosc', None}, default None
  - If complevel is > 0 apply compression to objects written in the store wherever possible
- **fletcher32**: bool, default False
  - If applying compression use the fletcher32 checksum
- **dropna**: boolean, default False.
  - If true, ALL nan rows will not be written to store.

**pandas.Series.to_sql**

`Series.to_sql(name, con, flavor='sqlite', schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None)`

Write records stored in a DataFrame to a SQL database.

**Parameters**

- **name**: string
  - Name of SQL table
- **con**: SQLAlchemy engine or DBAPI2 connection (legacy mode)
  - Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.
flavor : {'sqlite', 'mysql'}, default 'sqlite'

The flavor of SQL to use. Ignored when using SQLAlchemy engine. 'mysql' is deprecated and will be removed in future versions, but it will be further supported through SQLAlchemy engines.

schema : string, default None

Specify the schema (if database flavor supports this). If None, use default schema.

if_exists : {'fail', 'replace', 'append'}, default 'fail'

- fail: If table exists, do nothing.
- replace: If table exists, drop it, recreate it, and insert data.
- append: If table exists, insert data. Create if does not exist.

index : boolean, default True

Write DataFrame index as a column.

index_label : string 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, default None

If not None, then rows will be written in batches of this size at a time. If None, all rows will be written at once.

dtype : dict of column name to SQL type, default None

Optional specifying the datatype for columns. The SQL type should be a SQLAlchemy type, or a string for sqlite3 fallback connection.

pandas.Series.to_msgpack

Series.to_msgpack (path_or_buf=None, **kwargs)

msgpack (serialize) object to input file path

THIS IS AN EXPERIMENTAL LIBRARY and the storage format may not be stable until a future release.

Parameters path : string File path, buffer-like, or None

if None, return generated string

append : boolean whether to append to an existing msgpack

(default is False)

compress : type of compressor (zlib or blosc), default to None (no compression)

pandas.Series.to_json

Series.to_json (path_or_buf=None, orient=None, date_format='epoch', double_precision=10, force_ascii=True, date_unit='ms', default_handler=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**: the path or buffer to write the result string

- if this is None, return a StringIO of the converted string

**orient**: string
- **Series**
  - default is ‘index’
  - allowed values are: {'split', 'records', 'index'}
- **DataFrame**
  - default is ‘columns’
  - allowed values are: {'split', 'records', 'index', 'columns', 'values'}
- 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 -> {index -> value}}
  - values: just the values array

**date_format**: {'epoch', 'iso'}
Type of date conversion. *epoch* = epoch milliseconds, *iso* = ISO8601, default is epoch.

**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**: string, 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.

**Returns** same type as input object with filtered info axis

**pandas.Series.to_sparse**

Series.to_sparse(*kind='block', fill_value=None*)
Convert Series to SparseSeries

**Parameters**
- **kind**: {'block', 'integer'}
- **fill_value**: float, defaults to NaN (missing)

**Returns** sp: SparseSeries
pandas.Series.to_dense

Series.to_dense()
Return dense representation of NDFrame (as opposed to sparse)

pandas.Series.to_string

Series.to_string(buf=None, na_rep='NaN', float_format=None, header=True, length=False, dtype=False, name=False, max_rows=None)
Render a string representation of the Series

**Parameters**

- **buf**: StringIO-like, optional
  buffer to write to
- **na_rep**: string, optional
  string representation of NAN to use, default ‘NaN’
- **float_format**: one-parameter function, optional
  formatter function to apply to columns’ elements if they are floats default None
- **header**: boolean, default True
  Add the Series header (index name)
- **length**: boolean, default False
  Add the Series length
- **dtype**: boolean, default False
  Add the Series dtype
- **name**: boolean, 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.

**Returns**

formatted : string (if not buffer passed)

pandas.Series.to_clipboard

Series.to_clipboard(excel=None, sep=None, **kwargs)
Attempt to write text representation of object to the system clipboard This can be pasted into Excel, for example.

**Parameters**

- **excel**: boolean, defaults to True
  if True, use the provided separator, writing in a csv format for allowing easy pasting into excel. if False, write a string representation of the object to the clipboard
- **sep**: optional, defaults to tab
- **other keywords are passed to to_csv**
Notes

Requirements for your platform
- Linux: xclip, or xsel (with gtk or PyQt4 modules)
- Windows: none
- OS X: none

34.3.18 Sparse methods

SparseSeries.to_coo(row_levels=..., column_levels=...) Create a scipy.sparse.coo_matrix from a SparseSeries with MultiIndex.
SparseSeries.from_coo(A[, dense_index]) Create a SparseSeries from a scipy.sparse.coo_matrix.

pandas.SparseSeries.to_coo

SparseSeries.to_coo (row_levels=(0,), column_levels=(1,), sort_labels=False)
Create a scipy.sparse.coo_matrix from a SparseSeries 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).
New in version 0.16.0.

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
>>> from numpy import nan
>>> s = Series([3.0, nan, 1.0, 3.0, nan, nan])
>>> s.index = 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'])
```
```
>>> ss = s.to_sparse()
>>> A, rows, columns = ss.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>

```python
>>> A.todense()
matrix([[ 0., 0., 1., 3.],
        [ 3., 0., 0., 0.],
        [ 0., 0., 0., 0.]])
```

```python
>>> rows
[(1, 1), (1, 2), (2, 1)]
```

```python
>>> columns
[('a', 0), ('a', 1), ('b', 0), ('b', 1)]
```

### pandas.SparseSeries.from_coo

classmethod **SparseSeries.from_coo** *(A, dense_index=False)*  
Create a SparseSeries from a scipy.sparse.coo_matrix.

New in version 0.16.0.

**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** : SparseSeries

**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))
```

```python
>>> 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 = SparseSeries.from_coo(A)
```

```python
>>> ss
0 2 1
3 2
1 0 3
dtype: float64
```

34.4 DataFrame

34.4.1 Constructor
**DataFrame**

Two-dimensional size-mutable, potentially heterogeneous tabular data structure with labeled axes (rows and columns). Arithmetic operations align on both row and column labels. Can be thought of as a dict-like container for Series objects. The primary pandas data structure

**Parameters**
- **data**: numpy ndarray (structured or homogeneous), dict, or DataFrame
  - Dict can contain Series, arrays, constants, or list-like objects
- **index**: Index or array-like
  - Index to use for resulting frame. Will default to np.arange(n) if no indexing information part of input data and no index provided
- **columns**: Index or array-like
  - Column labels to use for resulting frame. Will default to np.arange(n) if no column labels are provided
- **dtype**: dtype, default None
  - Data type to force, otherwise infer
- **copy**: boolean, default False
  - Copy data from inputs. Only affects DataFrame / 2d ndarray input

**See also:**
- `DataFrame.from_records`
- `DataFrame.from_dict`
- `DataFrame.from_items`
- `pandas.read_csv`, `pandas.read_table`, `pandas.read_clipboard`

**Examples**

```python
>>> d = {'col1': ts1, 'col2': ts2}
>>> df = DataFrame(data=d, index=index)
>>> df2 = DataFrame(np.random.randn(10, 5))
>>> df3 = DataFrame(np.random.randn(10, 5),
...                 columns=['a', 'b', 'c', 'd', 'e'])
```

**Attributes**

- **T**
  - Transpose index and columns
- **at**
  - Fast label-based scalar accessor
- **axes**
  - Return a list with the row axis labels and column axis labels as the only members.
- **blocks**
  - Internal property, property synonym for as_blocks()
Table 34.52 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>dtypes</td>
<td>Return the dtypes in this object</td>
</tr>
<tr>
<td>empty</td>
<td>True if NDFrame is entirely empty [no items]</td>
</tr>
<tr>
<td>ftypes</td>
<td>Return the ftypes (indication of sparse/dense and dtype) in this object.</td>
</tr>
<tr>
<td>iat</td>
<td>Fast integer location scalar accessor.</td>
</tr>
<tr>
<td>iloc</td>
<td>Purely integer-location based indexing for selection by position.</td>
</tr>
<tr>
<td>is_copy</td>
<td>A primarily label-location based indexer, with integer position fallback.</td>
</tr>
<tr>
<td>ix</td>
<td>Purely label-location based indexer for selection by label.</td>
</tr>
<tr>
<td>loc</td>
<td>Number of axes / array dimensions</td>
</tr>
<tr>
<td>ndim</td>
<td>Number of axes / array dimensions</td>
</tr>
<tr>
<td>shape</td>
<td>Return a tuple representing the dimensionality of the DataFrame.</td>
</tr>
<tr>
<td>size</td>
<td>number of elements in the NDFrame</td>
</tr>
<tr>
<td>values</td>
<td>Numpy representation of NDFrame</td>
</tr>
</tbody>
</table>

**pandas.DataFrame.T**

DataFrame.T

Transpose index and columns

**pandas.DataFrame.at**

DataFrame.at

Fast label-based scalar accessor

Similarly to loc, at provides label based scalar lookups. You can also set using these indexers.

**pandas.DataFrame.axes**

DataFrame.axes

Return a list with the row axis labels and column axis labels as the only members. They are returned in that order.

**pandas.DataFrame.blocks**

DataFrame.blocks

Internal property, property synonym for as_blocks()

**pandas.DataFrame.dtypes**

DataFrame.dtypes

Return the dtypes in this object

**pandas.DataFrame.empty**

DataFrame.empty

True if NDFrame is entirely empty [no items]
pandas.DataFrame.ftypes

DataFrame.ftypes
Return the ftypes (indication of sparse/dense and dtype) in this object.

pandas.DataFrame.iat

DataFrame.iat
Fast integer location scalar accessor.

Similarly to iloc, iat provides integer based lookups. You can also set using these indexers.

pandas.DataFrame.iloc

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.

.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

pandas.DataFrame.is_copy

DataFrame.is_copy = None

pandas.DataFrame.ix

DataFrame.ix
A primarily label-location based indexer, with integer position fallback.

.ix[] supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type.

.ix is the most general indexer and will support any of the inputs in .loc and .iloc. .ix also supports floating point label schemes. .ix is exceptionally useful when dealing with mixed positional and label based hierarchical indexes.

However, when an axis is integer based, ONLY label based access and not positional access is supported. Thus, in such cases, it’s usually better to be explicit and use .iloc or .loc.

See more at Advanced Indexing.
pandas.DataFrame.loc

Dataframe.loc
Purely label-location based indexer for selection by label.
.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' (note that contrary to usual python slices, both the start and the stop are included!).
• A boolean array.
.loc will raise a KeyError when the items are not found.

See more at Selection by Label

pandas.DataFrame.ndim

Dataframe.ndim
Number of axes / array dimensions

pandas.DataFrame.shape

Dataframe.shape
Return a tuple representing the dimensionality of the DataFrame.

pandas.DataFrame.size

Dataframe.size
Number of elements in the NDFrame

pandas.DataFrame.values

Dataframe.values
Numpy representation of NDFrame

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 upcase to int32.
Methods

abs()  Return an object with absolute value taken.
add(other[, axis, level, fill_value])  Addition of dataframe and other, element-wise (binary operator add).
add_prefix(prefix)  Concatenate prefix string with panel items names.
add_suffix(suffix)  Concatenate suffix string with panel items names.
align(other[, join, axis, level, copy, ...])  Align two object on their axes with the
all([axis, bool_only, skipna, level])  Return whether all elements are True over requested axis
any([axis, bool_only, skipna, level])  Return whether any element is True over requested axis
append(other[, ignore_index, verify_integrity])  Append rows of other to the end of this frame, returning a new object.
apply(func[, axis, broadcast, raw, reduce, args])  Applies function along input axis of DataFrame.
applymap(func)  Apply a function to a DataFrame that is intended to operate elementwise, i.e.
as_blocks([copy])  Convert the frame to a dict of dtype -> Constructor Types that each has a homogeneous dtype.
as_matrix([columns])  Convert the frame to its Numpy-array representation.
asfreq(freq[, method, how, normalize])  Convert all TimeSeries inside to specified frequency using DateOffset objects.
assign(**kwargs)  Assign new columns to a DataFrame, returning a new object (a copy) with all the Cast object to input numpy.dtype
astype(dtype[, copy, raise_on_error])  Select values at particular time of day (e.g.
at_time(time[, asof])  Convert the frame to its Numpy-array representation.
between_time(start_time, end_time[, ...])  Convert all TimeSeries inside to specified frequency using DateOffset objects.
bfill([axis, inplace, limit, downcast])  Assign new columns to a DataFrame, returning a new object (a copy) with all the Cast object to input numpy.dtype
bfill([axis, inplace, limit, downcast])  Select values at particular times of the day (e.g., 9:00-9:30 AM)
bool()  Synonym for NDFrame.fillna(method='bfill')
boxplot([column, by, ax, fontsize, rot, ...])  Return the bool of a single element PandasObject
clip([lower, upper, out, axis])  Make a box plot from DataFrame column optionally grouped by some columns
clip_lower(threshold[, axis])  Trim values at input threshold(s)
clip_upper(threshold[, axis])  Return copy of the input with values below given value(s) truncated
combine(other, func[, fill_value, overwrite])  Add two DataFrame objects and do not propagate NaN values, so if for a
combineAdd(other)  DEPRECATED.
combineMult(other)  DEPRECATED.
combine_first(other)  Combine two DataFrame objects and default to non-null values in frame calling the method.
compound([axis, skipna, level])  Return the compound percentage of the values for the requested axis
consolidate([inplace])  Compute NDFrame with “consolidated” internals (data of each dtype grouped together)
convert_objects([convert_dates, ...])  Attempt to infer better dtype for object columns
copy([deep])  Make a copy of this object
corr([method, min_periods])  Make a copy of this object
corrwith(other[, axis, drop])  Compute pairwise correlation of columns, excluding NA/null values
count([axis, level, numeric_only])  Compute pairwise correlation between rows or columns of two DataFrame objects.
cov([min_periods])  Return Series with number of non-NA/null observations over requested axis.
cummax([axis, dtype, out, skipna])  Compute pairwise covariance of columns, excluding NA/null values
cummin([axis, dtype, out, skipna])  Return cumulative max over requested axis.
cumprod([axis, dtype, out, skipna])  Return cumulative min over requested axis.
cumsum([axis, dtype, out, skipna])  Return cumulative prod over requested axis.
describe([percentiles, include, exclude])  Return cumulative sum over requested axis.
diff([periods, axis])  Generate various summary statistics, excluding NaN values.
div([other[, axis, level, fill_value]])  1st discrete difference of object
divide([other[, axis, level, fill_value]])  Floating division of dataframe and other, element-wise (binary operator true_divide)
dot([other])  Floating division of dataframe and other, element-wise (binary operator true_divide)
drop([labels[, axis, level, inplace, errors]])  Matrix multiplication with DataFrame or Series objects
drop_duplicates([*args, **kwvars])  Return new object with labels in requested axis removed
dropna([axis, how, thresh, subset, inplace])  Return DataFrame with duplicate rows removed, optionally only
duplicated([*args, **kwvars])  Return object with labels on given axis omitted where alternately any
eq(other[, axis, level])  Wrapper for flexible comparison methods eq
equals(other)  Determines if two NDFrame objects contain the same elements.
pandas: powerful Python data analysis toolkit, Release 0.17.0

Table 34.53 – continued from previous page

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>eval(expr, **kwargs)</code></td>
<td>Evaluate an expression in the context of the calling DataFrame instance.</td>
</tr>
<tr>
<td><code>ffill(axis, inplace, limit, downcast)</code></td>
<td>Synonym for NDFrame.fillna(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>Restrict the info axis to set of items or wildcard</td>
</tr>
<tr>
<td><code>first(offset)</code></td>
<td>Convenience method for subsetting initial periods of time series data</td>
</tr>
<tr>
<td><code>first_valid_index()</code></td>
<td>Return label for first non-NA/null value</td>
</tr>
<tr>
<td><code>floordiv(other[, axis, level, fill_value])</code></td>
<td>Integer division of dataframe and other, element-wise (binary operator <code>floordiv</code>).</td>
</tr>
<tr>
<td><code>from_csv(path[, header, sep, index_col, ...])</code></td>
<td>Read CSV file (DISCOURAGED, please use <code>pandas.read_csv()</code> instead).</td>
</tr>
<tr>
<td><code>from_dict(data[, orient, dtype])</code></td>
<td>Construct DataFrame from dict of array-like or dicts</td>
</tr>
<tr>
<td><code>from_items(items[, columns, orient])</code></td>
<td>Convert (key, value) pairs to DataFrame.</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>Wrapper for flexible comparison methods <code>ge</code>.</td>
</tr>
<tr>
<td><code>get(key[, default])</code></td>
<td>Get item from object for given key (DataFrame column, Panel slice, etc.).</td>
</tr>
<tr>
<td><code>get_dtype_counts()</code></td>
<td>Return the counts of dtypes in this object</td>
</tr>
<tr>
<td><code>get_ftype_counts()</code></td>
<td>Return the counts of ftypes in this object</td>
</tr>
<tr>
<td><code>get_value(index, col[, takeable])</code></td>
<td>Quickly retrieve single value at passed column and index</td>
</tr>
<tr>
<td><code>get_values()</code></td>
<td>Same as values (but handles sparseness conversions)</td>
</tr>
<tr>
<td><code>groupby(by, axis, level, as_index, sort, ...)</code></td>
<td>Group series using mapper (dict or key function, apply given function)</td>
</tr>
<tr>
<td><code>gt(other[, axis, level])</code></td>
<td>Wrapper for flexible comparison methods <code>gt</code></td>
</tr>
<tr>
<td><code>head(n)</code></td>
<td>Returns first n rows</td>
</tr>
<tr>
<td><code>hist(data[, column, by, grid, xlabels, ...])</code></td>
<td>Draw histogram of the DataFrame’s series using matplotlib / pylab.</td>
</tr>
<tr>
<td><code>icol(i)</code></td>
<td>DEPRECATED.</td>
</tr>
<tr>
<td><code>idmax((axis, skipna))</code></td>
<td>Return index of first occurrence of maximum over requested axis.</td>
</tr>
<tr>
<td><code>idmin((axis, skipna))</code></td>
<td>Return index of first occurrence of minimum over requested axis.</td>
</tr>
<tr>
<td><code>iget_value(i, j)</code></td>
<td>DEPRECATED.</td>
</tr>
<tr>
<td><code>info(verbose, buf, max_cols, memory_usage, ...)</code></td>
<td>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>Interpolate values according to different methods.</td>
</tr>
<tr>
<td><code>irow(i[, copy])</code></td>
<td>DEPRECATED.</td>
</tr>
<tr>
<td><code>isin(values)</code></td>
<td>Return boolean DataFrame showing whether each element in the DataFrame is in values</td>
</tr>
<tr>
<td><code>iteritems()</code></td>
<td>Return a boolean same-sized object indicating if the values are null</td>
</tr>
<tr>
<td><code>iterkv(*args, **kwargs)</code></td>
<td>Iterator over (column name, Series) pairs.</td>
</tr>
<tr>
<td><code>iterrows()</code></td>
<td>Iter over the rows of a DataFrame as (index, Series) pairs.</td>
</tr>
<tr>
<td><code>itertuples([index])</code></td>
<td>Iterate over the rows of DataFrame as tuples, with index value as first element of tuple.</td>
</tr>
<tr>
<td><code>join(other[, on, how, lsuffix, rsuffix, sort])</code></td>
<td>Join columns with other DataFrame either on index or on a key column.</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 using Fishers definition of kurtosis</td>
</tr>
<tr>
<td><code>kurtosis([axis, skipna, level, numeric_only])</code></td>
<td>Return unbiased kurtosis over requested axis using Fishers definition of kurtosis</td>
</tr>
<tr>
<td><code>last(offset)</code></td>
<td>Convenience method for subsetting final periods of time series data</td>
</tr>
<tr>
<td><code>last_valid_index()</code></td>
<td>Return label for last non-NA/null value</td>
</tr>
<tr>
<td><code>le(other[, axis, level])</code></td>
<td>Wrapper for flexible comparison methods <code>le</code></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>Wrapper for flexible comparison methods <code>lt</code></td>
</tr>
<tr>
<td><code>max([axis, skipna, level, numeric_only])</code></td>
<td>Return the mean absolute deviation of the values for the requested axis</td>
</tr>
<tr>
<td><code>mean([axis, skipna, level, numeric_only])</code></td>
<td>Return an object of same shape as self and whose corresponding entries are from other.</td>
</tr>
<tr>
<td><code>median([axis, skipna, level, numeric_only])</code></td>
<td>This method returns the maximum of the values in the object.</td>
</tr>
<tr>
<td><code>memory_usage([index])</code></td>
<td>Return the mean of the values for the requested axis</td>
</tr>
<tr>
<td><code>merge(right[, how, on, left_on, right_on, ...])</code></td>
<td>Return the median of the values for the requested axis</td>
</tr>
<tr>
<td><code>min([axis, skipna, level, numeric_only])</code></td>
<td>Memory usage of DataFrame columns.</td>
</tr>
<tr>
<td><code>merge(right[, how, on, left_on, right_on, ...])</code></td>
<td>Merge DataFrame objects by performing a database-style join operation by column values.</td>
</tr>
<tr>
<td><code>mean([axis, skipna, level, numeric_only])</code></td>
<td>This method returns the minimum of the values in the object.</td>
</tr>
</tbody>
</table>
Table 34.53 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>mod(other[, axis, level, fill_value])</code></td>
<td>Modulo of dataframe and other, element-wise (binary operator <code>mod</code>).</td>
</tr>
<tr>
<td><code>mode([axis, numeric_only])</code></td>
<td>Gets the mode(s) of each element along the axis selected.</td>
</tr>
<tr>
<td><code>mul(other[, axis, level, fill_value])</code></td>
<td>Multiplication of dataframe and other, element-wise (binary operator <code>mul</code>).</td>
</tr>
<tr>
<td><code>multiply(other[, axis, level, fill_value])</code></td>
<td>Multiplication of dataframe and other, element-wise (binary operator <code>mul</code>).</td>
</tr>
<tr>
<td><code>ne(other[, axis, level])</code></td>
<td>Wrapper for flexible comparison methods <code>ne</code>.</td>
</tr>
<tr>
<td><code>nlargest(n, columns[, keep])</code></td>
<td>Get the rows of a DataFrame sorted by the n largest values of columns.</td>
</tr>
<tr>
<td><code>notnull()</code></td>
<td>Return a boolean same-sized object indicating if the values are</td>
</tr>
<tr>
<td><code>nsmallest(n, columns[, keep])</code></td>
<td>Get the rows of a DataFrame sorted by the n smallest values of columns.</td>
</tr>
<tr>
<td><code>pct_change([periods, fill_method, limit, freq])</code></td>
<td>Percent change over given number of periods.</td>
</tr>
<tr>
<td><code>pipe(func, *args, **kwargs)</code></td>
<td>Apply <code>func</code> with arguments and keyword arguments.</td>
</tr>
<tr>
<td><code>pivot(index, columns, values)</code></td>
<td>Create a spreadsheet-style pivot table as a DataFrame.</td>
</tr>
<tr>
<td><code>pivot_table(data[, values, index, columns, ...])</code></td>
<td>Alias of <code>FramePlotMethods</code></td>
</tr>
<tr>
<td><code>plot</code></td>
<td>Return item and drop from frame.</td>
</tr>
<tr>
<td><code>pow(other[, axis, level, fill_value])</code></td>
<td>Exponential power of dataframe and other, element-wise (binary operator <code>pow</code>).</td>
</tr>
<tr>
<td><code>prod([axis, skipna, level, numeric_only])</code></td>
<td>Return the product of the values for the requested axis</td>
</tr>
<tr>
<td><code>product([axis, skipna, level, numeric_only])</code></td>
<td>Return the product of the values for the requested axis</td>
</tr>
<tr>
<td><code>quantile([q, axis, numeric_only])</code></td>
<td>Return values at the given quantile over requested axis, a la <code>numpy.percentile</code>.</td>
</tr>
<tr>
<td><code>query(crit[, axis])</code></td>
<td>Query the columns of a frame with a boolean expression.</td>
</tr>
<tr>
<td><code>radd(other[, axis, level, fill_value])</code></td>
<td>Addition of dataframe and other, element-wise (binary operator <code>radd</code>).</td>
</tr>
<tr>
<td><code>rank([axis, numeric_only, method, ...])</code></td>
<td>Compute numerical data ranks (1 through n) along axis.</td>
</tr>
<tr>
<td><code>rdiv(other[, axis, level, fill_value])</code></td>
<td>Floating division of dataframe and other, element-wise (binary operator <code>rtruediv</code>).</td>
</tr>
<tr>
<td><code>reindex([index, columns])</code></td>
<td>Conform DataFrame to new index with optional filling logic, placing NA/NaN</td>
</tr>
<tr>
<td><code>reindex_axis(labels[, axis, method, level, ...])</code></td>
<td>Conform input object to new index with optional filling logic, placing NA/NaN</td>
</tr>
<tr>
<td><code>reindex_like(other[, method, copy, limit, ...])</code></td>
<td>Return an object with matching indexies to myself</td>
</tr>
<tr>
<td><code>rename_axis(mapper[, axis, copy, inplace])</code></td>
<td>Alter axes input function or functions.</td>
</tr>
<tr>
<td><code>rename_axis([mapper, axis, copy, inplace])</code></td>
<td>Alter index and / or columns using input function or functions.</td>
</tr>
<tr>
<td><code>reorder_levels(order[, axis])</code></td>
<td>Rearrange index levels using input order.</td>
</tr>
<tr>
<td><code>replace([to_replace, value, inplace, limit])</code></td>
<td>Replace values given in ‘to_replace’ with ‘value’.</td>
</tr>
<tr>
<td><code>reset_index([level, drop, inplace, ...])</code></td>
<td>Convenience method for frequency conversion and resampling of regular time-</td>
</tr>
<tr>
<td><code>rfloordiv(other[, axis, level, fill_value])</code></td>
<td>For DataFrame with multi-level index, return new DataFrame with labeling info.</td>
</tr>
<tr>
<td><code>rmod(other[, axis, level, fill_value])</code></td>
<td>Integer division of dataframe and other, element-wise (binary operator <code>rfloordiv</code>).</td>
</tr>
<tr>
<td><code>rmul(other[, axis, level, fill_value])</code></td>
<td>Modulo of dataframe and other, element-wise (binary operator <code>rmod</code>).</td>
</tr>
<tr>
<td><code>round([decimals, out])</code></td>
<td>Multiplication of dataframe and other, element-wise (binary operator <code>rmul</code>).</td>
</tr>
<tr>
<td><code>rpow(other[, axis, level, fill_value])</code></td>
<td>Round a DataFrame to a variable number of decimal places.</td>
</tr>
<tr>
<td><code>rsub(other[, axis, level, fill_value])</code></td>
<td>Exponential power of dataframe and other, element-wise (binary operator <code>rpow</code>).</td>
</tr>
<tr>
<td><code>rtruediv(other[, axis, level, fill_value])</code></td>
<td>Subtraction of dataframe and other, element-wise (binary operator <code>rsub</code>).</td>
</tr>
<tr>
<td><code>sample([n, frac, replace, weights, ...])</code></td>
<td>Floating division of dataframe and other, element-wise (binary operator <code>rtruediv</code>).</td>
</tr>
<tr>
<td><code>select(crit[, axis])</code></td>
<td>Returns a random sample of items from an axis of object.</td>
</tr>
<tr>
<td><code>select_dtypes([include, exclude])</code></td>
<td>Return data corresponding to axis labels matching criteria</td>
</tr>
<tr>
<td><code>sem([axis, skipna, level, ddof, numeric_only])</code></td>
<td>Return unbiased standard error of the mean over requested axis.</td>
</tr>
<tr>
<td><code>set_axis([index, col, value[, takeable]])</code></td>
<td>Public verison of axis assignment</td>
</tr>
<tr>
<td><code>set_index(keys[, drop, append, inplace, ...])</code></td>
<td>Set the DataFrame index (row labels) using one or more existing columns.</td>
</tr>
<tr>
<td><code>set_value(index, col, value[, takeable])</code></td>
<td>Put single value at passed column and index</td>
</tr>
<tr>
<td><code>shift([periods, freq, axis])</code></td>
<td>Shift index by desired number of periods with an optional time freq</td>
</tr>
<tr>
<td><code>skew([axis, skipna, level, numeric_only])</code></td>
<td>Return unbiased skew over requested axis.</td>
</tr>
<tr>
<td><code>slice_shift([periods, axis])</code></td>
<td>Equivalent to <code>shift</code> without copying data.</td>
</tr>
<tr>
<td><code>sort([columns, axis, ascending, inplace, ...])</code></td>
<td>DEPRECATED: use <code>DataFrame.sort_values()</code></td>
</tr>
<tr>
<td><code>sort_index([axis, level, ascending, ...])</code></td>
<td>Sort object by labels (along an axis)</td>
</tr>
<tr>
<td><code>sort_values(by[, axis, ascending, inplace, ...])</code></td>
<td>Sort by the values along either axis</td>
</tr>
<tr>
<td><code>sortlevel([level, axis, ascending, inplace, ...])</code></td>
<td>Sort multilevel index by chosen axis and primary level.</td>
</tr>
</tbody>
</table>
### Table 34.53 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>squeeze()</td>
<td>squeeze length 1 dimensions</td>
</tr>
<tr>
<td>stack([level, dropna])</td>
<td>Pivot a level of the (possibly hierarchical) column labels, returning a DataFrame</td>
</tr>
<tr>
<td>std([axis, skipna, level, ddof, numeric_only])</td>
<td>Return unbiased standard deviation over requested axis.</td>
</tr>
<tr>
<td>sub(other[, axis, level, fill_value])</td>
<td>Subtraction of dataframe and other, element-wise (binary operator sub).</td>
</tr>
<tr>
<td>subtract([other[, axis, level, fill_value]])</td>
<td>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>tail([n])</td>
<td>Swap levels i and j in a MultiIndex on a particular axis</td>
</tr>
<tr>
<td>take(indices[, axis, convert, is_copy])</td>
<td>Returns last n rows</td>
</tr>
<tr>
<td>to_clipboard([excel, sep])</td>
<td>Analogous to ndarray.take</td>
</tr>
<tr>
<td>to_csv([path_or_buf, sep, na_rep, ...])</td>
<td>Attempt to write text representation of object to the system clipboard This can be pasted into Excel.</td>
</tr>
<tr>
<td>to_dense()</td>
<td>Write DataFrame to a comma-separated values (csv) file</td>
</tr>
<tr>
<td>to_dict(*args, **kwargs)</td>
<td>Return dense representation of NDFrame (as opposed to sparse)</td>
</tr>
<tr>
<td>to_excel(excel_writer[, sheet_name, na_rep, ...])</td>
<td>Convert DataFrame to dictionary.</td>
</tr>
<tr>
<td>to_gbq(destination_table, project_id[, ...])</td>
<td>Write DataFrame to a excel sheet</td>
</tr>
<tr>
<td>to_html(buf, columns, col_space, colSpace, ...)</td>
<td>Render a DataFrame as an HTML table.</td>
</tr>
<tr>
<td>to_json([path_or_buf, orient, date_format, ...])</td>
<td>Render a DataFrame to a tabular environment table.</td>
</tr>
<tr>
<td>to_msgpack([path_or_buf])</td>
<td>msgpack (serialize) object to input file path</td>
</tr>
<tr>
<td>to_period([freq, axis, copy])</td>
<td>Transform long (stacked) format (DataFrame) into wide (3D, Panel) format.</td>
</tr>
<tr>
<td>to_pickle(path)</td>
<td>Convert DataFrame from DatetimeIndex to PeriodIndex with desired</td>
</tr>
<tr>
<td>to_records([index, convert_datetime64])</td>
<td>Pickle (serialize) object to input file path</td>
</tr>
<tr>
<td>to_sparse([fill_value, kind])</td>
<td>Convert DataFrame to record array.</td>
</tr>
<tr>
<td>to_sql(name, con[, flavor, schema, ...])</td>
<td>Convert to SparseDataFrame</td>
</tr>
<tr>
<td>to_stata(fname[, convert_dates, ...])</td>
<td>Write records stored in a DataFrame to a SQL database.</td>
</tr>
<tr>
<td>to_timestamp([freq, how, axis, copy])</td>
<td>A class for writing Stata binary dta files from array-like objects</td>
</tr>
<tr>
<td>to_wide(*args, **kwargs)</td>
<td>Render a DataFrame to a console-friendly tabular output.</td>
</tr>
<tr>
<td>transpose()</td>
<td>Cast to DatetimeIndex of timestamps, at beginning of period</td>
</tr>
<tr>
<td>truediv(other[, axis, level, fill_value])</td>
<td>Transpose index and columns</td>
</tr>
<tr>
<td>truncate([before, after, axis, copy])</td>
<td>Floating division of dataframe and other, element-wise (binary operator truediv)</td>
</tr>
<tr>
<td>tshift([periods, freq, axis])</td>
<td>Truncates a sorted NDFrame before and/or after some particular dates.</td>
</tr>
<tr>
<td>tz_convert([tz, axis, level, copy])</td>
<td>Shift the time index, using the index’s frequency if available</td>
</tr>
<tr>
<td>tz_localize(*args, **kwargs)</td>
<td>Convert tz-aware axis to target time zone.</td>
</tr>
<tr>
<td>unstack([level])</td>
<td>Localize tz-naive TimeSeries to target time zone.</td>
</tr>
<tr>
<td>update(other[, join, overwrite, ...])</td>
<td>Pivot a level of the (necessarily hierarchical) index labels, returning a DataFrame.</td>
</tr>
<tr>
<td>var([axis, skipna, level, ddof, numeric_only])</td>
<td>Modify DataFrame in place using non-NA values from passed DataFrame.</td>
</tr>
<tr>
<td>where([cond, other, inplace, axis, level, ...])</td>
<td>Return unbiased variance over requested axis.</td>
</tr>
<tr>
<td>xs(key[, axis, level, copy, drop_level])</td>
<td>Return an object of same shape as self and whose corresponding entries are from the passed object.</td>
</tr>
<tr>
<td>Returns</td>
<td>abs: type of caller</td>
</tr>
</tbody>
</table>

**pandas.DataFrame.abs**

DataFrame.abs ()

Return an object with absolute value taken. Only applicable to objects that are all numeric

**Returns**

abs: type of caller
pandas.DataFrame.add

DataFrame.add(other, axis='columns', level=None, fill_value=None)
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.

Parameters
- **other**: Series, DataFrame, or constant
- **axis**: {0, 1, ‘index’, ‘columns’}
  For Series input, axis to match Series index on
- **fill_value**: None or float value, default None
  Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing
- **level**: int or name
  Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

See also:
DataFrame.radd

Notes
Mismatched indices will be unioned together

pandas.DataFrame.add_prefix

DataFrame.add_prefix(prefix)
Concatenate prefix string with panel items names.

Parameters
- **prefix**: string

Returns with_prefix : type of caller

pandas.DataFrame.add_suffix

DataFrame.add_suffix(suffix)
Concatenate suffix string with panel items names

Parameters
- **suffix**: string

Returns with_suffix : type of caller

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 object on their axes with the specified join method 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**: boolean, 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**: str, default None
  - **limit**: int, default None
  - **fill_axis**: {0, 1, ‘index’, ‘columns’}, default 0
    - Filling axis, method and limit
  - **broadcast_axis**: {0, 1, ‘index’, ‘columns’}, default None
    - Broadcast values along this axis, if aligning two objects of different dimensions
    - New in version 0.17.0.

**Returns**

- **(left, right)**: (DataFrame, type of other)
  - Aligned objects

---

**DataFrame.all**

- **DataFrame.all**(axis=None, bool_only=None, skipna=None, level=None, **kwargs)
  - Return whether all elements are True over requested axis

**Parameters**

- **axis**: {index (0), columns (1)}
  - **skipna**: boolean, 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
  - **bool_only**: boolean, default None
    - Include only boolean data. If None, will attempt to use everything, then use only boolean data

**Returns**

- **all**: Series or DataFrame (if level specified)
pandas.DataFrame.any

DataFrame.any (axis=None, bool_only=None, skipna=None, level=None, **kwargs)
Return whether any element is True over requested axis

Parameters
axis : {index (0), columns (1)}
skipna : boolean, 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
bool_only : boolean, default None
    Include only boolean data. If None, will attempt to use everything, then use only
    boolean data

Returns
any : Series or DataFrame (if level specified)

pandas.DataFrame.append

DataFrame.append (other, ignore_index=False, verify_integrity=False)
Append rows of other to the end of this frame, returning a new object. Columns not in this frame are
added as new columns.

Parameters
other : DataFrame or Series/dict-like object, or list of these
    The data to append.
ignore_index : boolean, default False
    If True, do not use the index labels.
verify_integrity : boolean, default False
    If True, raise ValueError on creating index with duplicates.

Returns
appended : DataFrame

See also:
pandas.concat  General function to concatenate DataFrame, Series or Panel 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.

Examples

```python
>>> df = pd.DataFrame([[[1, 2], [3, 4]], columns=list('AB'))
>>> df
   A  B
0  1  2
1  3  4
```
```python
>>> df2 = pd.DataFrame([[5, 6], [7, 8]], columns=list('AB'))
>>> df.append(df2)
   A  B
0  1  2
1  3  4
0  5  6
1  7  8

With `ignore_index` set to True:
```n
```python
>>> df.append(df2, ignore_index=True)
   A  B
0  1  2
1  3  4
2  5  6
3  7  8
```

**pandas.DataFrame.apply**

DataFrame.apply(func, axis=0, broadcast=False, raw=False, reduce=None, args=(), **kwds)

Applies function along input axis of DataFrame.

Objects passed to functions are Series objects having index either the DataFrame’s index (axis=0) or the columns (axis=1). Return type depends on whether passed function aggregates, or the reduce argument if the DataFrame is empty.

**Parameters**

- **func**: function
  Function to apply to each column/row
- **axis**: {0 or ‘index’, 1 or ‘columns’}, default 0
  - 0 or ‘index’: apply function to each column
  - 1 or ‘columns’: apply function to each row
- **broadcast**: boolean, default False
  For aggregation functions, return object of same size with values propagated
- **reduce**: boolean or None, default None
  Try to apply reduction procedures. If the DataFrame is empty, apply will use reduce to determine whether the result should be a Series or a DataFrame. If reduce is None (the default), apply’s return value will be guessed by calling func an empty Series (note: while guessing, exceptions raised by func will be ignored). If reduce is True a Series will always be returned, and if False a DataFrame will always be returned.
- **raw**: boolean, default False
  If False, convert each row or column into a Series. If raw=True the passed function will receive ndarray objects instead. If you are just applying a NumPy reduction function this will achieve much better performance
- **args**: tuple
  Positional arguments to pass to function in addition to the array/series

**Returns**

- **applied**: Series or DataFrame
See also:

**DataFrame.applymap** For elementwise operations

**Notes**

In the current implementation apply calls func twice on the first column/row to decide whether it can take a fast or slow code path. This can lead to unexpected behavior if func has side-effects, as they will take effect twice for the first column/row.

**Examples**

```python
>>> df.apply(numpy.sqrt)  # returns DataFrame
>>> df.apply(numpy.sum, axis=0)  # equiv to df.sum(0)
>>> df.apply(numpy.sum, axis=1)  # equiv to df.sum(1)
```

**pandas.DataFrame.applymap**

DataFrame.applymap(func)

Apply a function to a DataFrame that is intended to operate elementwise, i.e. like doing map(func, series) for each series in the DataFrame

**Parameters**

- **func** : function

  Python function, returns a single value from a single value

**Returns**

- **applied** : DataFrame

See also:

**DataFrame.apply** For operations on rows/columns

**pandas.DataFrame.as_blocks**

DataFrame.as_blocks(copy=True)

Convert the frame to a dict of dtype -> Constructor Types that each has a homogeneous dtype.

**NOTE:** the dtypes of the blocks WILL BE PRESERVED HERE (unlike in as_matrix)

**Parameters**

- **copy** : boolean, default True

**Returns**

- **values** : a dict of dtype -> Constructor Types

**pandas.DataFrame.as_matrix**

DataFrame.as_matrix(columns=None)

Convert the frame to its Numpy-array representation.

**Parameters**

- **columns** : list, optional, default: None

  If None, return all columns, otherwise, returns specified columns.
**Returns** values : ndarray

If the caller is heterogeneous and contains booleans or objects, the result will be of dtype=object. See Notes.

**See also:**
pandas.DataFrame.values

**Notes**

Return is NOT a Numpy-matrix, rather, a Numpy-array.

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 upcase to int32.

This method is provided for backwards compatibility. Generally, it is recommended to use `.values`.

**pandas.DataFrame.asfreq**

DataFrame.asfreq(freq, method=None, how=None, normalize=False)

Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

**Parameters**

- freq : DateOffset object, or string
- method : {'backfill', 'bfill', 'pad', 'ffill', 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 method
- how : {'start', 'end'}, default end
  For PeriodIndex only, see PeriodIndex.asfreq
- normalize : bool, default False
  Whether to reset output index to midnight

**Returns**
converted : type of caller

**pandas.DataFrame.assign**

DataFrame.assign(**kwargs)

Assign new columns to a DataFrame, returning a new object (a copy) with all the original columns in addition to the new ones.

New in version 0.16.0.

**Parameters**

- kwargs : keyword, value pairs
  keywords are the column names. If the values are callable, they are computed on the DataFrame and assigned to the new columns. If the values are not callable, (e.g. a Series, scalar, or array), they are simply assigned.
Returns **df** : DataFrame

A new DataFrame with the new columns in addition to all the existing columns.

Notes

Since `kwargs` is a dictionary, the order of your arguments may not be preserved. The make things predictable, the columns are inserted in alphabetical order, at the end of your DataFrame. Assigning multiple columns within the same `assign` is possible, but you cannot reference other columns created within the same `assign` call.

Examples

```python
>>> df = DataFrame({’A’: range(1, 11), ’B’: np.random.randn(10)})
```

Where the value is a callable, evaluated on `df`:

```python
>>> df.assign(ln_A = lambda x: np.log(x.A))
```

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>ln_A</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>0.426905</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>-0.780949</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>-0.418711</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
<td>-0.269708</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>-0.274002</td>
</tr>
<tr>
<td>5</td>
<td>6</td>
<td>-0.500792</td>
</tr>
<tr>
<td>6</td>
<td>7</td>
<td>1.649697</td>
</tr>
<tr>
<td>7</td>
<td>8</td>
<td>-1.495604</td>
</tr>
<tr>
<td>8</td>
<td>9</td>
<td>0.549296</td>
</tr>
<tr>
<td>9</td>
<td>10</td>
<td>-0.758542</td>
</tr>
</tbody>
</table>

Where the value already exists and is inserted:

```python
>>> newcol = np.log(df[’A’])
```  
```python
>>> df.assign(ln_A=newcol)
```

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>ln_A</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
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</tr>
<tr>
<td>5</td>
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<td>-0.500792</td>
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<td>8</td>
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<td>9</td>
<td>0.549296</td>
</tr>
<tr>
<td>9</td>
<td>10</td>
<td>-0.758542</td>
</tr>
</tbody>
</table>

**pandas.DataFrame.astype**

`DataFrame.astype(dtype, copy=True, raise_on_error=True, **kwargs)`

Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

Parameters  
- `dtype`: numpy.dtype or Python type
- `raise_on_error`: raise on invalid input
- `**kwargs`: keyword arguments to pass on to the constructor
pandas: powerful Python data analysis toolkit, Release 0.17.0

Returns casted : type of caller

**pandas.DataFrame.at_time**

`DataFrame.at_time(time, asof=False)`

Select values at particular time of day (e.g. 9:30AM)

Parameters time : datetime.time or string

Returns values_at_time : type of caller

**pandas.DataFrame.between_time**

`DataFrame.between_time(start_time, end_time, include_start=True, include_end=True)`

Select values between particular times of the day (e.g., 9:00-9:30 AM)

Parameters start_time : datetime.time or string

end_time : datetime.time or string

include_start : boolean, default True

include_end : boolean, default True

Returns values_between_time : type of caller

**pandas.DataFrame.bfill**

`DataFrame.bfill(axis=None, inplace=False, limit=None, downcast=None)`

Synonym for NDFrame.fillna(method='bfill')

**pandas.DataFrame.bool()**

Return the bool of a single element PandasObject This must be a boolean scalar value, either True or False

Raise a ValueError if the PandasObject does not have exactly 1 element, or that element is not boolean

**pandas.DataFrame.boxplot**

`DataFrame.boxplot(column=None, by=None, ax=None, fontsize=None, rot=0, grid=True, figsize=None, layout=None, return_type=None, **kwds)`

Make a box plot from DataFrame column optionally grouped by some columns or other inputs

Parameters data : the pandas object holding the data

column : column name or list of names, or vector

Can be any valid input to groupby

by : string or sequence

Column in the DataFrame to group by
ax : Matplotlib axes object, optional

**fontsize** : int or string

**rot** : label rotation angle

**figsize** : A tuple (width, height) in inches

**grid** : Setting this to True will show the grid

**layout** : tuple (optional)

(rows, columns) for the layout of the plot

**return_type** : {‘axes’, ‘dict’, ‘both’}, default ‘dict’

The kind of object to return. ‘dict’ returns a dictionary whose values are the

Matplotlib Lines of the boxplot; ‘axes’ returns the Matplotlib axes the boxplot is
drawn on; ‘both’ returns a namedtuple with the axes and dict.

When grouping with by, a dict mapping columns to return_type is returned.

**kwds** : other plotting keyword arguments to be passed to matplotlib boxplot

function

**Returns**

**lines** : dict

  ax : matplotlib Axes

  (ax, lines): namedtuple

**Notes**

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.

**pandas.DataFrame.clip**

DataFrame.clip(lower=None, upper=None, out=None, axis=None)

Trim values at input threshold(s)

**Parameters**

lower : float or array_like, default None

upper : float or array_like, default None

axis : int or string axis name, optional

Align object with lower and upper along the given axis.

**Returns**

clipped : Series

**Examples**

```python
>>> df
   0  1
0  0.335232 -1.256177
1 -1.367855  0.746646
2  0.027753 -1.176076
3  0.230930 -0.679613
4  1.261967  0.570967
```
```python
>>> df.clip(-1.0, 0.5)
   0   1
0  0.335232 -1.000000
1 -1.000000  0.500000
2  0.027753 -1.000000
3  0.230930 -0.679613
4  0.500000  0.500000

>>> t
0  -0.3  
1  -0.2  
2  -0.1  
3   0.0  
4   0.1  
dtype: float64

>>> df.clip(t, t + 1, axis=0)
   0   1
0  0.335232 -0.300000
1 -0.200000  0.746646
2  0.027753 -0.100000
3  0.230930  0.000000
4  1.100000  0.570967
```

**pandas.DataFrame.clip_lower**

DataFrame.clip_lower(threshold, axis=None)
Return copy of the input with values below given value(s) truncated

**Parameters**

- **threshold** : float or array_like
- **axis** : int or string axis name, optional

Align object with threshold along the given axis.

**Returns**

clip : same type as input

**See also:**

clip

**pandas.DataFrame.clip_upper**

DataFrame.clip_upper(threshold, axis=None)
Return copy of input with values above given value(s) truncated

**Parameters**

- **threshold** : float or array_like
- **axis** : int or string axis name, optional

Align object with threshold along the given axis.

**Returns**

clip : same type as input

**See also:**

clip
pandas.DataFrame.combine

DataFrame.combine(other, func, fill_value=None, overwrite=True)
Add two DataFrame objects and do not propagate NaN values, so if for a (column, time) one frame is
missing a value, it will default to the other frame’s value (which might be NaN as well)

Parameters
other : DataFrame
func : function
fill_value : scalar value
overwrite : boolean, default True

If True then overwrite values for common keys in the calling frame

Returns
result : DataFrame

pandas.DataFrame.combineAdd

DataFrame.combineAdd(other)
DEPRECATED. Use DataFrame.add(other, fill_value=0.) instead.
Add two DataFrame objects and do not propagate NaN values, so if for a (column, time) one frame is
missing a value, it will default to the other frame’s value (which might be NaN as well)

Parameters
other : DataFrame

Returns
DataFrame

See also:
DataFrame.add

pandas.DataFrame.combineMult

DataFrame.combineMult(other)
DEPRECATED. Use DataFrame.mul(other, fill_value=1.) instead.
Multiply two DataFrame objects and do not propagate NaN values, so if for a (column, time) one frame
is missing a value, it will default to the other frame’s value (which might be NaN as well)

Parameters
other : DataFrame

Returns
DataFrame

See also:
DataFrame.mul

pandas.DataFrame.combine_first

DataFrame.combine_first(other)
Combine two DataFrame objects and default to non-null values in frame calling the method. Result index
columns will be the union of the respective indexes and columns

Parameters
other : DataFrame

Returns
combined : DataFrame
Examples

a’s values prioritized, use values from b to fill holes:

```python
>>> a.combine_first(b)
```

**pandas.DataFrame.compound**

DataFrame.

The compound percentage of the values for the requested axis

**Parameters**

- `axis`: index (0), columns (1)
- `skipna`: boolean, 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
- `numeric_only`: boolean, default None
  - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**

- ` compounded`: Series or DataFrame (if level specified)

**pandas.DataFrame.consolidate**

DataFrame.

Compute NDFrame with “consolidated” internals (data of each dtype grouped together in a single ndarray). Mainly an internal API function, but available here to the savvy user

**Parameters**

- `inplace`: boolean, default False
  - If False return new object, otherwise modify existing object

**Returns**

- ` consolidated`: type of caller

**pandas.DataFrame.convert_objects**

DataFrame.

Attempt to infer better dtype for object columns

**Parameters**

- `convert_dates`: boolean, default True
  - If True, convert to date where possible. If ‘coerce’, force conversion, with unconvertible values becoming NaT.
- `convert_numeric`: boolean, default False
  - If True, attempt to coerce to numbers (including strings), with unconvertible values becoming NaN.
- `convert_timedeltas`: boolean, default True
If True, convert to timedelta where possible. If ‘coerce’, force conversion, with unconvertible values becoming NaT.

**copy**: boolean, default True

If True, return a copy even if no copy is necessary (e.g. no conversion was done). Note: This is meant for internal use, and should not be confused with inplace.

**Returns converted**: same as input object

**pandas.DataFrame.copy**

```py
DataFrame.copy(deep=True)
```

Make a copy of this object

**Parameters deep**: boolean or string, default True

Make a deep copy, i.e. also copy data

**Returns copy**: type of caller

**pandas.DataFrame.corr**

```py
DataFrame.corr(method='pearson', min_periods=1)
```

Compute pairwise correlation of columns, excluding NA/null values

**Parameters method**: {‘pearson’, ‘kendall’, ‘spearman’}

- pearson : standard correlation coefficient
- kendall : Kendall Tau correlation coefficient
- spearman : Spearman rank correlation

**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 y**: DataFrame

**pandas.DataFrame.corrwith**

```py
DataFrame.corrwith(other, axis=0, drop=False)
```

Compute pairwise correlation between rows or columns of two DataFrame objects.

**Parameters other**: DataFrame

**axis**: {0 or ‘index’, 1 or ‘columns’}, default 0

0 or ‘index’ to compute column-wise, 1 or ‘columns’ for row-wise

**drop**: boolean, default False

Drop missing indices from result, default returns union of all

**Returns correls**: Series
pandas.DataFrame.count

DataFrame.count (axis=0, level=None, numeric_only=False)
Return Series with number of non-NA/null observations over requested axis. Works with non-floating point data as well (detects NaN and None)

Parameters axis : {0 or `index`, 1 or `columns`}, default 0
0 or `index` for row-wise, 1 or `columns` for column-wise

level : int or level name, default None
If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default False
Include only float, int, boolean data

Returns count : Series (or DataFrame if level specified)

pandas.DataFrame.cov

DataFrame.cov (min_periods=None)
Compute pairwise covariance of columns, excluding NA/null values

Parameters min_periods : int, optional
Minimum number of observations required per pair of columns to have a valid result.

Returns y : DataFrame

Notes

y contains the covariance matrix of the DataFrame’s time series. The covariance is normalized by N-1 (unbiased estimator).

pandas.DataFrame.cummax

DataFrame.cummax (axis=None, dtype=None, out=None, skipna=True, **kwargs)
Return cumulative max over requested axis.

Parameters axis : {index (0), columns (1)}

skipna : boolean, default True
Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns max : Series

pandas.DataFrame.cummin

DataFrame.cummin (axis=None, dtype=None, out=None, skipna=True, **kwargs)
Return cumulative min over requested axis.
pandas: powerful Python data analysis toolkit, Release 0.17.0

Parameters axis : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns min : Series

pandas.DataFrame.cumprod

DataFrame.cumprod(axis=None, dtype=None, out=None, skipna=True, **kwargs)

Return cumulative prod over requested axis.

Parameters axis : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns prod : Series

pandas.DataFrame.cumsum

DataFrame.cumsum(axis=None, dtype=None, out=None, skipna=True, **kwargs)

Return cumulative sum over requested axis.

Parameters axis : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns sum : Series

pandas.DataFrame.describe

DataFrame.describe(percentiles=None, include=None, exclude=None)

Generate various summary statistics, excluding NaN values.

Parameters percentiles : array-like, optional

The percentiles to include in the output. Should all be in the interval [0, 1]. By default percentiles is [.25, .5, .75], returning the 25th, 50th, and 75th percentiles.

include, exclude : list-like, ‘all’, or None (default)

Specify the form of the returned result. Either:

• None to both (default). The result will include only numeric-typed columns or, if none are, only categorical columns.

• A list of dtypes or strings to be included/excluded. To select all numeric types use numpy number. To select categorical objects use type object. See also the select_dtypes documentation. eg. df.describe(include=['O'])

• If include is the string ‘all’, the output column-set will match the input one.

Returns summary: NDFrame of summary statistics

See also:

DataFrame.select_dtypes

34.4. DataFrame 1203
Notes

The output DataFrame index depends on the requested dtypes:
For numeric dtypes, it will include: count, mean, std, min, max, and lower, 50, and upper percentiles.
For object dtypes (e.g. timestamps or strings), the index will include the count, unique, most common, and frequency of the most common. Timestamps also include the first and last items.
For mixed dtypes, the index will be the union of the corresponding output types. Non-applicable entries will be filled with NaN. Note that mixed-dtype outputs can only be returned from mixed-dtype inputs and appropriate use of the include/exclude arguments.
If multiple values have the highest count, then the count and most common pair will be arbitrarily chosen from among those with the highest count.
The include, exclude arguments are ignored for Series.

pandas.DataFrame.diff

DataFrame.diff(periods=1, axis=0)
1st discrete difference of object
Parameters  
periods : int, default 1
Periods to shift for forming difference
axis : {0 or ‘index’, 1 or ‘columns’}, default 0
Take difference over rows (0) or columns (1).

Returns  
diffed : DataFrame

pandas.DataFrame.div

DataFrame.div(other, axis='columns', level=None, fill_value=None)
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.
Parameters  
other : Series, DataFrame, or constant
axis : {0, 1, ‘index’, ‘columns’}
For Series input, axis to match Series index on
fill_value : None or float value, default None
Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing
level : int or name
Broadcast across a level, matching Index values on the passed MultiIndex level

Returns  
result : DataFrame

See also:

DataFrame.rtruediv
**Notes**

Mismatched indices will be unioned together

**pandas.DataFrame.divide**

`DataFrame.divide(other, axis='columns', level=None, fill_value=None)`

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.

**Parameters**

- `other` : Series, DataFrame, or constant
  - `axis` : {0, 1, ‘index’, ‘columns’}
  - For Series input, axis to match Series index on
  - `fill_value` : None or float value, default None
  - Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing
  - `level` : int or name
  - Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns** `result` : DataFrame

**See also:**

`DataFrame.rtruediv`

**Notes**

Mismatched indices will be unioned together

**pandas.DataFrame.dot**

`DataFrame.dot(other)`

Matrix multiplication with DataFrame or Series objects

**Parameters**

- `other` : DataFrame or Series

**Returns** `dot_product` : DataFrame or Series

**pandas.DataFrame.drop**

`DataFrame.drop(labels, axis=0, level=None, inplace=False, errors='raise')`

Return new object with labels in requested axis removed

**Parameters**

- `labels` : single label or list-like
  - `axis` : int or axis name
  - `level` : int or level name, default None
    - For MultiIndex

34.4. DataFrame
inplace : bool, default False
    If True, do operation inplace and return None.

errors : {'ignore', 'raise'}, default 'raise'
    If 'ignore', suppress error and existing labels are dropped.
    New in version 0.16.1.

Returns dropped : type of caller

pandas.DataFrame.drop_duplicates

DataFrame.drop_duplicates(*args, **kwargs)
Return DataFrame with duplicate rows removed, optionally only considering certain columns

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'
    • first : Drop duplicates except for the first occurrence.
    • last : Drop duplicates except for the last occurrence.
    • False : Drop all duplicates.

take_last : deprecated

inplace : boolean, default False
    Whether to drop duplicates in place or to return a copy

cols : kwargs only argument of subset [deprecated]

Returns deduplicated : DataFrame

pandas.DataFrame.dropna

DataFrame.dropna(axis=0, how='any', thresh=None, subset=None, inplace=False)
Return object with labels on given axis omitted where alternately any or all of the data are missing

Parameters axis : {0 or ‘index’, 1 or ‘columns’}, or tuple/list thereof
    Pass tuple or list to drop on multiple axes

how : {'any', 'all'}
    • any : if any NA values are present, drop that label
    • all : if all values are NA, drop that label

thresh : int, default None
    int value : require that many non-NA values

subset : array-like
    Labels along other axis to consider, e.g. if you are dropping rows these would be
    a list of columns to include

inplace : boolean, default False
If True, do operation inplace and return None.

**Returns dropped**: DataFrame

```python
pandas.DataFrame.duplicated
```

**DataFrame.duplicated(*args, **kwargs)**

Return boolean Series denoting duplicate rows, optionally only considering certain columns

**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’

- **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.

**take_last**: deprecated

**cols**: kwargs only argument of subset [deprecated]

**Returns duplicated**: Series

```python
pandas.DataFrame.eq
```

**DataFrame.eq(other, axis='columns', level=None)**

Wrapper for flexible comparison methods eq

```python
pandas.DataFrame.equals
```

**DataFrame.equals(other)**

Determines if two NDFrame objects contain the same elements. NaNs in the same location are considered equal.

```python
pandas.DataFrame.eval
```

**DataFrame.eval(expr, **kwargs)**

Evaluate an expression in the context of the calling DataFrame instance.

**Parameters expr**: string

The expression string to evaluate.

**kwargs**: dict

See the documentation for `eval()` for complete details on the keyword arguments accepted by `query()`.

**Returns ret**: ndarray, scalar, or pandas object

---

34.4. DataFrame
Notes

For more details see the API documentation for `eval()`. For detailed examples see *enhancing performance with eval*.

Examples

```python
>>> from numpy.random import randn
>>> from pandas import DataFrame

>>> df = DataFrame(randn(10, 2), columns=list('ab'))
>>> df.eval('a + b')
>>> df.eval('c = a + b')
```

```
>>>
```

**pandas.DataFrame.ffill**

DataFrame.[**ffill**](http://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.ffill.html) *(axis=None, inplace=False, limit=None, downcast=None)*

Synonym for NDFrame.fillna(method='ffill')

```
>>>
```

**pandas.DataFrame.fillna**

DataFrame.[**fillna**](http://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.fillna.html) *(value=None, method=None, axis=None, inplace=False, limit=None, downcast=None, **kwargs)*

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, 1, ‘index’, ‘columns’}

- **inplace**: boolean, 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.

- **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 filled : DataFrame

See also:
reindex, asfreq

pandas.DataFrame.filter

DataFrame.filter(items=None, like=None, regex=None, axis=None)
Restrict the info axis to set of items or wildcard

Parameters items : list-like
List of info axis to restrict to (must not all be present)

like : string
Keep info axis where “arg in col == True”

regex : string (regular expression)
Keep info axis with re.search(regex, col) == True

axis : int or None
The axis to filter on. By default this is the info axis. The “info axis” is the axis
that is used when indexing with[]. For example, df = DataFrame({'a':
[1, 2, 3, 4]}); df['a']. So, the DataFrame columns are the info
axis.

Notes
Arguments are mutually exclusive, but this is not checked for

pandas.DataFrame.first

DataFrame.first(offset)
Convenience method for subsetting initial periods of time series data based on a date offset

Parameters offset : string, DateOffset, dateutil.relativedelta

Returns subset : type of caller

Examples

ts.last(‘10D’) -> First 10 days

pandas.DataFrame.first_valid_index

DataFrame.first_valid_index()
Return label for first non-NA/null value
pandas.DataFrame.floordiv

DataFrame.floordiv(other, axis='columns', level=None, fill_value=None)

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.

**Parameters**
other : Series, DataFrame, or constant

axis : {0, 1, ‘index’, ‘columns’}
For Series input, axis to match Series index on

fill_value : None or float value, default None
Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name
Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**
result : DataFrame

See also:
DataFrame.rfloordiv

**Notes**
Mismatched indices will be unioned together

pandas.DataFrame.from_csv

classmethod DataFrame.from_csv(path, header=0, sep=' ', index_col=0, parse_dates=True, encoding=None, tupleize_cols=False, infer_datetime_format=False)

Read CSV file (DISCOURAGED, please use pandas.read_csv() instead).

It is preferable to use the more powerful pandas.read_csv() for most general purposes, but from_csv makes for an easy roundtrip to and from a file (the exact counterpart of to_csv), especially with a DataFrame of time series data.

This method only differs from the preferred pandas.read_csv() in some defaults:

*index_col is 0 instead of None (take first column as index by default)*

*parse_dates is True instead of False (try parsing the index as datetime by default)*

So a pd.DataFrame.from_csv(path) can be replaced by pd.read_csv(path, index_col=0, parse_dates=True).

**Parameters**
path : string file path or file handle / StringIO

header : int, default 0
Row to use as header (skip prior rows)

sep : string, default ‘,’
Field delimiter
index_col : int or sequence, default 0
    Column to use for index. If a sequence is given, a MultiIndex is used. Different
default from read_table

parse_dates : boolean, default True
    Parse dates. Different default from read_table

tupleize_cols : boolean, default False
    write multi_index columns as a list of tuples (if True) or new (expanded format)
    if False)

infer_datetime_format : boolean, default False
    If True and parse_dates is True for a column, try to infer the datetime format
    based on the first datetime string. If the format can be inferred, there often will
    be a large parsing speed-up.

Returns y : DataFrame

See also:
    pandas.read_csv

pandas.DataFrame.from_dict

classmethod DataFrame.from_dict(data, orient='columns', dtype=None)
    Construct DataFrame from dict of array-like or dicts

Parameters data : dict
    {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

Returns DataFrame

pandas.DataFrame.from_items

classmethod DataFrame.from_items(items, columns=None, orient='columns')
    Convert (key, value) pairs to DataFrame. The keys will be the axis index (usually the columns, but depends
    on the specified orientation). The values should be arrays or Series.

Parameters items : sequence of (key, value) pairs
    Values should be arrays or Series.

columns : sequence of column labels, optional
    Must be passed if orient='index'.

orient : {'columns', 'index'}, default 'columns'
The “orientation” of the data. If the keys of the input correspond to column labels, pass ‘columns’ (default). Otherwise if the keys correspond to the index, pass ‘index’.

**Returns** frame : DataFrame

### 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

**Parameters**

- **data** : ndarray (structured dtype), list of tuples, dict, or DataFrame
- **index** : string, 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** : boolean, default False
  - Attempt to convert values to non-string, non-numeric objects (like decimal.Decimal) to floating point, useful for SQL result sets

**Returns** df : DataFrame

### pandas.DataFrame.ge

DataFrame.ge(*other, axis='columns', level=None*)

Wrapper for flexible comparison methods ge

### pandas.DataFrame.get

DataFrame.get(*key, default=None*)

Get item from object for given key (DataFrame column, Panel slice, etc.). Returns default value if not found

**Parameters** key : object

**Returns** value : type of items contained in object

### pandas.DataFrame.get_dtype_counts

DataFrame.get_dtype_counts()

Return the counts of dtypes in this object
**pandas.DataFrame.get_ftype_counts**

Dataframe.get_ftype_counts()

Return the counts of ftypes in this object

**pandas.DataFrame.get_value**

Dataframe.get_value(index, col, takeable=False)

Quickly retrieve single value at passed column and index

- **Parameters**
  - index: row label
  - col: column label
  - takeable: interpret the index/col as indexers, default False

- **Returns**
  - value: scalar value

**pandas.DataFrame.get_values**

Dataframe.get_values()

same as values (but handles sparseness conversions)

**pandas.DataFrame.groupby**

Dataframe.groupby(by=None, axis=0, level=None, as_index=True, sort=True, group_keys=True, squeeze=False)

Group series using mapper (dict or key function, apply given function to group, return result as series) or by a series of columns

- **Parameters**
  - by: mapping function / list of functions, dict, Series, or tuple / list of column names. Called on each element of the object index to determine the groups. If a dict or Series is passed, the Series or dict VALUES will be used to determine the groups
  - axis: int, default 0
  - level: int, level name, or sequence of such, default None
  - as_index: boolean, default True
  - sort: boolean, default True
  - group_keys: boolean, default True
  - squeeze: boolean, default False

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.

When calling apply, add group keys to index to identify pieces

squeeze: boolean, default False
reduce the dimensionality of the return type if possible, otherwise return a consistent type

**Returns** GroupBy object

**Examples**

DataFrame results

```python
>>> data.groupby(func, axis=0).mean()
>>> data.groupby(['col1', 'col2'])['col3'].mean()
```

DataFrame with hierarchical index

```python
>>> data.groupby(['col1', 'col2']).mean()
```

---

**pandas.DataFrame.gt**

DataFrame Methods

```python
pandas.DataFrame.gt
```

DataFrame Methods

```python
DataFrame.gt(other, axis='columns', level=None)
```

Wrapper for flexible comparison methods gt

---

**pandas.DataFrame.head**

DataFrame Methods

```python
pandas.DataFrame.head
```

DataFrame Methods

```python
DataFrame.head(n=5)
```

Returns first n rows

---

**pandas.DataFrame.hist**

DataFrame Methods

```python
pandas.DataFrame.hist
```

DataFrame Methods

```python
DataFrame.hist(data, 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, **kwds)
```

Draw histogram of the DataFrame’s series using matplotlib / pylab.

**Parameters**

- **data**: DataFrame
  - **column**: string 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**: boolean, 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
  - **ax**: object, optional
    - If specified changes the y-axis label size
  - **sharex**: boolean, default False
    - Whether to share the x-axis limits
  - **sharey**: boolean, default False
    - Whether to share the y-axis limits
  - **figsize**: tuple, default None
    - Figure size
  - **layout**: int, default None
    - Figure layout
  - **bins**: int, default 10
    - Number of bins
  - ****kwds**: dict
    - Other arguments
yrot : float, default None
    rotation of y axis labels

ax : matplotlib axes object, default None

sharex : boolean, 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 subplots in a
figure!

sharey : boolean, default False
    In case subplots=True, share y axis and set some y axis labels to invisible

figsize : tuple
    The size of the figure to create in inches by default

layout: (optional) a tuple (rows, columns) for the layout of the histograms

bins: integer, default 10
    Number of histogram bins to be used

cw : other plotting keyword arguments
    To be passed to hist function

pandas.DataFrame.iloc

DataFrame.iloc(i)
    DEPRECATED. Use .iloc[:, i] instead

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
    0 or ‘index’ for row-wise, 1 or ‘columns’ for column-wise

skipna : boolean, default True
    Exclude NA/null values. If an entire row/column is NA, the result will be first
index.

Returns

idxmax : Series

See also:
Series.idxmax

Notes

This method is the DataFrame version of ndarray.argmax.
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
  - 0 or ‘index’ for row-wise, 1 or ‘columns’ for column-wise
- **skipna**: boolean, default True
  - Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns

- **idxmin**: Series

See also:

Series.idxmin

Notes

This method is the DataFrame version of ndarray.argmin.

pandas.DataFrame.iget_value

DataFrame.iget_value(i, j)
DEPRECATED. Use .iat[i, j] instead

pandas.DataFrame.info

DataFrame.info(verbos None, buf=None, max_cols=None, memory_usage=None, null_counts=None)
Concise summary of a DataFrame.

Parameters

- **verbose**: {None, True, False}, optional
  - Whether to print the full summary. None follows the display.max_info_columns setting. True or False overrides the display.max_info_columns setting.
- **buf**: writable buffer, defaults to sys.stdout
- **max_cols**: int, default None
  - Determines whether full summary or short summary is printed. None follows the display.max_info_columns setting.
- **memory_usage**: boolean, default None
  - Specifies whether total memory usage of the DataFrame elements (including index) should be displayed. None follows the display.memory_usage setting. True or False overrides the display.memory_usage setting. Memory usage is shown in human-readable units (base-2 representation).
- **null_counts**: boolean, default None
  - Whether to show the non-null counts If None, then only show if the frame is smaller than max_info_rows and max_info_columns. If True, always show counts. If False, never show counts.
**pandas.DataFrame.insert**

DataFrame.insert(loc, column, value, allow_duplicates=False)

Insert column into DataFrame at specified location.

If allow_duplicates is False, raises Exception if column is already contained in the DataFrame.

**Parameters**

- **loc**: int
  
  Must have 0 <= loc <= len(columns)

- **column**: object

- **value**: int, Series, or array-like

**pandas.DataFrame.interpolate**

DataFrame.interpolate(method='linear', axis=0, limit=None, inplace=False, limit_direction='forward', downcast=None, **kwargs)

Interpolate values according to different methods.

Please note that only method='linear' is supported for DataFrames/Series with a MultiIndex.

**Parameters**

- **method**: {'linear', 'time', 'index', 'values', 'nearest', 'zero', 'slinear', 'quadratic', 'cubic', 'barycentric', 'krogh', 'polynomial', 'spline', 'piecewise_polynomial', 'pchip'}

  - 'linear': ignore the index and treat the values as equally spaced. This is the only method supported on MultiIndexes. default
  - 'time': interpolation works on daily and higher resolution data to interpolate given length of interval
  - 'index', 'values': use the actual numerical values of the index
  - 'nearest', 'zero', 'slinear', 'quadratic', 'cubic', 'barycentric', 'polynomial', 'spline' is passed to scipy.interpolate.interp1d. Both 'polynomial' and 'spline' require that you also specify an order (int), e.g. df.interpolate(method='polynomial', order=4). These use the actual numerical values of the index.
  - 'krogh', 'piecewise_polynomial', 'spline', and 'pchip' are all wrappers around the scipy interpolation methods of similar names. These use the actual numerical values of the index. See the scipy documentation for more on their behavior here and here

- **axis**: {0, 1}, default 0

  - 0: fill column-by-column
  - 1: fill row-by-row

- **limit**: int, default None.

  Maximum number of consecutive NaNs to fill.

- **limit_direction**: {'forward', 'backward', 'both'}, defaults to 'forward'

  If limit is specified, consecutive NaNs will be filled in this direction.

New in version 0.17.0.
inplace : bool, default False
Update the NDFrame in place if possible.
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 of same shape interpolated at the NaNs

See also: reindex, replace, fillna

Examples

Filling in NaNs

```python
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s.interpolate()
0 0  
1 1  
2 2  
3 3  
dtype: float64
```

pandas.DataFrame.irow

DataFrame.irow(i, copy=False)
DEPRECATED. Use .iloc[i] instead

pandas.DataFrame.isin

DataFrame.isin(values)
Return boolean DataFrame showing whether each element in the DataFrame is contained in values.

Parameters values : iterable, Series, DataFrame or dictionary
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 dictionary, 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 of booleans

Examples

When values is a list:

```python
>>> df = DataFrame({'A': [1, 2, 3], 'B': ['a', 'b', 'f']})
>>> df.isin([1, 3, 12, 'a'])
   A  B
0  True  True
1   False  True
2   False  False
```
When values is a dict:

```python
>>> df = DataFrame({'A': [1, 2, 3], 'B': [1, 4, 7]})
>>> df.isin({'A': [1, 3], 'B': [4, 7, 12]})
   A  B
0  True  False  # Note that B didn't match the 1 here.
1  False   True
2   True   True
```

When values is a Series or DataFrame:

```python
>>> df = DataFrame({'A': [1, 2, 3], 'B': ['a', 'b', 'f']})
>>> other = DataFrame({'A': [1, 3, 3, 2], 'B': ['e', 'f', 'f', 'e']})
>>> df.isin(other)
   A  B
0  True  False
1  False  False  # Column A in 'other' has a 3, but not at index 1.
2   True   True
```

### pandas.DataFrame.isnull

`DataFrame.isnull()`
Return a boolean same-sized object indicating if the values are null

See also:

- `notnull` boolean inverse of isnull

### pandas.DataFrame.iteritems

`DataFrame.iteritems()`  
Iterator over (column name, Series) pairs.

See also:

- `iterrows` Iterate over the rows of a DataFrame as (index, Series) pairs.
- `itertuples` Iterate over the rows of a DataFrame as tuples of the values.

### pandas.DataFrame.iterkv

`DataFrame.iterkv(*args, **kwargs)`  
iteritems alias used to get around 2to3. Deprecated

### pandas.DataFrame.iterrows

`DataFrame.iterrows()`  
Iterate over the rows of a DataFrame as (index, Series) pairs.

Returns `it`: generator
A generator that iterates over the rows of the frame.

See also:
**itertuples** Iterate over the rows of a DataFrame as tuples of the values.

**iteritems** Iterate over (column name, Series) pairs.

**Notes**

1. Because `itertuples` returns a Series for each row, it does not preserve dtypes across the rows (dtypes are preserved across columns for DataFrames). For example,

```python
def = pd.DataFrame([\[1, 1.5\]], columns=[\'int\', \'float\'])
row = next(df.itertuples())[1]
```

```python
row
int 1.0
float 1.5
Name: 0, dtype: float64
```

```python
print(row[\'int\'].dtype)
float64
```

```python
print(df[\'int\'].dtype)
int64
```

To preserve dtypes while iterating over the rows, it is better to use `itertuples()` which returns tuples of the values and which is generally faster as `itertuples`.

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)

Iterate over the rows of DataFrame as tuples, with index value as first element of the tuple.

**Parameters**

- **index**: boolean, default True

  If True, return the index as the first element of the tuple.

**See also:**

- `itertuples` Iterate over the rows of a DataFrame as (index, Series) pairs.
- `iteritems` Iterate over (column name, Series) pairs.

**Examples**

```python
def = pd.DataFrame({\'col1\': [1, 2], \'col2\': [0.1, 0.2]}, index=[\'a\', \'b\'])
def
```

```python
coll  col2
a 1 0.1
b 2 0.2
```

```python
for row in df.itertuples():
    print(row)
    \('a', 1, 0.10000000000000001\)
    \('b', 2, 0.20000000000000001\)
```
### pandas.DataFrame.join

**DataFrame.join**(other, on=None, how='left', lsuffix='', rsuffix='', sort=False)

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 with name field set, 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** : column name, tuple/list of column names, or array-like
  - Column(s) to use for joining, otherwise join on index. If multiples columns given, the passed DataFrame must have a MultiIndex. Can pass an array as the join key if not already contained in the calling DataFrame. Like an Excel VLOOKUP operation
- **how** : {'left', 'right', 'outer', 'inner'}
  - How to handle indexes of the two objects. Default: ‘left’ for joining on index, None otherwise
    - left: use calling frame’s index
    - right: use input frame’s index
    - outer: form union of indexes
    - inner: use intersection of indexes
- **lsuffix** : string
  - Suffix to use from left frame’s overlapping columns
- **rsuffix** : string
  - Suffix to use from right frame’s overlapping columns
- **sort** : boolean, default False
  - Order result DataFrame lexicographically by the join key. If False, preserves the index order of the calling (left) DataFrame

**Returns**

- **joined** : DataFrame

**Notes**

- on, lsuffix, and rsuffix options are not supported when passing a list of DataFrame objects

### pandas.DataFrame.keys

**DataFrame.keys()**

Get the ‘info axis’ (see Indexing for more)

This is index for Series, columns for DataFrame and major_axis for Panel.
pandas.DataFrame.kurt

DataFrame.kurt(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)
Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

**Parameters**
- **axis**: {index (0), columns (1)}
- **skipna**: boolean, 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
- **numeric_only**: boolean, default None
  - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**
- **kurt**: 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 using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

**Parameters**
- **axis**: {index (0), columns (1)}
- **skipna**: boolean, 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
- **numeric_only**: boolean, default None
  - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**
- **kurt**: Series or DataFrame (if level specified)

pandas.DataFrame.last

DataFrame.last(offset)
Convenience method for subsetting final periods of time series data based on a date offset

**Parameters**
- **offset**: string, dateutil.relativedelta

**Returns**
- **subset**: type of caller

**Examples**

ts.last(‘5M‘) -> Last 5 months
pandas.DataFrame.last_valid_index

DataFrame.last_valid_index()
Return label for last non-NA/null value

pandas.DataFrame.le

DataFrame.le(other, axis='columns', level=None)
Wrapper for flexible comparison methods le

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

Notes

Akin to:
result = []
for row, col in zip(row_labels, col_labels):
    result.append(df.get_value(row, col))

Examples

values [ndarray] The found values

pandas.DataFrame.lt

DataFrame.lt(other, axis='columns', level=None)
Wrapper for flexible comparison methods lt

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)}

skipna : boolean, 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
numeric_only : boolean, default None
Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns mad : Series or DataFrame (if level specified)

pandas.DataFrame.mask

DataFrame.mask (cond, other=nan, inplace=False, axis=None, level=None, try_cast=False, raise_on_error=True)
Return an object of same shape as self and whose corresponding entries are from self where cond is False and otherwise are from other.

Parameters cond : boolean NDFrame or array
other : scalar or NDFrame
inplace : boolean, default False
Whether to perform the operation in place on the data
axis : alignment axis if needed, default None
level : alignment level if needed, default None
try_cast : boolean, default False
try to cast the result back to the input type (if possible),
raise_on_error : boolean, default True
Whether to raise on invalid data types (e.g. trying to where on strings)

Returns wh : same type as caller

pandas.DataFrame.max

DataFrame.max (axis=None, skipna=None, level=None, numeric_only=None, **kwargs)
This method returns the maximum of the values in the object. 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)}
skipna : boolean, 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
numeric_only : boolean, default None
Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns max : Series or DataFrame (if level specified)
**pandas.DataFrame.mean**

DataFrame.mean(axi\s=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)}  
- **skipna**: boolean, 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  
- **numeric_only**: boolean, default None  
  Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data  

**Returns**  
- **mean**: Series or DataFrame (if level specified)

**pandas.DataFrame.median**

DataFrame.median(axi\s=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)}  
- **skipna**: boolean, 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  
- **numeric_only**: boolean, default None  
  Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data  

**Returns**  
- **median**: Series or DataFrame (if level specified)

**pandas.DataFrame.memory_usage**

DataFrame.memory_usage(index=False)  
Memory usage of DataFrame columns.  

**Parameters**  
- **index**: bool  
  Specifies whether to include memory usage of DataFrame’s index in returned Series. If index=True (default is False) the first index of the Series is Index.  

**Returns**  
- **sizes**: Series  
  A series with column names as index and memory usage of columns with units of bytes.
See also:
	numpy.ndarray.nbytes

Notes

Memory usage does not include memory consumed by elements that are not components of the array.

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)

Merge DataFrame objects by performing a database-style join operation by 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

how : {'left', 'right', 'outer', 'inner'}, default 'inner'

• 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)

on : label or list

Field names to join on. Must be found in both DataFrames. If on is None and not merging on indexes, then it merges on the intersection of the columns by default.

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_index : boolean, 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 : boolean, default False

Use the index from the right DataFrame as the join key. Same caveats as left_index

sort : boolean, default False

Sort the join keys lexicographically in the result DataFrame

suffixes : 2-length sequence (tuple, list, ...)
Suffix to apply to overlapping column names in the left and right side, respectively

**copy** : boolean, default True

If False, do not copy data unnecessarily

**indicator** : boolean or string, default False

If True, adds a column to output DataFrame called “_merge” with information on the source of each row. If string, column with information on source of each row will be added to output DataFrame, and column will be named value of string. Information column is Categorical-type and takes on a value of “left_only” for observations whose merge key only appears in ‘left’ DataFrame, “right_only” for observations whose merge key only appears in ‘right’ DataFrame, and “both” if the observation’s merge key is found in both.

New in version 0.17.0.

**Returns**  
merged : DataFrame

The output type will be same as ‘left’, if it is a subclass of DataFrame.

### Examples

```python
gf
A
lkey value
0 foo 1
1 bar 2
2 baz 3
3 foo 4

B
rkey value
0 foo 5
1 bar 6
2 qux 7
3 bar 8

merge(A, B, left_on='lkey', right_on='rkey', how='outer')

lkey value_x rkey value_y
0 foo 1 foo 5
1 foo 4 foo 5
2 bar 2 bar 6
3 bar 2 bar 8
4 baz 3 NaN NaN
5 NaN NaN qux 7
```

**pandas.DataFrame.min**

DataFrame.min (axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

This method returns the minimum of the values in the object. 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)}

**skipna** : boolean, 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

**numeric_only** : boolean, default None
Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**  min: Series or DataFrame (if level specified)

### pandas.DataFrame.mod

**DataFrame.mod**(other, axis='columns', level=None, fill_value=None)

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.

**Parameters**  other: Series, DataFrame, or constant

axis: {0, 1, ‘index’, ‘columns’}

For Series input, axis to match Series index on

fill_value: None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level: int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**  result: DataFrame

**See also:**

DataFrame.rmod

**Notes**

Mismatched indices will be unioned together

### pandas.DataFrame.mode

**DataFrame.mode**(axis=0, numeric_only=False)

Gets the mode(s) of each element along the axis selected. Empty if nothing has 2+ occurrences. Adds a row for each mode per label, fills in gaps with nan.

Note that there could be multiple values returned for the selected axis (when more than one item share the maximum frequency), which is the reason why a dataframe is returned. If you want to impute missing values with the mode in a dataframe df, you can just do this: df.fillna(df.mode().iloc[0])

**Parameters**  axis: {0 or ‘index’, 1 or ‘columns’}, default 0

- 0 or ‘index’: get mode of each column
- 1 or ‘columns’: get mode of each row

numeric_only: boolean, default False

if True, only apply to numeric columns

**Returns**  modes: DataFrame (sorted)
Examples

```python
>>> df = pd.DataFrame({'A': [1, 2, 1, 2, 1, 2, 3]})
>>> df.mode()
    A
0  1
1  2
```

**pandas.DataFrame.mul**

DataFrame.mul(other, axis=`columns`, level=``None``., fill_value='``None``')

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.

**Parameters**

- **other**: Series, DataFrame, or constant
- **axis**: `{0, 1, ‘index’, ‘columns’}`
  - For Series input, axis to match Series index on
- **fill_value**: None or float value, default None
  - Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing
- **level**: int or name
  - Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**

result : DataFrame

**See also:**

DataFrame.rmull

**Notes**

Mismatched indices will be unioned together

**pandas.DataFrame.multiply**

DataFrame.multiply(other, axis=`columns`, level=``None``., fill_value='``None``')

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.

**Parameters**

- **other**: Series, DataFrame, or constant
- **axis**: `{0, 1, ‘index’, ‘columns’}`
  - For Series input, axis to match Series index on
- **fill_value**: None or float value, default None
  - Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing
level : int or name
Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

See also:
DataFrame.rmul

Notes
Mismatched indices will be unioned together

pandas.DataFrame.ne

DataFrame.ne (other, axis='columns', level=None)
Wrapper for flexible comparison methods ne

pandas.DataFrame.nlargest

DataFrame.nlargest (n, columns, keep='first')
Get the rows of a DataFrame sorted by the n largest values of columns.
New in version 0.17.0.

Parameters n : int
Number of items to retrieve

columns : list or str
Column name or names to order by

keep : {'first', 'last', False}, default 'first'
Where there are duplicate values: - first: take the first occurrence. - last: take the last occurrence.

Returns DataFrame

Examples

>>> df = DataFrame({'a': [1, 10, 8, 11, -1],
...                 'b': list('abdce'),
...                 'c': [1.0, 2.0, np.nan, 3.0, 4.0]})
>>> df.nlargest(3, 'a')
   a  b  c
3  11 c 3
1  10 b 2
2   8 d NaN
pandas.DataFrame.notnull

DataFrame.notnull()

Return a boolean same-sized object indicating if the values are not null

See also:

isnull boolean inverse of notnull

pandas.DataFrame.nsmallest

DataFrame.nsmallest(n, columns, keep='first')

Get the rows of a DataFrame sorted by the n smallest values of columns.

New in version 0.17.0.

Parameters  
n : int

Number of items to retrieve

columns : list or str

Column name or names to order by

keep : {'first', 'last', False}, default ‘first’

Where there are duplicate values: - first : take the first occurrence. - last : take the last occurrence.

Returns  DataFrame

Examples

>>> df = DataFrame({'a': [1, 10, 8, 11, -1],
...                  'b': list('abdce'),
...                  'c': [1.0, 2.0, np.nan, 3.0, 4.0]})

>>> df.nsmallest(3, 'a')
   a  b  c
0  1  a  1
2  8  d  NaN

pandas.DataFrame.pct_change

DataFrame.pct_change(periods=1, fill_method='pad', limit=None, freq=None, **kwargs)

Percent change over given number of periods.

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 offset alias string, optional

Increment to use from time series API (e.g. ‘M’ or BDay())

Returns chg: NDFrame

Notes

By default, the percentage change is calculated along the stat axis: 0, or Index, for DataFrame and 1, or minor for Panel. You can change this with the axis keyword argument.

pandas.DataFrame.pipe

DataFrame.pipe(func, *args, **kwargs)

Apply func(self, *args, **kwargs)

New in version 0.16.2.

Parameters func: function

function to apply to the NDFrame. 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 NDFrame.

args: positional arguments passed into func.

kwargs: a dictionary of keyword arguments passed into func.

Returns object: the return type of func.

See also:

pandas.DataFrame.apply, pandas.DataFrame.applymap, pandas.Series.map

Notes

Use .pipe when chaining together functions that expect on Series or DataFrames. Instead of writing

```python
>>> f(g(h(df), arg1=a), arg2=b, arg3=c)
```

You can write

```python
>>> (df.pipe(h)
...     .pipe(g, arg1=a)
...     .pipe(f, 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((f, 'arg2'), arg1=a, arg3=c)
... )
```
**pandas.DataFrame.pivot**

DataFrame.pivot(index=None, columns=None, values=None)

Reshape data (produce a “pivot” table) based on column values. Uses unique values from index / columns to form axes and return either DataFrame or Panel, depending on whether you request a single value column (DataFrame) or all columns (Panel)

**Parameters**

- **index**: string or object, optional
  - Column name to use to make new frame’s index. If None, uses existing index.

- **columns**: string or object
  - Column name to use to make new frame’s columns

- **values**: string or object, optional
  - Column name to use for populating new frame’s values

**Returns**

- **pivoted**: DataFrame
  - If no values column specified, will have hierarchically indexed columns

**Notes**

For finer-tuned control, see hierarchical indexing documentation along with the related stack/unstack methods

**Examples**

```python
>>> df
    foo  bar  baz
0   one  A   1.
1   one  B   2.
2   one  C   3.
3   two  A   4.
4   two  B   5.
5   two  C   6.

>>> df.pivot('foo', 'bar', 'baz')
    A  B  C
one 1  2  3
two 4  5  6

>>> df.pivot('foo', 'bar')['baz']
    A  B  C
one 1  2  3
two 4  5  6
```

**pandas.DataFrame.pivot_table**

DataFrame.pivot_table(data, values=None, index=None, columns=None, aggfunc='mean', fill_value=None, margins=False, dropna=True)

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
- **values**: column to aggregate, optional
- **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, default numpy.mean, or list of functions
  - 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)
- **fill_value**: scalar, default None
  - Value to replace missing values with
- **margins**: boolean, default False
  - Add all row / columns (e.g. for subtotal / grand totals)
- **dropna**: boolean, default True
  - Do not include columns whose entries are all NaN

**Returns**

- **table**: DataFrame

**Examples**

```python
>>> df
   A    B     C   D
0  foo  one    small  1
1  foo  one    large  2
2  foo  one    large  2
3  foo  two    small  3
4  foo  two    small  3
5   bar  one    large  4
6   bar  one    small  5
7   bar  two    small  6
8   bar  two    large  7

>>> table = pivot_table(df, values='D', index=['A', 'B'], columns=['C'], aggfunc=np.sum)
>>> table
      small   large
foo    one  1   4
    two  6   NaN
bar    one  5   4
    two  6   7
```
pandas.DataFrame.plot

DataFrame.plot (x=None, y=None, kind='line', ax=None, subplots=False, sharex=None, sharey=False, layout=None, figsize=None, use_index=True, title=None, grid=None, legend=True, style=None, logx=False, logy=False, loglog=False, xticks=None, yticks=None, xlim=None, ylim=None, rot=None, fontsize=None, colormap=None, table=False, yerr=None, xerr=None, secondary_y=False, sort_columns=False, **kwds)

Make plots of DataFrame using matplotlib / pylab.

New in version 0.17.0: Each plot kind has a corresponding method on the DataFrame.plot accessor:

df.plot(kind='line') is equivalent to df.plot.line().

Parameters data : DataFrame
    x : label or position, default None
    y : label or position, default None
        Allows plotting of one column versus another
    kind : str
        • ‘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
    subplots : boolean, default False
        Make separate subplots for each column
    sharex : boolean, 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 : boolean, 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
    use_index : boolean, default True
Use index as ticks for x axis

title : string
    Title to use for the plot

grid : boolean, default None (matlab style default)
    Axis grid lines

legend : False/True/'reverse'
    Place legend on axis subplots

style : list or dict
    matplotlib line style per column

logx : boolean, default False
    Use log scaling on x axis

logy : boolean, default False
    Use log scaling on y axis

loglog : boolean, default False
    Use log scaling on both x and y axes

xticks : sequence
    Values to use for the xticks

yticks : sequence
    Values to use for the yticks

xlim : 2-tuple/list

ylim : 2-tuple/list

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 : boolean, 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)

layout : tuple (optional)
    (rows, columns) for the layout of the plot

table : boolean, 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** : same types as yerr.

**stacked** : boolean, default False in line and bar plots, and True in area plot. If True, create stacked plot.

**sort_columns** : boolean, default False

Sort column names to determine plot ordering

**secondary_y** : boolean 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** : boolean, default True

When using a secondary_y axis, automatically mark the column labels with “(right)” in the legend

**kwds** : keywords

Options to pass to matplotlib plotting method

**Returns** axes : matplotlib.AxesSubplot or np.array of them

**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)

•If kind = ‘scatter’ and the argument c is the name of a dataframe column, the values of that column are used to color each point.

•If kind = ‘hexbin’, you can control the size of the bins with the gridsize argument. 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).

**pandas.DataFrame.pop**

**DataFrame.pop**(item)

Return item and drop from frame. Raise KeyError if not found.

**pandas.DataFrame.pow**

**DataFrame.pow**(other, axis=’columns’, level=None, fill_value=None)

Exponential power of dataframe and other, element-wise (binary operator pow).
pandas: powerful Python data analysis toolkit, Release 0.17.0

Equivalent to \texttt{dataframe \** other}, but with support to substitute a \texttt{fill\_value} for missing data in one of the inputs.

**Parameters**
- \texttt{other} : Series, DataFrame, or constant
  - \texttt{axis} : \{0, 1, ‘index’, ‘columns’\}
    - For Series input, axis to match Series index on
  - \texttt{fill\_value} : None or float value, default None
    - Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing
  - \texttt{level} : int or name
    - Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**
- \texttt{result} : DataFrame

**See also:**
- \texttt{DataFrame.rpow}

**Notes**

Mismatched indices will be unioned together

\texttt{pandas.DataFrame.prod}

\texttt{DataFrame.prod(axis=None, skipna=None, level=None, numeric\_only=None, **kwargs)}

Return the product of the values for the requested axis

**Parameters**
- \texttt{axis} : \{index (0), columns (1)\}
  - \texttt{skipna} : boolean, default True
    - Exclude NA/null values. If an entire row/column is NA, the result will be NA
  - \texttt{level} : int or level name, default None
    - If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series
  - \texttt{numeric\_only} : boolean, default None
    - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**
- \texttt{prod} : Series or DataFrame (if level specified)

\texttt{pandas.DataFrame.product}

\texttt{DataFrame.product(axis=None, skipna=None, level=None, numeric\_only=None, **kwargs)}

Return the product of the values for the requested axis

**Parameters**
- \texttt{axis} : \{index (0), columns (1)\}
  - \texttt{skipna} : boolean, default True
    - Exclude NA/null values. If an entire row/column is NA, the result will be NA
**pandas.DataFrame.quantile**

DataFrame.quantile(*q=0.5, axis=0, numeric_only=True*)

Return values at the given quantile over requested axis, a la numpy.percentile.

**Parameters**

- **q**: float or array-like, default 0.5 (50% quantile)
  
  0 <= q <= 1, the quantile(s) to compute

- **axis**: {0, 1, ‘index’, ‘columns’} (default 0)
  
  0 or ‘index’ for row-wise, 1 or ‘columns’ for column-wise

**Returns**

- **quantiles**: 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.

**Examples**

```python
>>> df = DataFrame(np.array([[1, 1], [2, 10], [3, 100], [4, 100]]),
                   columns=[‘a’, ‘b’])
>>> df.quantile(.1)
da  1.3
b  3.7
dtype: float64
>>> df.quantile([.1, .5])
da  b
0.1  1.3  3.7
0.5  2.5  55.0
```

**pandas.DataFrame.query**

DataFrame.query(*expr, **kwargs*)

Query the columns of a frame with a boolean expression.

New in version 0.13.

**Parameters**

- **expr**: string
  
  The query string to evaluate. You can refer to variables in the environment by prefixing them with an ‘@’ character like @a + b.

- **kwargs**: dict
See the documentation for `pandas.eval()` for complete details on the keyword arguments accepted by `DataFrame.query()`.

**Returns** q : DataFrame

**See also:**

`pandas.eval`, `DataFrame.eval`

**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 `pandas.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.

For further details and examples see the `query` documentation in `indexing`.

**Examples**

```python
>>> import numpy.random as randn
>>> import pandas as pd

>>> df = pd.DataFrame(randn(10, 2), columns=list('ab'))

>>> df.query('a > b')

>>> df[df.a > df.b]  # same result as the previous expression
```

**pandas.DataFrame.radd**

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.

**Parameters**

- **other** : Series, DataFrame, or constant
  - **axis** : {0, 1, ‘index’, ‘columns’}  
    For Series input, axis to match Series index on
  - **fill_value** : None or float value, default None
Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

**level** : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns result** : DataFrame

**See also:**

*DataFrame.add*

**Notes**

Mismatched indices will be unioned together

---

**pandas.DataFrame.rank**

*DataFrame.rank*(axis=0, numeric_only=None, method='average', na_option='keep', ascending=True, pct=False)*

Compute numerical data ranks (1 through n) along axis. 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

Ranks over columns (0) or rows (1)

**numeric_only** : boolean, default None

Include only float, int, boolean data


• 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

**na_option** : {'keep’, ‘top’, ‘bottom’}

• keep: leave NA values where they are
• top: smallest rank if ascending
• bottom: smallest rank if descending

**ascending** : boolean, default True

False for ranks by high (1) to low (N)

**pct** : boolean, default False

Computes percentage rank of data

**Returns ranks** : DataFrame
**pandas.DataFrame.rdiv**

`DataFrame.rdiv(other, axis='columns', level=None, fill_value=None)`

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.

**Parameters**

- **other**: Series, DataFrame, or constant
- **axis**: {0, 1, ‘index’, ‘columns’}
  - For Series input, axis to match Series index on
- **fill_value**: None or float value, default None
  - Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing
- **level**: int or name
  - Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**

- **result**: DataFrame

**See also:**

`DataFrame.truediv`

**Notes**

Mismatched indices will be unioned together

**pandas.DataFrame.reindex**

`DataFrame.reindex(index=None, columns=None, **kwargs)`

Conform DataFrame to new index with optional filling logic, placing 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, columns**: array-like, optional (can be specified in order, or as keywords) New labels / index to conform to. Preferably an Index object to avoid duplicating data
- **method**: {None, ‘backfill’/’bfill’, ‘pad’/’ffill’, ‘nearest’}, optional
  - **Method to use for filling holes in reindexed DataFrame:**
    - 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**: boolean, 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 \( \text{abs(index[indexer] - target)} \leq \text{tolerance} \).

New in version 0.17.0.

**Returns reindexed** : DataFrame

**Examples**

```python
df.reindex(index=[date1, date2, date3], columns=['A', 'B', 'C'])
```

**pandas.DataFrame.reindex_axis**

DataFrame.reindex_axis (labels, axis=0, method=None, level=None, copy=True, limit=None, fill_value=nan)

Conform input object to new index with optional filling logic, placing 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 labels** : array-like

New labels / index to conform to. Preferably an Index object to avoid duplicating data

**axis** : \{0, 1, ‘index’, ‘columns’\}

**method** : \{None, ‘backfill’/’bfill’, ‘pad’/’ffill’, ‘nearest’\}, optional

**Method to use for filling holes in reindexed DataFrame:**

- 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** : boolean, 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

**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
\[ |\text{index}[\text{indexer}] - \text{target}| \leq \text{tolerance} \].

New in version 0.17.0.

Returns reindexed : DataFrame

See also:
reindex, reindex_like

Examples

```python
>>> df.reindex_axis(['A', 'B', 'C'], axis=1)
```

pandas.DataFrame.reindex_like

DataFrame.reindex_like(other, method=None, copy=True, limit=None, tolerance=None)

return an object with matching indices to myself

Parameters other : Object

method : string or None

copy : boolean, default True

limit : int, default None

Maximum number of consecutive labels to fill for inexact matches.

tolerance : optional

Maximum distance between labels of the other object and this object for inexact
matches.

New in version 0.17.0.

Returns reindexed : same as input

Notes

Like calling s.reindex(index=other.index, columns=other.columns, method=...)

pandas.DataFrame.rename

DataFrame.rename(index=None, columns=None, **kwargs)

Alter axes input function or functions. Function / dict values must be unique (1-to-1). Labels not contained
in a dict / Series will be left as-is.

Parameters index, columns : dict-like or function, optional

Transformation to apply to that axis values

copy : boolean, default True

Also copy underlying data
inplace : boolean, default False
Whether to return a new DataFrame. If True then value of copy is ignored.

Returns renamed : DataFrame (new object)

pandas.DataFrame.rename_axis

DataFrame.rename_axis(mapper, axis=0, copy=True, inplace=False)
Alter index and / or columns using input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters mapper : dict-like or function, optional
axis : int or string, default 0
copy : boolean, default True
Also copy underlying data
inplace : boolean, default False

Returns renamed : type of caller

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 : int
Where to reorder levels.

Returns type of caller (new object)

pandas.DataFrame.replace

DataFrame.replace(to_replace=None, value=None, inplace=False, limit=None, regex=False, method='pad', axis=None)
Replace values given in ‘to_replace’ with ‘value’.

Parameters to_replace : str, regex, list, dict, Series, numeric, or None
- str or regex:
  - 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 inter-
    preted 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 and regex rules apply as above.

- dict:
  - Nested dictionaries, e.g., {'a': {'b': nan}}, are read as follows: look in column 'a' for the value 'b' and replace it with nan. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) cannot be regular expressions.
  - Keys map to column names and values map to substitution values. You can treat this as a special case of passing two lists except that you are specifying the column to search in.

- 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 use to fill holes (e.g. 0), alternately a dict of values specifying 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** : boolean, default False

If True, in place. Note: this will modify any other views on this object (e.g. a column form 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. Otherwise, to_replace must be None because this parameter will be interpreted as a regular expression or a list, dict, or array of regular expressions.

**method** : string, optional, {'pad', 'ffill', 'bfill'}

The method to use when for replacement, when to_replace is a list.

**Returns** : NDFrame

**Raises** :

- AssertionError
  - If regex is not a bool and to_replace is not None.

- TypeError
  - 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.

- ValueError
  - If to_replace and value are lists or ndarrays, but they are not the same length.
See also:

NDFrame.reindex, NDFrame.asfreq, NDFrame.fillna

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.

**pandas.DataFrame.resample**

`DataFrame.resample(rule, how=None, axis=0, fill_method=None, closed=None, label=None, convention='start', kind=None, loffset=None, limit=None, base=0)`

Convenience method for frequency conversion and resampling of regular time-series data.

**Parameters**

- `rule` : string
  the offset string or object representing target conversion

- `how` : string
  method for down- or re-sampling, default to ‘mean’ for downsampling

- `axis` : int, optional, default 0

- `fill_method` : string, default None
  fill_method for upsampling

- `closed` : {'right', 'left'}
  Which side of bin interval is closed

- `label` : {'right', 'left'}
  Which bin edge label to label bucket with

- `convention` : {'start', 'end', 's', 'e'}

- `kind` : “period”/”timestamp”

- `loffset` : timedelta
  Adjust the resampled time labels

- `limit` : int, default None
  Maximum size gap to when reindexing with fill_method

- `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
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', how='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', how='sum', label='right')
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', how='sum', label='right', closed='right')
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')[0:5]  # select first 5 rows
2000-01-01 00:00:00    0
2000-01-01 00:00:30   NaN
2000-01-01 00:01:00    1
2000-01-01 00:01:30   NaN
2000-01-01 00:02:00    2
Freq: 30S, dtype: float64
```

Upsample the series into 30 second bins and fill the NaN values using the pad method.

```python
Upsample the series into 30 second bins and fill the NaN values using the bfill method.

```python
>>> series.resample('30S', fill_method='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 to how.

```python
>>> def custom_resampler(array_like):
...     return np.sum(array_like)+5

>>> series.resample('3T', how=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
```

### pandas.DataFrame.reset_index

DataFrame.reset_index(**level=None, drop=False, inplace=False, col_level=0, col_fill='''**)

For DataFrame with multi-level index, return new DataFrame with labeling information in the columns under the index names, defaulting to 'level_0', 'level_1', etc. if any are None. For a standard index, the index name will be used (if set), otherwise a default 'index' or 'level_0' (if 'index' is already taken) will be used.

**Parameters**

- **level**: int, str, tuple, or list, default None
  - Only remove the given levels from the index. Removes all levels by default
- **drop**: boolean, default False
  - Do not try to insert index into dataframe columns. This resets the index to the default integer index.
- **inplace**: boolean, 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**

- **resetted**: DataFrame
**pandas.DataFrame.rfloordiv**

```python
DataFrame.rfloordiv(other, axis='columns', level=None, fill_value=None)
```

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.

**Parameters**

- **other**: Series, DataFrame, or constant
- **axis**: `{0, 1, ‘index’, ‘columns’}`
  - For Series input, axis to match Series index on
- **fill_value**: None or float value, default None
  - Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing
- **level**: int or name
  - Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**

- **result**: DataFrame

**See also:**

- `DataFrame.floordiv`

**Notes**

Mismatched indices will be unioned together

**pandas.DataFrame.rmod**

```python
DataFrame.rmod(other, axis='columns', level=None, fill_value=None)
```

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.

**Parameters**

- **other**: Series, DataFrame, or constant
- **axis**: `{0, 1, ‘index’, ‘columns’}`
  - For Series input, axis to match Series index on
- **fill_value**: None or float value, default None
  - Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing
- **level**: int or name
  - Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**

- **result**: DataFrame

**See also:**

- `DataFrame.mod`
Notes

Mismatched indices will be unioned together

pandas.DataFrame.rmul

DataFrame.\texttt{rmul}(\textit{other}, \textit{axis}='columns', \textit{level}=None, \textit{fill\_value}=None)

Multiplication of dataframe and other, element-wise (binary operator \texttt{rmul}).

Equivalent to \textit{other} * dataframe, but with support to substitute a \textit{fill\_value} for missing data in one of the inputs.

**Parameters**
\textit{other} : Series, DataFrame, or constant

\textit{axis} : {0, 1, ‘index’, ‘columns’}

For Series input, axis to match Series index on

\textit{fill\_value} : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

\textit{level} : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**
\textit{result} : DataFrame

See also:

DataFrame.mul

Notes

Mismatched indices will be unioned together

pandas.DataFrame.round

DataFrame.\texttt{round}(\textit{decimals}=0, \textit{out}=None)

Round a DataFrame to a variable number of decimal places.

New in version 0.17.0.

**Parameters**
\textit{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 \textit{decimals} is a dict-like, or in the index if \textit{decimals} is a Series. Any columns not included in \textit{decimals} will be left as is. Elements of \textit{decimals} which are not columns of the input will be ignored.

**Returns**
\textit{DataFrame} object
Examples

```python
>>> df = pd.DataFrame(np.random.random([3, 3]),
                   columns=['A', 'B', 'C'], index=['first', 'second', 'third'])
>>> df
   A     B     C
first 0.028208 0.992815 0.173891
second 0.038683 0.645646 0.577595
third 0.877076 0.149370 0.491027
>>> df.round(2)
   A     B     C
first   0.03   0.99   0.17
second   0.04   0.65   0.58
third    0.88   0.15   0.49
>>> df.round({'A': 1, 'C': 2})
   A     B     C
first   0.0   0.9928   0.17
second   0.0   0.6456   0.58
third    0.9   0.1494   0.49
>>> decimals = pd.Series([1, 0, 2], index=['A', 'B', 'C'])
>>> df.round(decimals)
   A     B     C
first   0.0 1.0000   0.17
second   0.0 0.6456   0.58
third    0.9 0.1494   0.49
```

### pandas.DataFrame.rpow

DataFrame.rpow(other, axis='columns', level=None, fill_value=None)

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.

**Parameters**
- **other** : Series, DataFrame, or constant
- **axis** : 0, 1, ‘index’, ‘columns’
  - For Series input, axis to match Series index on
- **fill_value** : None or float value, default None
  - Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing
- **level** : int or name
  - Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**
- **result** : DataFrame

**See also:**
- DataFrame.pow

**Notes**

Mismatched indices will be unioned together
pandas.DataFrame.rsub

DataFrame.\texttt{rsub}(\texttt{other}, \texttt{axis}='columns', \texttt{level}=None, \texttt{fill}_\texttt{value}=None)  
Subtraction of dataframe and other, element-wise (binary operator \texttt{rsub}).

Equivalent to \texttt{other} - \texttt{dataframe}, but with support to substitute a \texttt{fill}_\texttt{value} for missing data in one of the inputs.

**Parameters**  
\texttt{other} : Series, DataFrame, or constant

\texttt{axis} : \{0, 1, ‘index’, ‘columns’\}  
For Series input, axis to match Series index on

\texttt{fill}_\texttt{value} : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

\texttt{level} : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**  
\texttt{result} : DataFrame

\textbf{See also:}

DataFrame.\texttt{sub}

\textbf{Notes}

Mismatched indices will be unioned together

pandas.DataFrame.rtruediv

DataFrame.\texttt{rtruediv}(\texttt{other}, \texttt{axis}='columns', \texttt{level}=None, \texttt{fill}_\texttt{value}=None)  
Floating division of dataframe and other, element-wise (binary operator \texttt{rtruediv}).

Equivalent to \texttt{other} / \texttt{dataframe}, but with support to substitute a \texttt{fill}_\texttt{value} for missing data in one of the inputs.

**Parameters**  
\texttt{other} : Series, DataFrame, or constant

\texttt{axis} : \{0, 1, ‘index’, ‘columns’\}  
For Series input, axis to match Series index on

\texttt{fill}_\texttt{value} : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

\texttt{level} : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**  
\texttt{result} : DataFrame

\textbf{See also:}

DataFrame.\texttt{truediv}
Notes

Mismatched indices will be unioned together

**pandas.DataFrame.sample**

`DataFrame.sample(n=None, frac=None, replace=False, weights=None, random_state=None, axis=None)`

Returns a random sample of items from an axis of object.

New in version 0.16.1.

**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**: boolean, optional
  
  Sample with or without replacement. Default = False.

- **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. inf and -inf values not allowed.

- **random_state**: int or numpy.random.RandomState, optional
  
  Seed for the random number generator (if int), or numpy RandomState object.

- **axis**: int or string, optional
  
  Axis to sample. Accepts axis number or name. Default is stat axis for given data type (0 for Series and DataFrames, 1 for Panels).

**Returns**

A new object of same type as caller.

**pandas.DataFrame.select**

`DataFrame.select(crit, axis=0)`

Return data corresponding to axis labels matching criteria

**Parameters**

- **crit**: function
  
  To be called on each index (label). Should return True or False

- **axis**: int

**Returns**

`selection` : type of caller
pandas.DataFrame.select_dtypes

DataFrame.select_dtypes(include=None, exclude=None)
Return a subset of a DataFrame including/excluding columns based on their dtype.

Parameters include, exclude : list-like
   A list of dtypes or strings to be included/excluded. You must pass in a non-empty
   sequence for at least one of these.

Returns subset : 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.

TypeError
   • If either of include or exclude is not a sequence

Notes

• To select all numeric types use the numpy dtype numpy.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 Pandas categorical dtypes, use 'category'

Examples

```python
>>> df = pd.DataFrame({'a': np.random.randn(6).astype('f4'),
... 'b': [True, False] * 3,
... 'c': [1.0, 2.0] * 3})
>>> df
   a   b  c
0  0.3962  True  1
1  0.1459  False  2
2  0.2623  True  1
3  0.0764  False  2
4 -0.9703  True  1
5 -1.2094  False  2
>>> df.select_dtypes(include=['float64'])
  c
0  1
1  2
2  1
3  2
4  1
5  2
>>> df.select_dtypes(exclude=['floating'])
```
pandas: powerful Python data analysis toolkit, Release 0.17.0

b
0  True
1  False
2  True
3  False
4  True
5  False

**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**: boolean, 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
- **numeric_only**: boolean, default None
  - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**

- **sem**: Series or DataFrame (if level specified)

**pandas.DataFrame.set_axis**

DataFrame.**set_axis**(axis, labels)

public version of axis assignment

**pandas.DataFrame.set_index**

DataFrame.**set_index**(keys, drop=True, append=False, inplace=False, verify_integrity=False)

Set the DataFrame index (row labels) using one or more existing columns. By default yields a new object.

**Parameters**

- **keys**: column label or list of column labels / arrays
- **drop**: boolean, default True
  - Delete columns to be used as the new index
- **append**: boolean, default False
  - Whether to append columns to existing index
- **inplace**: boolean, default False
  - Modify the DataFrame in place (do not create a new object)
- **verify_integrity**: boolean, 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 : DataFrame

Examples

```python
grouped_df = df.groupby(["A", 
>>> indexed_df = df.set_index(["A", 
>>> indexed_df2 = df.set_index(["A", [0, 0, 1, 1, 0, 1, 2]])
>>> indexed_df3 = df.set_index([[0, 1, 2, 0, 1, 2]])

pandas.DataFrame.set_value

DataFrame.set_value(index, col, value, takeable=False)
Put single value at passed column and index

Parameters index : row label
    col : column label
    value : scalar value
    takeable : interpret the index/col as indexers, default False

Returns frame : DataFrame
If label pair is contained, will be reference to calling DataFrame, otherwise a new object

pandas.DataFrame.shift

DataFrame.shift(periods=1, freq=None, axis=0)
Shift index by desired number of periods with an optional time freq

Parameters periods : int
    Number of periods to move, can be positive or negative
    freq : DateOffset, timedelta, or time rule string, optional
        Increment to use from datetools module or time rule (e.g. ‘EOM’). See Notes.
    axis : {0, 1, ‘index’, ‘columns’}

Returns shifted : DataFrame

Notes
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.

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)}

**skipna** : boolean, 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

**numeric_only** : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns skew** : 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**

**DataFrame.sort**(columns=None, axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last')

DEPRECATED: use DataFrame.sort_values()

Sort DataFrame either by labels (along either axis) or by the values in column(s)

**Parameters columns** : object

Column name(s) in frame. Accepts a column name or a list for a nested sort. A tuple will be interpreted as the levels of a multi-index.

**ascending** : boolean or list, default True

Sort ascending vs. descending. Specify list for multiple sort orders

**axis** : {0 or ‘index’, 1 or ‘columns’}, default 0

Sort index/rows versus columns

**inplace** : boolean, default False

Sort the DataFrame without creating a new instance

**kind** : {'quicksort', ‘mergesort’, ‘heapsort’}, optional

This option is only applied when sorting on a single column or label.
na_position : {'first', 'last'} (optional, default='last')

'first' puts NaNs at the beginning 'last' puts NaNs at the end

Returns sorted : DataFrame

Examples

```python
>>> result = df.sort(['A', 'B'], ascending=[1, 0])
```

pandas.DataFrame.sort_index

DataFrame.sort_index (axis=0, level=None, ascending=True, inplace=False, kind='quicksort',
na_position='last', sort_remaining=True, by=None)
Sort object by labels (along an axis)

Parameters axis : index, columns to direct sorting

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 : boolean, default True

Sort ascending vs. descending

inplace : bool

if True, perform operation in-place

kind : {'quicksort', 'mergesort', 'heapsort'}

Choice of sorting algorithm. See also ndarray.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'}

'first' puts NaNs at the beginning, 'last' puts NaNs at the end

sort_remaining : bool

if true and sorting by level and index is multilevel, sort by other levels too (in order) after sorting by specified level

Returns sorted_obj : DataFrame

pandas.DataFrame.sort_values

DataFrame.sort_values (by, axis=0, ascending=True, inplace=False, kind='quicksort',
na_position='last')
Sort by the values along either axis

New in version 0.17.0.

Parameters by : string name or list of names which refer to the axis items

axis : index, columns to direct sorting

ascending : bool or list of bool
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
if True, perform operation in-place

kind : {"quicksort", "mergesort", "heapsort"}
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'}
first puts NaNs at the beginning, last puts NaNs at the end

Returns sorted_obj : DataFrame

**pandas.DataFrame.sortlevel**

DataFrame.sortlevel (level=0, axis=0, ascending=True, inplace=False, sort_remaining=True)
Sort multilevel index by chosen axis and primary level. Data will be lexicographically sorted by the chosen level followed by the other levels (in order)

Parameters level : int
axis : {0 or ‘index’, 1 or ‘columns’}, default 0
ascending : boolean, default True
inplace : boolean, default False
Sort the DataFrame without creating a new instance
sort_remaining : boolean, default True
Sort by the other levels too.

Returns sorted : DataFrame

See also:
DataFrame.sort_index

**pandas.DataFrame.squeeze**

DataFrame.squeeze ()
squeeze length 1 dimensions

**pandas.DataFrame.stack**

DataFrame.stack (level=-1, dropna=True)
Pivot a level of the (possibly hierarchical) column labels, returning a DataFrame (or Series in the case of an object with a single level of column labels) having a hierarchical index with a new inner-most level of row labels. The level involved will automatically get sorted.

Parameters level : int, string, or list of these, default last level
Level(s) to stack, can pass level name
**dropna**: boolean, default True

Whether to drop rows in the resulting Frame/Series with no valid values

**Returns**  
stacked: DataFrame or Series

**Examples**

```python
nen s
 a b
one 1. 2.
two 3. 4.

>>> s.stack()
one a 1
 b  2
two a 3
 b  4
```

**pandas.DataFrame.std**

Dataframe.__std__(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)  

Return unbiased 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: boolean, 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

numeric_only: boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**  
std: Series or DataFrame (if level specified)

**pandas.DataFrame.sub**

Dataframe.__sub__(other, axis='columns', level=None, fill_value=None)  

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.

**Parameters**

other: Series, DataFrame, or constant

axis: {0, 1, ‘index’, ‘columns’}

For Series input, axis to match Series index on

fill_value: None or float value, default None
Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name
Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

See also:
DataFrame.rsub

Notes
Mismatched indices will be unioned together

pandas.DataFrame.subtract

DataFrame.subtract(other, axis='columns', level=None, fill_value=None)
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.

Parameters other : Series, DataFrame, or constant
axis : {0, 1, ‘index’, ‘columns’}
For Series input, axis to match Series index on
fill_value : None or float value, default None
Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing
level : int or name
Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

See also:
DataFrame.rsub

Notes
Mismatched indices will be unioned together

pandas.DataFrame.sum

DataFrame.sum(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)
Return the sum of the values for the requested axis

Parameters axis : {index (0), columns (1)}
skipna : boolean, default True
Exclude NA/null values. If an entire row/column is NA, the result will be NA
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**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**: boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**

- *sum*: Series or DataFrame (if level specified)

**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, j, axis=0)

Swap levels i and j in a MultiIndex on a particular axis

**Parameters**

- *i, j*: int, string (can be mixed)

  Level of index to be swapped. Can pass level name as string.

**Returns**

- *swapped*: type of caller (new object)

**pandas.DataFrame.tail**

DataFrame.tail(n=5)

Returns last n rows

**pandas.DataFrame.take**

DataFrame.take(indices, axis=0, convert=True, is_copy=True)

Analogous to ndarray.take

**Parameters**

- *indices*: list / array of ints

  - *axis*: int, default 0

  - *convert*: translate neg to pos indices (default)

  - *is_copy*: mark the returned frame as a copy

**Returns**

- *taken*: type of caller

**pandas.DataFrame.to_clipboard**

DataFrame.to_clipboard(excel=None, sep=None, **kwargs)

Attempt to write text representation of object to the system clipboard. This can be pasted into Excel, for example.
Parameters  excel : boolean, defaults to True

    if True, use the provided separator, writing in a csv format for allowing easy pasting into excel. If False, write a string representation of the object to the clipboard

    sep : optional, defaults to tab

    other keywords are passed to to_csv

Notes

Requirements for your platform

- Linux: xclip, or xsel (with gtk or PyQt4 modules)
- Windows: none
- OS X: none

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, quoting=None, quotechar='', line_terminator='
', chunksize=None, tupleize_cols=False, date_format=None, doublequote=True, escapechar=None, decimal='.', **kwds)

Write DataFrame to a comma-separated values (csv) file

Parameters  path_or_buf : string or file handle, default None

    File path or object, if None is provided the result is returned as a string.

    sep : character, default ‘,’

    Field delimiter for the output file.

    na_rep : string, default ‘’

    Missing data representation

    float_format : string, default None

    Format string for floating point numbers

    columns : sequence, optional

    Columns to write

    header : boolean or list of string, default True

    Write out column names. If a list of string is given it is assumed to be aliases for the column names

    index : boolean, default True

    Write row names (index)

    index_label : string 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 DataFrame uses MultiIndex. If False do not print fields for index names. Use index_label=False for easier importing in R
nanRep: None

deprecated, use na_rep

mode: str

Python write mode, default ‘w’

encoding: string, optional

A string representing the encoding to use in the output file, defaults to ‘ascii’ on Python 2 and ‘utf-8’ on Python 3.

line_terminator: string, default ‘n’

The newline character or character sequence to use in the output file

quoting: optional constant from csv module

defaults to csv.QUOTE_MINIMAL

quotechar: string (length 1), default ‘”’

character used to quote fields

doublequote: boolean, default True

Control quoting of quotechar inside a field

escapechar: string (length 1), default None

character used to escape sep and quotechar when appropriate

chunksize: int or None

rows to write at a time

tupleize_cols: boolean, default False

write multi_index columns as a list of tuples (if True) or new (expanded format) if False

date_format: string, default None

Format string for datetime objects

decimal: string, default ‘.’

Character recognized as decimal separator. E.g. use ‘,’ for European data

New in version 0.16.0.

pandas.DataFrame.to_dense

DataFrame.to_dense()

Return dense representation of NDFrame (as opposed to sparse)

pandas.DataFrame.to_dict

DataFrame.to_dict(*args, **kwargs)

Convert DataFrame to dictionary.


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}}

New in version 0.17.0.
Abbreviations are allowed. $s$ indicates series and $sp$ indicates split.

Returns result : dict like {column -> {index -> value}}

`pandas.DataFrame.to_excel`

`DataFrame.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)`

Write DataFrame to a excel sheet

Parameters excel_writer : string or ExcelWriter object

File path or existing ExcelWriter

sheet_name : string, default ‘Sheet1’

Name of sheet which will contain DataFrame

na_rep : string, default ‘‘

Missing data representation

float_format : string, default None

Format string for floating point numbers

columns : sequence, optional

Columns to write

header : boolean or list of string, default True

Write out column names. If a list of string is given it is assumed to be aliases for the column names

index : boolean, default True

Write row names (index)

index_label : string or sequence, 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 DataFrame uses MultiIndex.

startrow :

upper left cell row to dump data frame

startcol :
upper left cell column to dump data frame

**engine**: string, default None

write engine to use - you can also set this via the options
`io.excel.xlsx.writer`, `io.excel.xls.writer`, and
`io.excel.xlsm.writer`.

**merge_cells**: boolean, default True

Write MultiIndex and Hierarchical Rows as merged cells.

**encoding**: string, default None

encoding of the resulting excel file. Only necessary for xlwt, other writers support
unicode natively.

**inf_rep**: string, default 'inf'

Representation for infinity (there is no native representation for infinity in Excel)

Notes

If passing an existing ExcelWriter object, then the sheet will be added to the existing workbook. This can
be used to save different DataFrames to one workbook:

```python
>>> writer = ExcelWriter('output.xlsx')
>>> df1.to_excel(writer,'Sheet1')
>>> df2.to_excel(writer,'Sheet2')
>>> writer.save()
```

For compatibility with to_csv, to_excel serializes lists and dicts to strings before writing.

**pandas.DataFrame.to_gbq**

DataFrame.to_gbq(destination_table, project_id, chunksize=10000, verbose=True, reauth=False, if_exists='fail')

Write a DataFrame to a Google BigQuery table.

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- **Parameters**
  - **dataframe**: DataFrame
    - DataFrame to be written
  - **destination_table**: string
    - Name of table to be written, in the form ‘dataset.tablename’
  - **project_id**: str
    - Google BigQuery Account project ID.
  - **chunksize**: int (default 10000)
    - Number of rows to be inserted in each chunk from the dataframe.
  - **verbose**: boolean (default True)
    - Show percentage complete
  - **reauth**: boolean (default False)
Force Google BigQuery to reauthenticate the user. This is useful if multiple accounts are used.

`if_exists` : {'fail', 'replace', 'append'}, default ‘fail’

‘fail’: If table exists, do nothing. ‘replace’: If table exists, drop it, recreate it, and insert data. ‘append’: If table exists, insert data. Create if does not exist.

New in version 0.17.0.

**pandas.DataFrame.to_hdf**

DataFrame.to_hdf(path_or_buf, key, **kwargs)

activate the HDFStore

**Parameters**

- **path_or_buf**: the path (string) or HDFStore object
- **key**: string
  - identifier for the group in the store
- **mode**: optional, {'a', 'w', 'r', 'r+'}, default ‘a’
  - ‘r’. Read-only; no data can be modified.
  - ‘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+’. It is similar to ‘a’, but the file must already exist.
- **format**: ‘fixed(f)|table(t)’, default is ‘fixed’
  - fixed(f) [Fixed format] Fast writing/reading. Not-appendable, nor searchable
  - table(t) [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**: boolean, default False
  - For Table formats, append the input data to the existing
- **complevel**: int, 1-9, default 0
  - If a complib is specified compression will be applied where possible
- **complib**: {'zlib', 'bzip2', 'lzma', 'blosc', None}, default None
  - If complevel is > 0 apply compression to objects written in the store wherever possible
- **fletcher32**: bool, default False
  - If applying compression use the fletcher32 checksum
- **dropna**: boolean, default False.
  - If true, ALL nan rows will not be written to store.
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pandas.DataFrame.to_html

**DataFrame.to_html**  
(buf=None, columns=None, col_space=None, colSpace=None, header=True, index=True, na_rep='NaN', formatters=None, float_format=None, sparsify=None, index_names=True, justify=None, bold_rows=True, classes=None, escape=True, max_rows=None, max_cols=None, show_dimensions=False, notebook=False)

Render a DataFrame as an HTML table.

to_html-specific options:

bold_rows  [boolean, 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  [boolean, default True] Convert the characters <, >, and & to HTML-safe sequences=

max_rows  [int, optional] Maximum number of rows to show before truncating. If None, show all.

max_cols  [int, optional] Maximum number of columns to show before truncating. If None, show all.

**Parameters**

buf : StringIO-like, optional

buffer to write to

columns : sequence, optional

the subset of columns to write; default None writes all columns

col_space : int, optional

the minimum width of each column

header : bool, optional

whether to print column labels, default True

index : bool, optional

whether to print index (row) labels, default True

na_rep : string, optional

string representation of NaN to use, default ‘NaN’

formatters : list or dict of one-parameter functions, optional

formatter functions to apply to columns’ elements by position or name, default None. 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, optional

formatter function to apply to columns’ elements if they are floats, default None. The result of this function must be a unicode string.

sparsify : bool, optional

Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row, default True

index_names : bool, optional

Prints the names of the indexes, default True

justify : {‘left’, ‘right’}, default None
Left or right-justify the column labels. If `None` uses the option from the print configuration (controlled by `set_option`), ‘right’ out of the box.

Returns `formatted` : string (or unicode, depending on data and options)

```
pandas.DataFrame.to_json
```

```
DataFrame.to_json(path_or_buf=None, orient=None, date_format='epoch', double_precision=10, force_ascii=True, date_unit='ms', default_handler=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` : the path or buffer to write the result string

if this is `None`, return a `StringIO` of the converted string

orient : string

- Series
  - default is ‘index’
  - allowed values are: {'split','records','index’}
- DataFrame
  - default is ‘columns’
  - allowed values are: {'split','records','index’,'columns’,'values’}
- 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 -> {index -> value}}
  - values : just the values array

date_format : {'epoch’, ‘iso’}

Type of date conversion. `epoch` = epoch milliseconds, `iso` = ISO8601, default is epoch.

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 : string, 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.

**Returns** same type as input object with filtered info axis

### pandas.DataFrame.to_latex

DataFrame.to_latex(buf=None, columns=None, col_space=None, colSpace=None, header=True, index=True, na_rep='NaN', formatters=None, float_format=None, sparsify=None, index_names=True, bold_rows=True, column_format=None, longtable=False, escape=True)

Render a DataFrame to a tabular environment table. You can splice this into a LaTeX document. Requires usepackage{booktabs}.

to_latex-specific options:

- **bold_rows** [boolean, default True] Make the row labels bold in the output
- **column_format** [str, default None] The columns format as specified in LaTeX table format e.g. 'rcl' for 3 columns
- **longtable** [boolean, default False] Use a longtable environment instead of tabular. Requires adding a usepackage{longtable} to your LaTeX preamble.
- **escape** [boolean, default True] When set to False prevents from escaping latex special characters in column names.

**Parameters**

- **buf** : StringIO-like, optional
  buffer to write to
- **columns** : sequence, optional
  the subset of columns to write; default None writes all columns
- **col_space** : int, optional
  the minimum width of each column
- **header** : bool, optional
  whether to print column labels, default True
- **index** : bool, optional
  whether to print index (row) labels, default True
- **na_rep** : string, optional
  string representation of NaN to use, default ‘NaN’
- **formatters** : list or dict of one-parameter functions, optional
  formatter functions to apply to columns’ elements by position or name, default None. 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, optional
  formatter function to apply to columns’ elements if they are floats, default None. The result of this function must be a unicode string.
- **sparsify** : bool, optional
Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row, default True

@index_names : bool, optional
Prints the names of the indexes, default True

Returns formatted : string (or unicode, depending on data and options)

**pandas.DataFrame.to_msgpack**

`DataFrame.to_msgpack(path_or_buf=None, **kwargs)`

msgpack (serialize) object to input file path

THIS IS AN EXPERIMENTAL LIBRARY and the storage format may not be stable until a future release.

Parameters path : string File path, buffer-like, or None
if None, return generated string

append : boolean whether to append to an existing msgpack
(default is False)

compress : type of compressor (zlib or blosc), default to None (no compression)

**pandas.DataFrame.to_panel**

`DataFrame.to_panel()`

Transform long (stacked) format (DataFrame) into wide (3D, Panel) format.
Currently the index of the DataFrame must be a 2-level MultiIndex. This may be generalized later

Returns panel : Panel

**pandas.DataFrame.to_period**

`DataFrame.to_period(freq=None, axis=0, copy=True)`

Convert DataFrame from DatetimeIndex to PeriodIndex with desired frequency (inferred from index if not passed)

Parameters freq : string, default

axis : {0 or ‘index’, 1 or ‘columns’}, default 0
The axis to convert (the index by default)

copy : boolean, default True
If False then underlying input data is not copied

Returns ts : TimeSeries with PeriodIndex
pandas.DataFrame.to_pickle

DataFrame.to_pickle(path)
Pickle (serialize) object to input file path

Parameters
- **path**: string
  - File path

pandas.DataFrame.to_records

DataFrame.to_records(index=True, convert_datetime64=True)
Convert DataFrame to record array. Index will be put in the ‘index’ field of the record array if requested

Parameters
- **index**: boolean, default True
  - Include index in resulting record array, stored in ‘index’ field
- **convert_datetime64**: boolean, default True
  - Whether to convert the index to datetime.datetime if it is a DatetimeIndex

Returns
- **y**: recarray

pandas.DataFrame.to_sparse

DataFrame.to_sparse(fill_value=None, kind='block')
Convert to SparseDataFrame

Parameters
- **fill_value**: float, default NaN
  - kind: {'block', 'integer'}

Returns
- **y**: SparseDataFrame

pandas.DataFrame.to_sql

DataFrame.to_sql(name, con, flavor='sqlite', schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None)
Write records stored in a DataFrame to a SQL database.

Parameters
- **name**: string
  - Name of SQL table
- **con**: SQLAlchemy engine or DBAPI2 connection (legacy mode)
  - Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.
- **flavor**: {'sqlite', 'mysql'}, default ‘sqlite’
  - The flavor of SQL to use. Ignored when using SQLAlchemy engine. ‘mysql’ is deprecated and will be removed in future versions, but it will be further supported through SQLAlchemy engines.
- **schema**: string, default None
  - Specify the schema (if database flavor supports this). If None, use default schema.
- **if_exists**: {'fail', ‘replace’, ‘append’}, default ‘fail’
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- fail: If table exists, do nothing.
- replace: If table exists, drop it, recreate it, and insert data.
- append: If table exists, insert data. Create if does not exist.

**index**: boolean, default True

Write DataFrame index as a column.

**index_label**: string 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, default None

If not None, then rows will be written in batches of this size at a time. If None, all rows will be written at once.

**dtype**: dict of column name to SQL type, default None

Optional specifying the datatype for columns. The SQL type should be a SQLAlchemy type, or a string for sqlite3 fallback connection.

**pandas.DataFrame.to_stata**

DataFrame.to_stata(fname, convert_dates=None, write_index=True, encoding='latin-1', byteorder=None, time_stamp=None, data_label=None)

A class for writing Stata binary dta files from array-like objects

**Parameters**

**fname**: file path or buffer

Where to save the dta file.

**convert_dates**: dict

Dictionary mapping column of datetime types to the stata internal format that you want to use for the dates. Options are ‘tc’, ‘td’, ‘tm’, ‘tw’, ‘th’, ‘tq’, ‘ty’. Column can be either a number or a name.

**encoding**: str

Default is latin-1. Note that Stata does not support unicode.

**byteorder**: str

Can be “>”, “<”, “little”, or “big”. The default is None which uses sys.byteorder

**Examples**

```python
>>> writer = StataWriter('./data_file.dta', data)
>>> writer.write_file()
```

Or with dates

```python
>>> writer = StataWriter('./date_data_file.dta', data, {2 : 'tw'})
>>> writer.write_file()
```
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, line_width=None, max_rows=None, max_cols=None, show_dimensions=False)

Render a DataFrame to a console-friendly tabular output.

**Parameters**

- **buf**: StringIO-like, optional
  - buffer to write to
- **columns**: sequence, optional
  - the subset of columns to write; default None writes all columns
- **col_space**: int, optional
  - the minimum width of each column
- **header**: bool, optional
  - whether to print column labels, default True
- **index**: bool, optional
  - whether to print index (row) labels, default True
- **na_rep**: string, optional
  - string representation of NAN to use, default ‘NaN’
- **formatters**: list or dict of one-parameter functions, optional
  - formatter functions to apply to columns’ elements by position or name, default None. 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, optional
  - formatter function to apply to columns’ elements if they are floats, default None. The result of this function must be a unicode string.
- **sparsify**: bool, optional
  - Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row, default True
- **index_names**: bool, optional
  - Prints the names of the indexes, default True
- **justify**: {'left', 'right'}, default None
  - Left or right-justify the column labels. If None uses the option from the print configuration (controlled by set_option), ‘right’ out of the box.

**Returns**

- **formatted**: string (or unicode, depending on data and options)

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**: string, 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** : boolean, default True

If false then underlying input data is not copied

**Returns**

| df | DataFrame with DatetimeIndex |

**pandas.DataFrame.to_wide**

DataFrame.to_wide(*args, **kwargs)

**pandas.DataFrame.transpose**

DataFrame.transpose()

Transpose index and columns

**pandas.DataFrame.truediv**

DataFrame.truediv(other, axis='columns', level=None, fill_value=None)

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.

**Parameters**

- **other** : Series, DataFrame, or constant
- **axis** : {0, 1, ‘index’, ‘columns’}

For Series input, axis to match Series index on

- **fill_value** : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

- **level** : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**

| result | DataFrame |

**See also**

DataFrame.rtruediv

**Notes**

Mismatched indices will be unioned together
pandas.DataFrame.truncate

DataFrame.truncate(before=None, after=None, axis=None, copy=True)
Truncates a sorted NDFrame before and/or after some particular dates.

Parameters

- **before**: date
  - Truncate before date
- **after**: date
  - Truncate after date
- **axis**: the truncation axis, defaults to the stat axis
- **copy**: boolean, default is True,
  - return a copy of the truncated section

Returns **truncated** : type of caller

pandas.DataFrame.tshift

DataFrame.tshift(periods=1, freq=None, axis=0)
Shift the time index, using the index’s frequency if available

Parameters

- **periods** : int
  - Number of periods to move, can be positive or negative
- **freq** : DateOffset, timedelta, or time rule string, default None
  - Increment to use from datetools module or time rule (e.g. ‘EOM’)
- **axis** : int or basestring
  - Corresponds to the axis that contains the Index

Returns **shifted** : NDFrame

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** : string or pytz.timezone object
- **axis** : the axis to convert
- **level** : int, str, default None
  - If axis ia a MultiIndex, convert a specific level. Otherwise must be None
- **copy** : boolean, default True
  - Also make a copy of the underlying data
Raises `TypeError`

If the axis is tz-naive.

---

**pandas.DataFrame.tz_localize**

```
DataFrame.tz_localize(*args, **kwargs)
```

Localize tz-naive TimeSeries to target time zone

**Parameters**

- **tz**: string or pytz.timezone object
- **axis**: the axis to localize
- **level**: int, str, default None
  - If axis ia a MultiIndex, localize a specific level. Otherwise must be None
- **copy**: boolean, default True
  - Also make a copy of the underlying data
- **ambiguous**: ‘infer’, bool-ndarray, ‘NaT’, default ‘raise’
  - ‘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
- **infer_dst**: boolean, default False (DEPRECATED)
  - Attempt to infer fall dst-transition hours based on order

** Raises `TypeError`

If the TimeSeries is tz-aware and tz is not None.

---

**pandas.DataFrame.unstack**

```
DataFrame.unstack(level=-1)
```

Pivot a level of the (necessarily hierarchical) index labels, returning 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). The level involved will automatically get sorted.

**Parameters**

- **level**: int, string, or list of these, default -1 (last level)
  - Level(s) of index to unstack, can pass level name

**Returns**

- **unstacked**: DataFrame or Series

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  
b 2  
two a 3  
b 4
dtype: float64
>>> s.unstack(level=-1)
   a  b
one 1 2
two 3 4

>>> s.unstack(level=0)
   one  two
   a  1  3
   b  2  4

>>> df = s.unstack(level=0)
>>> df.unstack()
   one  a  1.
   b  3.
   two a  2.
   b  4.
```

**pandas.DataFrame.update**

DataFrames can be updated in place using non-NA values from another DataFrame. Aligns on indices.

**Parameters**

- **other** : DataFrame, or object coercible into a DataFrame
- **join** : {'left'}, default ‘left’
- **overwrite** : boolean, default True
  - If True then overwrite values for common keys in the calling frame
- **filter_func** : callable(1d-array) -> 1d-array<boolean>, default None
  - Can choose to replace values other than NA. Return True for values that should be updated
- **raise_conflict** : boolean
  - If True, will raise an error if the DataFrame and other both contain data in the same place.

**pandas.DataFrame.var**

DataFrames can compute the variance.

**Parameters**

- **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.
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**Parameters**

- **axis**: {index (0), columns (1)}
  - **skipna**: boolean, 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
  - **numeric_only**: boolean, default None
  - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**

- **var**: Series or DataFrame (if level specified)

---

**pandas.DataFrame.where**

DataFrame.where (cond, other=nan, inplace=False, axis=None, level=None, try_cast=False, raise_on_error=True)

Return an object of same shape as self and whose corresponding entries are from self where cond is True and otherwise are from other.

**Parameters**

- **cond**: boolean NDFrame or array
  - **other**: scalar or NDFrame
  - **inplace**: boolean, default False
    - Whether to perform the operation in place on the data
  - **axis**: alignment axis if needed, default None
  - **level**: alignment level if needed, default None
  - **try_cast**: boolean, default False
    - try to cast the result back to the input type (if possible).
  - **raise_on_error**: boolean, default True
    - Whether to raise on invalid data types (e.g. trying to where on strings)

**Returns**

- **wh**: same type as caller

---

**pandas.DataFrame.xs**

DataFrame.xs (key, axis=0, level=None, copy=None, drop_level=True)

Returns a cross-section (row(s) or column(s)) from the Series/DataFrame. Defaults to cross-section on the rows (axis=0).

**Parameters**

- **key**: object
  - Some label contained in the index, or partially in a MultiIndex
- **axis**: int, 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.

**copy** : boolean [deprecated]
Whether to make a copy of the data

**drop_level** : boolean, default True
If False, returns object with same levels as self.

**Returns**  
**xs**: Series or DataFrame

**Notes**

xs is only for getting, not setting 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
>>> df
     A   B   C
a  4  5  2
b  4  0  9
c  9  7  3

>>> df.xs('a')
     A   B   C
    4   5   2

Name: a

>>> df.xs('C', axis=1)
     a   b   c
   2   9   3

Name: C

>>> df
  first  second  third
  bar   one  1  4  1  8  9
      two  1  7  5  5  0
  baz   one  1  6  6  8  0
      three  2  5  3  5  3

>>> df.xs(('baz', 'three'))
  A   B   C   D
third 2  5  3  5  3

>>> df.xs('one', level=1)
  first  third
  bar  1  4  1  8  9
  baz  1  6  6  8  0

>>> df.xs(('baz', 2), level=[0, 'third'])
  A   B   C   D
second 5  3  5  3
```
34.4.2 Attributes and underlying data

Axes

- **index**: row labels
- **columns**: column labels

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataFrame.as_matrix([columns])</td>
<td>Convert the frame to its Numpy-array representation.</td>
</tr>
<tr>
<td>DataFrame.dtypes</td>
<td>Return the dtypes in this object</td>
</tr>
<tr>
<td>DataFrame.ftypes</td>
<td>Return the ftypes (indication of sparse/dense and dtype) in this object.</td>
</tr>
<tr>
<td>DataFrame.get_dtype_counts()</td>
<td>Return the counts of dtypes in this object</td>
</tr>
<tr>
<td>DataFrame.get_ftype_counts()</td>
<td>Return the counts of ftypes in this object</td>
</tr>
<tr>
<td>DataFrame.select_dtypes(include, exclude)</td>
<td>Return a subset of a DataFrame including/excluding columns based on their</td>
</tr>
<tr>
<td></td>
<td>Numpy representation of NDFrame</td>
</tr>
<tr>
<td>DataFrame.axes</td>
<td>Return a list with the row axis labels and column axis labels as the only</td>
</tr>
<tr>
<td></td>
<td>members.</td>
</tr>
<tr>
<td>DataFrame.ndim</td>
<td>Number of axes / array dimensions</td>
</tr>
<tr>
<td>DataFrame.size</td>
<td>number of elements in the NDFrame</td>
</tr>
<tr>
<td>DataFrame.shape</td>
<td>Return a tuple representing the dimensionality of the DataFrame.</td>
</tr>
</tbody>
</table>

**pandas.DataFrame.as_matrix**

DataFrame.as_matrix(columns=None)

Convert the frame to its Numpy-array representation.

**Parameters**

- **columns**: list, optional, default:None

If None, return all columns, otherwise, returns specified columns.

**Returns**

- **values**: ndarray

If the caller is heterogeneous and contains booleans or objects, the result will be of
dtype=object. See Notes.

**See also:**

pandas.DataFrame.values

**Notes**

Return is NOT a Numpy-matrix, rather, a Numpy-array.

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.

This method is provided for backwards compatibility. Generally, it is recommended to use `.values`.

**pandas.DataFrame.dtypes**

DataFrame.dtypes

Return the dtypes in this object
pandas.DataFrame.ftypes

DataFrame.ftypes
Return the ftypes (indication of sparse/dense and dtype) in this object.

pandas.DataFrame.get_dtype_counts

DataFrame.get_dtype_counts()
Return the counts of dtypes in this object

pandas.DataFrame.get_ftype_counts

DataFrame.get_ftype_counts()
Return the counts of ftypes in this object

pandas.DataFrame.select_dtypes

DataFrame.select_dtypes(include=None, exclude=None)
Return a subset of a DataFrame including/excluding columns based on their dtype.

Parameters include, exclude : list-like
A list of dtypes or strings to be included/excluded. You must pass in a non-empty sequence for at least one of these.

Returns subset : 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.

TypeError
• If either of include or exclude is not a sequence

Notes
• To select all numeric types use the numpy dtype numpy.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 Pandas categorical dtypes, use ‘category’

Examples
>>> df = pd.DataFrame({'a': np.random.randn(6).astype('f4'),
...                     'b': [True, False] * 3,
...                     'c': [1.0, 2.0] * 3})
>>> df
   a     b     c
0  0.3962  True   1
1  0.1459  False  2
2  0.2623   True   1
3  0.0764  False  2
4 -0.9703   True   1
5 -1.2094  False  2
>>> df.select_dtypes(include=['float64'])
   c
0  1
1  2
2  1
3  2
4  1
5  2
>>> df.select_dtypes(exclude=['floating'])
   b
0  True
1  False
2  True
3  False
4  True
5  False

pandas.DataFrame.values

DataFrame.values
Numpy representation of NDFrame

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 upcase to int32.

pandas.DataFrame.axes

DataFrame.axes
Return a list with the row axis labels and column axis labels as the only members. They are returned in that
order.

pandas.DataFrame.ndim

DataFrame.ndim
Number of axes / array dimensions
pandas.DataFrame.size

DataFrame.size
number of elements in the NDFrame

pandas.DataFrame.shape

DataFrame.shape
Return a tuple representing the dimensionality of the DataFrame.

34.4.3 Conversion

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataFrame.astype</td>
<td>Cast object to input numpy.dtype</td>
</tr>
<tr>
<td>DataFrame.convert_objects</td>
<td>Attempt to infer better dtype for object columns</td>
</tr>
<tr>
<td>DataFrame.copy</td>
<td>Make a copy of this object</td>
</tr>
<tr>
<td>DataFrame.isnull</td>
<td>Return a boolean same-sized object indicating if the values are null</td>
</tr>
<tr>
<td>DataFrame.notnull</td>
<td>Return a boolean same-sized object indicating if the values are not null</td>
</tr>
</tbody>
</table>

pandas.DataFrame.astype

DataFrame.astype(dtype[, copy, raise_on_error])
Cast object to input numpy.dtype
Return a copy when copy = True (be really careful with this!)

Parameters:
dtype : numpy.dtype or Python type
raise_on_error : raise on invalid input
kwarg : keyword arguments to pass on to the constructor

Returns:
casted : type of caller

pandas.DataFrame.convert_objects

DataFrame.convert_objects([convert_dates, ...])
Attempt to infer better dtype for object columns

Parameters:
convert_dates : boolean, default True
If True, convert to date where possible. If ‘coerce’, force conversion, with unconvertible values becoming NaT.
convert_numeric : boolean, default False
If True, attempt to coerce to numbers (including strings), with unconvertible values becoming NaN.
convert_timedeltas : boolean, default True
If True, convert to timedelta where possible. If ‘coerce’, force conversion, with unconvertible values becoming NaT.
copy : boolean, default True
If True, return a copy even if no copy is necessary (e.g. no conversion was done).
Note: This is meant for internal use, and should not be confused with inplace.
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Returns converted: same as input object

pandas.DataFrame.copy

DataFrame.copy (deep=True)
Make a copy of this object

Parameters deep: boolean or string, default True
Make a deep copy, i.e. also copy data

Returns copy: type of caller

pandas.DataFrame.isnull

DataFrame.isnull()
Return a boolean same-sized object indicating if the values are null

See also:

notnull boolean inverse of isnull

pandas.DataFrame.notnull

DataFrame.notnull()
Return a boolean same-sized object indicating if the values are not null

See also:

isnull boolean inverse of notnull

34.4.4 Indexing, iteration

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataFrame.head([n])</td>
<td>Returns first n rows</td>
</tr>
<tr>
<td>DataFrame.at</td>
<td>Fast label-based scalar accessor</td>
</tr>
<tr>
<td>DataFrame.iat</td>
<td>Fast integer location scalar accessor.</td>
</tr>
<tr>
<td>DataFrame.loc</td>
<td>A primarily label-location based indexer, with integer position fallback.</td>
</tr>
<tr>
<td>DataFrame.iiloc</td>
<td>Purely label-location based indexer for selection by label.</td>
</tr>
<tr>
<td>DataFrame.insert(loc, column, value[, ...])</td>
<td>Purely integer-location based indexing for selection by position.</td>
</tr>
<tr>
<td>DataFrame.<strong>iter</strong>()</td>
<td>Insert column into DataFrame at specified location.</td>
</tr>
<tr>
<td>DataFrame.iteritems()</td>
<td>Iterate over infor axis</td>
</tr>
<tr>
<td>DataFrame.iterrows()</td>
<td>Iterator over (column name, Series) pairs.</td>
</tr>
<tr>
<td>DataFrame.itertuples([index])</td>
<td>Iterate over the rows of a DataFrame as (index, Series) pairs.</td>
</tr>
<tr>
<td>DataFrame.lookup(row_labels, col_labels)</td>
<td>Iterate over the rows of DataFrame as tuples, with index value as first element of the tuple.</td>
</tr>
<tr>
<td>DataFrame.xs(key[, axis, level, copy, ...])</td>
<td>Label-based “fancy indexing” function for DataFrame.</td>
</tr>
<tr>
<td>DataFrame.pop(item)</td>
<td>Return item and drop from frame.</td>
</tr>
<tr>
<td>DataFrame.tail([n])</td>
<td>Returns last n rows</td>
</tr>
<tr>
<td>DataFrame.xs(key[, axis, level, copy, ...])</td>
<td>Returns a cross-section (row(s) or column(s)) from the Series/DataFrame.</td>
</tr>
<tr>
<td>DataFrame.isin(values)</td>
<td>Return boolean DataFrame showing whether each element in the DataFrame is in the given list of values.</td>
</tr>
<tr>
<td>DataFrame.where(cond[, other, inplace, ...])</td>
<td>Return an object of same shape as self and whose corresponding entries are from other.</td>
</tr>
<tr>
<td>DataFrame.mask(cond[, other, inplace, axis, ...])</td>
<td>Return an object of same shape as self and whose corresponding entries are from other.</td>
</tr>
<tr>
<td>DataFrame.query(expr, **kwargs)</td>
<td>Query the columns of a frame with a boolean expression.</td>
</tr>
</tbody>
</table>
**pandas.DataFrame.head**

Dataframe. `head(n=5)`  
Returns first n rows

**pandas.DataFrame.at**

Dataframe. `at`  
Fast label-based scalar accessor  
Similarly to `loc`, `at` provides label based scalar lookups. You can also set using these indexers.

**pandas.DataFrame.iat**

Dataframe. `iat`  
Fast integer location scalar accessor.  
Similarly to `iloc`, `iat` provides integer based lookups. You can also set using these indexers.

**pandas.DataFrame.ix**

Dataframe. `ix`  
A primarily label-location based indexer, with integer position fallback.  
`.ix[]` supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type.  
`.ix` is the most general indexer and will support any of the inputs in `.loc` and `.iloc`. `.ix` also supports floating point label schemes. `.ix` is exceptionally useful when dealing with mixed positional and label based hierarchical indexes.  
However, when an axis is integer based, ONLY label based access and not positional access is supported. Thus, in such cases, it’s usually better to be explicit and use `.iloc` or `.loc`.  
See more at `Advanced Indexing`.

**pandas.DataFrame.loc**

Dataframe. `loc`  
Purely label-location based indexer for selection by label.  
`.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’ (note that contrary to usual python slices, both the start and the stop are included!).  
• A boolean array.  
`.loc` will raise a `KeyError` when the items are not found.  
See more at `Selection by Label`
pandas.DataFrame.iloc

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.

.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

pandas.DataFrame.insert

DataFrame.insert(loc, column, value, allow_duplicates=False)
Insert column into DataFrame at specified location.

If allow_duplicates is False, raises Exception if column is already contained in the DataFrame.

Parameters loc : int
   Must have 0 <= loc <= len(columns)

    column : object

    value : int, Series, or array-like

pandas.DataFrame.__iter__

DataFrame.__iter__()
Iterate over infor axis

pandas.DataFrame.iteritems

DataFrame.iteritems()
Iterator over (column name, Series) pairs.

See also:

iterrows Iterate over the rows of a DataFrame as (index, Series) pairs.

itertuples Iterate over the rows of a DataFrame as tuples of the values.
**pandas.DataFrame.iterrows**

DataFrame.iterrows()  
Iterate over the rows of a DataFrame as (index, Series) pairs.

**Returns**  
it : generator  
A generator that iterates over the rows of the frame.

**See also:**

* itertuples  
  Iterate over the rows of a DataFrame as tuples of the values.

* iteritems  
  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,

   ```
   >>> 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 tuples 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)  
Iterate over the rows of DataFrame as tuples, with index value as first element of the tuple.

**Parameters**  
index : boolean, default True  
If True, return the index as the first element of the tuple.

**See also:**

* iterrows  
  Iterate over the rows of a DataFrame as (index, Series) pairs.

* iteritems  
  Iterate over (column name, Series) pairs.

**Examples**
```python
>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [0.1, 0.2]}, index=['a', 'b'])
>>> df
  col1 col2
a   1   0.1
b   2   0.2
>>> for row in df.itertuples():
...    print(row)
('a', 1, 0.10000000000000001)
('b', 2, 0.20000000000000001)
```

### 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

**Notes**
Akin to:
```
result = []
for row, col in zip(row_labels, col_labels):
    result.append(df.get_value(row, col))
```

**Examples**

values [ndarray] The found values

### pandas.DataFrame.pop

DataFrame.pop(item)
Return item and drop from frame. Raise KeyError if not found.

### pandas.DataFrame.tail

DataFrame.tail(n=5)
Returns last n rows

### pandas.DataFrame.xs

DataFrame.xs(key, axis=0, level=None, copy=None, drop_level=True)
Returns a cross-section (row(s) or column(s)) from the Series/DataFrame. Defaults to cross-section on the rows (axis=0).
Parameters

- **key**: object
  - Some label contained in the index, or partially in a MultiIndex

- **axis**: int, 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.

- **copy**: boolean [deprecated]
  - Whether to make a copy of the data

- **drop_level**: boolean, default True
  - If False, returns object with same levels as self.

Returns

- **xs**: Series or DataFrame

Notes

xs is only for getting, not setting 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
>>> df
   A  B  C
a  1  2  3
b  4  5  6
c  7  8  9

>>> df.xs('a')
   A  B  C
  a  4  5  2

>>> df.xs('C', axis=1)
   a  2
   b  9
   c  3

>>> df.xs(('baz', 'three'))
   A  B  C  D
third
  2  5  3  3

>>> df.xs('one', level=1)
```

34.4. **DataFrame**
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A  B  C  D
first third
bar 1  4 1 8 9
baz 1 6 6 8 0
>>> df.xs(('baz', 2), level=[0, 'third'])
A   B   C   D
second
three 5 3 5 3

pandas.DataFrame.isin

DataFrame.isin(values)
Return boolean DataFrame showing whether each element in the DataFrame is contained in values.

Parameters values : iterable, Series, DataFrame or dictionary

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 dictionary, 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 of booleans

Examples

When values is a list:

>>> df = DataFrame({'A': [1, 2, 3], 'B': ['a', 'b', 'f']})
>>> df.isin([1, 3, 12, 'a'])
A  B
0  True  True
1  False False
2  True  False

When values is a dict:

>>> df = DataFrame({'A': [1, 2, 3], 'B': [1, 4, 7]})
>>> df.isin({'A': [1, 3], 'B': [4, 7, 12]})
A  B
0  True False # Note that B didn't match the 1 here.
1  False True
2  True  True

When values is a Series or DataFrame:

>>> df = DataFrame({'A': [1, 2, 3], 'B': ['a', 'b', 'f']})
>>> other = DataFrame({'A': [1, 3, 3, 2], 'B': ['e', 'f', 'f', 'e']})
>>> df.isin(other)
A  B
0  True False # Column A in `other` has a 3, but not at index 1.
1  False False
2  True  True
DataFrame.where

DataFrame\:\where\ (cond,\ other=nan,\ inplace=False,\ axis=None,\ level=None,\ try_cast=False,\ raise_on_error=True)\n
Return an object of same shape as self and whose corresponding entries are from self where cond is True and otherwise are from other.

**Parameters**
- **cond**: boolean NDFrame or array
- **other**: scalar or NDFrame
- **inplace**: boolean, default False
  Whether to perform the operation in place on the data
- **axis**: alignment axis if needed, default None
- **level**: alignment level if needed, default None
- **try_cast**: boolean, default False
  try to cast the result back to the input type (if possible),
- **raise_on_error**: boolean, default True
  Whether to raise on invalid data types (e.g. trying to where on strings)

**Returns**
- **wh**: same type as caller

DataFrame.mask

DataFrame\:\mask\ (cond,\ other=nan,\ inplace=False,\ axis=None,\ level=None,\ try_cast=False,\ raise_on_error=True)\n
Return an object of same shape as self and whose corresponding entries are from self where cond is False and otherwise are from other.

**Parameters**
- **cond**: boolean NDFrame or array
- **other**: scalar or NDFrame
- **inplace**: boolean, default False
  Whether to perform the operation in place on the data
- **axis**: alignment axis if needed, default None
- **level**: alignment level if needed, default None
- **try_cast**: boolean, default False
  try to cast the result back to the input type (if possible),
- **raise_on_error**: boolean, default True
  Whether to raise on invalid data types (e.g. trying to where on strings)

**Returns**
- **wh**: same type as caller

DataFrame.query

DataFrame\:\query\ (expr,\ **kwargs)\n
Query the columns of a frame with a boolean expression.

New in version 0.13.
Parameters `expr : string`

The query string to evaluate. You can refer to variables in the environment by prefixing them with an '@' character like @a + b.

`kwargs : dict`

See the documentation for `pandas.eval()` for complete details on the keyword arguments accepted by `DataFrame.query()`.

Returns `q : DataFrame`

See also:

`pandas.eval, DataFrame.eval`

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 `pandas.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.

For further details and examples see the `query` documentation in indexing.

Examples

```python
>>> from numpy.random import randn
>>> from pandas import DataFrame

>>> df = DataFrame(randn(10, 2), columns=list('ab'))
>>> df.query('a > b')

# same result as the previous expression
```

For more information on `.at`, `.iat`, `.ix`, `.loc`, and `.iloc`, see the indexing documentation.

### 34.4.5 Binary operator functions

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>DataFrame.add(other[, axis, level, fill_value])</code></td>
<td>Addition of dataframe and other, element-wise (binary operator <code>add</code>).</td>
</tr>
<tr>
<td><code>DataFrame.sub(other[, axis, level, fill_value])</code></td>
<td>Subtraction of dataframe and other, element-wise (binary operator <code>sub</code>).</td>
</tr>
<tr>
<td><code>DataFrame.mul(other[, axis, level, fill_value])</code></td>
<td>Multiplication of dataframe and other, element-wise (binary operator <code>mul</code>).</td>
</tr>
<tr>
<td><code>DataFrame.div(other[, axis, level, fill_value])</code></td>
<td>Floating division of dataframe and other, element-wise (binary operator <code>truediv</code>).</td>
</tr>
<tr>
<td><code>DataFrame.truediv(other[, axis, level, ...])</code></td>
<td>Floating division of dataframe and other, element-wise (binary operator <code>truediv</code>).</td>
</tr>
</tbody>
</table>
Table 34.57 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataFrame.floordiv</td>
<td>Integer division of dataframe and other, element-wise</td>
</tr>
<tr>
<td>DataFrame.mod</td>
<td>Modulo of dataframe and other, element-wise</td>
</tr>
<tr>
<td>DataFrame.pow</td>
<td>Exponential power of dataframe and other, element-wise</td>
</tr>
<tr>
<td>DataFrame.radd</td>
<td>Addition of dataframe and other, element-wise</td>
</tr>
<tr>
<td>DataFrame.rmul</td>
<td>Multiplication of dataframe and other, element-wise</td>
</tr>
<tr>
<td>DataFrame.rdiv</td>
<td>Floating division of dataframe and other, element-wise</td>
</tr>
<tr>
<td>DataFrame.rfloordiv</td>
<td>Integer division of dataframe and other, element-wise</td>
</tr>
<tr>
<td>DataFrame.rmod</td>
<td>Modulo of dataframe and other, element-wise</td>
</tr>
<tr>
<td>DataFrame.rpow</td>
<td>Exponential power of dataframe and other, element-wise</td>
</tr>
<tr>
<td>DataFrame.lt</td>
<td>Wrapper for flexible comparison methods lt</td>
</tr>
<tr>
<td>DataFrame.gt</td>
<td>Wrapper for flexible comparison methods gt</td>
</tr>
<tr>
<td>DataFrame.le</td>
<td>Wrapper for flexible comparison methods le</td>
</tr>
<tr>
<td>DataFrame.ge</td>
<td>Wrapper for flexible comparison methods ge</td>
</tr>
<tr>
<td>DataFrame.ne</td>
<td>Wrapper for flexible comparison methods ne</td>
</tr>
<tr>
<td>DataFrame.eq</td>
<td>Wrapper for flexible comparison methods eq</td>
</tr>
<tr>
<td>DataFrame.combine</td>
<td>Add two DataFrame objects and do not propagate NaN values</td>
</tr>
<tr>
<td>DataFrame.combine_first</td>
<td>Combine two DataFrame objects and default to non-null values</td>
</tr>
</tbody>
</table>

**pandas.DataFrame.add**

DataFrame.add(other[, axis, level=0, fill_value=None])

Addition of dataframe and other, element-wise (binary operator \texttt{add}).

Equivalent to \texttt{dataframe + other}, but with support to substitute a \texttt{fill_value} for missing data in one of the inputs.

**Parameters**

- **other** : Series, DataFrame, or constant
  - **axis** : \{0, 1, ‘index’, ‘columns’\}
    - For Series input, axis to match Series index on
  - **fill_value** : None or float value, default None
    - Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing
  - **level** : int or name
    - Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**

- **result** : DataFrame

**See also**

DataFrame.radd

**Notes**

Mismatched indices will be unioned together
pandas: powerful Python data analysis toolkit, Release 0.17.0

pandas.DataFrame.sub

DataFrame.sub(other, axis='columns', level=None, fill_value=None)
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.

Parameters other : Series, DataFrame, or constant
axis : {0, 1, ‘index’, ‘columns’}
For Series input, axis to match Series index on
fill_value : None or float value, default None
Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing
level : int or name
Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

See also:
DataFrame.rsub

Notes
Mismatched indices will be unioned together

pandas.DataFrame.mul

DataFrame.mul(other, axis='columns', level=None, fill_value=None)
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.

Parameters other : Series, DataFrame, or constant
axis : {0, 1, ‘index’, ‘columns’}
For Series input, axis to match Series index on
fill_value : None or float value, default None
Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing
level : int or name
Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

See also:
DataFrame.rmul
Notes

Mismatched indices will be unioned together

**pandas.DataFrame.div**

DataFrame.div(other, axis='columns', level=None, fill_value=None)

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.

**Parameters**
other : Series, DataFrame, or constant

axis : {0, 1, ‘index’, ‘columns’}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**
result : DataFrame

**See also:**

DataFrame.rtruediv

Notes

Mismatched indices will be unioned together

**pandas.DataFrame.truediv**

DataFrame.truediv(other, axis='columns', level=None, fill_value=None)

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.

**Parameters**
other : Series, DataFrame, or constant

axis : {0, 1, ‘index’, ‘columns’}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**
result : DataFrame
pandas: powerful Python data analysis toolkit, Release 0.17.0

See also:

Dataframe.rtruediv

Notes

Mismatched indices will be unioned together

pandas.DataFrame.floordiv

Dataframe.floordiv(other, axis='columns', level=None, fill_value=None)

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.

Parameters

other : Series, DataFrame, or constant

axis : {0, 1, ‘index’, ‘columns’}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns

result : DataFrame

See also:

Dataframe.rfloordiv

Notes

Mismatched indices will be unioned together

pandas.DataFrame.mod

Dataframe.mod(other, axis='columns', level=None, fill_value=None)

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.

Parameters

other : Series, DataFrame, or constant

axis : {0, 1, ‘index’, ‘columns’}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing
**pandas.DataFrame.pow**

DataFrame.pow(other, axis='columns', level=None, fill_value=None)

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.

**Parameters**

- **other**: Series, DataFrame, or constant
  - **axis**: {0, 1, ‘index’, ‘columns’}
    - For Series input, axis to match Series index on
  - **fill_value**: None or float value, default None
    - Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing
  - **level**: int or name
    - Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**

- **result**: DataFrame

**See also**

DataFrame.rpow

**Notes**

Mismatched indices will be unioned together

**pandas.DataFrame.radd**

DataFrame.radd(other, axis='columns', level=None, fill_value=None)

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.

**Parameters**

- **other**: Series, DataFrame, or constant
  - **axis**: {0, 1, ‘index’, ‘columns’}
    - For Series input, axis to match Series index on

**Returns**

- **result**: DataFrame

**See also**

DataFrame.rpow

**Notes**

Mismatched indices will be unioned together

---

34.4. **DataFrame**
fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing,
the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

See also:

DataFrame.add

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rsub

DataFrame.rsub (other, axis='columns', level=None, fill_value=None)

Subtraction of dataframe and other, element-wise (binary operator rsub).
Equivalent to other - dataframe, but with support to substitute a fill_value for missing data in one of the
inputs.

Parameters other : Series, DataFrame, or constant

axis : {0, 1, ‘index’, ‘columns’}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing,
the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

See also:

DataFrame.sub

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rmul

DataFrame.rmul (other, axis='columns', level=None, fill_value=None)

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.
**Parameters**

- **other**: Series, DataFrame, or constant
- **axis**: {0, 1, ‘index’, ‘columns’}
  
  For Series input, axis to match Series index on
- **fill_value**: None or float value, default None
  
  Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing
- **level**: int or name
  
  Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**

- **result**: DataFrame

**See also**

- `DataFrame.mul`

**Notes**

Mismatched indices will be unioned together

### pandas.DataFrame.rdiv

```python
DataFrame.rdiv(other, axis='columns', level=None, fill_value=None)
```

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.

**Parameters**

- **other**: Series, DataFrame, or constant
- **axis**: {0, 1, ‘index’, ‘columns’}
  
  For Series input, axis to match Series index on
- **fill_value**: None or float value, default None
  
  Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing
- **level**: int or name
  
  Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**

- **result**: DataFrame

**See also**

- `DataFrame.truediv`

**Notes**

Mismatched indices will be unioned together
pandas: powerful Python data analysis toolkit, Release 0.17.0

pandas.DataFrame.rtruediv

DataFrame.\texttt{rtruediv}(other, axis='columns', level=None, fill_value=None)
Floating division of dataframe and other, element-wise (binary operator \texttt{rtruediv}).

Equivalent to \texttt{other / dataframe}, but with support to substitute a fill_value for missing data in one of the inputs.

**Parameters**

- **other**: Series, DataFrame, or constant
  - **axis**: \{0, 1, ‘index’, ‘columns’\}
    - For Series input, axis to match Series index on
  - **fill_value**: None or float value, default None
    - Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing
  - **level**: int or name
    - Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**

- **result**: DataFrame

**See also:**

DataFrame.truediv

**Notes**

Mismatched indices will be unioned together

pandas.DataFrame.rfloordiv

DataFrame.\texttt{rfloordiv}(other, axis='columns', level=None, fill_value=None)
Integer division of dataframe and other, element-wise (binary operator \texttt{rfloordiv}).

Equivalent to \texttt{other // dataframe}, but with support to substitute a fill_value for missing data in one of the inputs.

**Parameters**

- **other**: Series, DataFrame, or constant
  - **axis**: \{0, 1, ‘index’, ‘columns’\}
    - For Series input, axis to match Series index on
  - **fill_value**: None or float value, default None
    - Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing
  - **level**: int or name
    - Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns**

- **result**: DataFrame

**See also:**

DataFrame.floordiv
Notes

Mismatched indices will be unioned together

pandas.DataFrame.rmod

DataFrame.rmod(other, axis='columns', level=None, fill_value=None)

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.

Parameters other : Series, DataFrame, or constant
  axis : {0, 1, ‘index’, ‘columns’}
    For Series input, axis to match Series index on
  fill_value : None or float value, default None
    Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing
  level : int or name
    Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

See also:
DataFrame.mod

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rpow

DataFrame.rpow(other, axis='columns', level=None, fill_value=None)

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.

Parameters other : Series, DataFrame, or constant
  axis : {0, 1, ‘index’, ‘columns’}
    For Series input, axis to match Series index on
  fill_value : None or float value, default None
    Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing
  level : int or name
    Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame
See also:

`DataFrame.pow`

Notes

Mismatched indices will be unioned together

**pandas.DataFrame.lt**

`DataFrame.lt(\textit{other, axis='columns', level=None})`

Wrapper for flexible comparison methods \texttt{lt}

**pandas.DataFrame.gt**

`DataFrame.gt(\textit{other, axis='columns', level=None})`

Wrapper for flexible comparison methods \texttt{gt}

**pandas.DataFrame.le**

`DataFrame.le(\textit{other, axis='columns', level=None})`

Wrapper for flexible comparison methods \texttt{le}

**pandas.DataFrame.ge**

`DataFrame.ge(\textit{other, axis='columns', level=None})`

Wrapper for flexible comparison methods \texttt{ge}

**pandas.DataFrame.ne**

`DataFrame.ne(\textit{other, axis='columns', level=None})`

Wrapper for flexible comparison methods \texttt{ne}

**pandas.DataFrame.eq**

`DataFrame.eq(\textit{other, axis='columns', level=None})`

Wrapper for flexible comparison methods \texttt{eq}

**pandas.DataFrame.combine**

`DataFrame.combine(\textit{other, func, fill_value=None, overwrite=True})`

Add two DataFrame objects and do not propagate NaN values, so if for a (column, time) one frame is missing a value, it will default to the other frame’s value (which might be NaN as well)

Parameters

\texttt{other} : DataFrame

\texttt{func} : function

\texttt{fill_value} : scalar value

\texttt{overwrite} : boolean, default True
If True then overwrite values for common keys in the calling frame

**Returns**  
result : DataFrame

### pandas.DataFrame.combine_first

**DataFrame.combine_first(other)**  
Combine two DataFrame objects and default to non-null values in frame calling the method. Result index columns will be the union of the respective indexes and columns

**Parameters**  
other : DataFrame

**Returns**  
combined : DataFrame

### Examples

a’s values prioritized, use values from b to fill holes:

```python
>>> a.combine_first(b)
```

### 34.4.6 Function application, GroupBy

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataFrame.apply(func[, axis, broadcast, ...])</td>
<td>Applies function along input axis of DataFrame.</td>
</tr>
<tr>
<td>DataFrame.applymap(func)</td>
<td>Apply a function to a DataFrame that is intended to operate elementwise, i.e.</td>
</tr>
<tr>
<td>DataFrame.groupby([by, axis, level, ...])</td>
<td>Group series using mapper (dict or key function, apply given function</td>
</tr>
</tbody>
</table>

### pandas.DataFrame.apply

**DataFrame.apply(func, axis=0, broadcast=False, raw=False, reduce=None, args=(), **kwds)**  
Applies function along input axis of DataFrame.

Objects passed to functions are Series objects having index either the DataFrame’s index (axis=0) or the columns (axis=1). Return type depends on whether passed function aggregates, or the reduce argument if the DataFrame is empty.

**Parameters**  
func : function

  Function to apply to each column/row

  axis : {0 or ‘index’, 1 or ‘columns’}, default 0

    • 0 or ‘index’: apply function to each column
    • 1 or ‘columns’: apply function to each row

  broadcast : boolean, default False

    For aggregation functions, return object of same size with values propagated

  reduce : boolean or None, default None

    Try to apply reduction procedures. If the DataFrame is empty, apply will use reduce to determine whether the result should be a Series or a DataFrame. If reduce is None (the default), apply’s return value will be guessed by calling func an empty Series (note: while guessing, exceptions raised by func will be ignored). If reduce is True a Series will always be returned, and if False a DataFrame will always be returned.
raw : boolean, default False
If False, convert each row or column into a Series. If raw=True the passed function will receive ndarray objects instead. If you are just applying a NumPy reduction function this will achieve much better performance

args : tuple
Positional arguments to pass to function in addition to the array/series

Additional keyword arguments will be passed as keywords to the function

Returns applied : Series or DataFrame

See also:
DataFrame.applymap For elementwise operations

Notes
In the current implementation apply calls func twice on the first column/row to decide whether it can take a fast or slow code path. This can lead to unexpected behavior if func has side-effects, as they will take effect twice for the first column/row.

Examples

>>> df.apply(numpy.sqrt) # returns DataFrame
>>> df.apply(numpy.sum, axis=0) # equiv to df.sum(0)
>>> df.apply(numpy.sum, axis=1) # equiv to df.sum(1)

pandas.DataFrame.applymap

DataFrame.applymap (func)
Apply a function to a DataFrame that is intended to operate elementwise, i.e. like doing map(func, series) for each series in the DataFrame

Parameters func : function
Python function, returns a single value from a single value

Returns applied : DataFrame

See also:

DataFrame.apply For operations on rows/columns

pandas.DataFrame.groupby

DataFrame.groupby(by=None, axis=0, level=None, as_index=True, sort=True, group_keys=True, squeeze=False)
Group series using mapper (dict or key function, apply given function to group, return result as series) or by a series of columns

Parameters by : mapping function / list of functions, dict, Series, or tuple /
list of column names. Called on each element of the object index to determine the
groups. If a dict or Series is passed, the Series or dict VALUES will be used to
determine the groups

**axis** : int, default 0

**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** : boolean, 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** : boolean, 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** : boolean, default True

When calling apply, add group keys to index to identify pieces

**squeeze** : boolean, default False

reduce the dimensionality of the return type if possible, otherwise return a consistent
type

**Returns** GroupBy object

**Examples**

**DataFrame results**

```python
>>> data.groupby(func, axis=0).mean()
>>> data.groupby(['col1', 'col2'])['col3'].mean()
```

**DataFrame with hierarchical index**

```python
>>> data.groupby(['col1', 'col2']).mean()
```

34.4.7 **Computations / Descriptive Stats**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataFrame.abs()</td>
<td>Return an object with absolute value taken.</td>
</tr>
<tr>
<td>DataFrame.all([axis, bool_only, skipna, level])</td>
<td>Return whether all elements are True over requested axis</td>
</tr>
<tr>
<td>DataFrame.any([axis, bool_only, skipna, level])</td>
<td>Return whether any element is True over requested axis</td>
</tr>
<tr>
<td>DataFrame.clip([lower, upper, out, axis])</td>
<td>Trim values at input threshold(s)</td>
</tr>
<tr>
<td>DataFrame.clip_lower(threshold[, axis])</td>
<td>Return copy of the input with values below given value(s) truncated</td>
</tr>
<tr>
<td>DataFrame.clip_upper(threshold[, axis])</td>
<td>Return copy of input with values above given value(s) truncated</td>
</tr>
<tr>
<td>DataFrame.corr([method, min_periods])</td>
<td>Compute pairwise correlation of columns, excluding NA/null values</td>
</tr>
<tr>
<td>DataFrame.corrwith(other[, axis, drop])</td>
<td>Compute pairwise correlation between rows or columns of two DataFrame objects</td>
</tr>
<tr>
<td>DataFrame.count([axis, level, numeric_only])</td>
<td>Return Series with number of non-NA/null observations over requested axis</td>
</tr>
<tr>
<td>DataFrame.cov([min_periods])</td>
<td>Compute pairwise covariance of columns, excluding NA/null values</td>
</tr>
<tr>
<td>DataFrame.cummax([axis, dtype, out, skipna])</td>
<td>Return cumulative max over requested axis</td>
</tr>
<tr>
<td>DataFrame.cummin([axis, dtype, out, skipna])</td>
<td>Return cumulative min over requested axis</td>
</tr>
</tbody>
</table>
### Table 34.59 – continued from previous page

- **DataFrame.cumprod**(axis, dtypes, out, skipna) Return cumulative prod over requested axis.
- **DataFrame.cumsum**(axis, dtypes, out, skipna) Return cumulative sum over requested axis.
- **DataFrame.describe**(percentiles, include, ...) Generate various summary statistics, excluding NaN values.
- **DataFrame.diff**(periods) 1st discrete difference of object
- **DataFrame.eval**(expr, **kwargs) Evaluate an expression in the context of the calling DataFrame instance.
- **DataFrame.kurt**(axis, skipna, level, ...) Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0).
- **DataFrame.mad**(axis, skipna, level) Return the mean absolute deviation of the values for the requested axis.
- **DataFrame.max**(axis, skipna, level, ...) Return the maximum of the values for the requested axis.
- **DataFrame.mean**(axis, skipna, level, ...) Return the mean of the values for the requested axis.
- **DataFrame.min**(axis, skipna, level, ...) Return the minimum of the values for the requested axis.
- **DataFrame.mode**(axis, numeric_only) Gets the mode(s) of each element along the axis selected.
- **DataFrame.pct_change**(periods, fill_method, ...) Percent change over given number of periods.
- **DataFrame.prod**(axis, skipna, level, ...) Return the product of the values for the requested axis.
- **DataFrame.quantile**(q, axis, numeric_only) Return values at the given quantile over requested axis, a la numpy.percentile.
- **DataFrame.rank**(axis, numeric_only, method, ...) Compute numerical data ranks (1 through n) along axis.
- **DataFrame.round**(decimals, out) Round a DataFrame to a variable number of decimal places.
- **DataFrame.sem**(axis, skipna, level, ddof, ...) Return unbiased standard error of the mean over requested axis.
- **DataFrame.skew**(axis, skipna, level, ...) Return unbiased skew over requested axis.
- **DataFrame.sum**(axis, skipna, level, ...) Return the sum of the values for the requested axis.
- **DataFrame.std**(axis, skipna, level, ddof, ...) Return unbiased standard deviation over requested axis.
- **DataFrame.var**(axis, skipna, level, ddof, ...) Return unbiased variance over requested axis.

### pandas.DataFrame.abs

DataFrame.abs() Return an object with absolute value taken. Only applicable to objects that are all numeric

**Returns** abs: type of caller

### pandas.DataFrame.all

DataFrame.all(axis=None, bool_only=None, skipna=None, level=None, **kwargs) Return whether all elements are True over requested axis

**Parameters**

- **axis** : {index (0), columns (1)}
- **skipna** : boolean, 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
- **bool_only** : boolean, default None
  
  Include only boolean data. If None, will attempt to use everything, then use only boolean data

**Returns** all : Series or DataFrame (if level specified)
### pandas.DataFrame.any

DataFrame.any(axis=None, bool_only=None, skipna=None, level=None, **kwargs)

Return whether any element is True over requested axis

**Parameters**
- axis : {index (0), columns (1)}
- bool_only : boolean, default None
- skipna : boolean, default True
- level : int or level name, default None

**Returns**
- any : Series or DataFrame (if level specified)

### pandas.DataFrame.clip

DataFrame.clip(lower=None, upper=None, out=None, axis=None)

Trim values at input threshold(s)

**Parameters**
- lower : float or array_like, default None
- upper : float or array_like, default None
- axis : int or string axis name, optional

**Returns**
- clipped : Series

#### Examples

```python
>>> df
  0   1
0 0.335232 -1.256177
1 -1.367855  0.746646
2  0.027753 -1.176076
3  0.230930 -0.679613
4  1.261967  0.570967

>>> df.clip(-1.0, 0.5)
  0   1
0 0.335232 -1.000000
1 -1.000000  0.500000
2  0.027753 -1.000000
3  0.230930 -0.679613
4  0.500000  0.500000

>>> t
0 -0.3
1 -0.2
2 -0.1
3  0.0
4  0.1
```
dtyped: float64
>>> df.clip(t, t + 1, axis=0)
0    0
1   -0.2
2   0.0
3   0.2
4   1.0

pandas.DataFrame.clip_lower

DataFrame.clip_lower(threshold, axis=None)
Return copy of the input with values below given value(s) truncated

Parameters threshold : float or array_like
axis : int or string axis name, optional
Align object with threshold along the given axis.

Returns clipped : same type as input

See also:
clip

pandas.DataFrame.clip_upper

DataFrame.clip_upper(threshold, axis=None)
Return copy of input with values above given value(s) truncated

Parameters threshold : float or array_like
axis : int or string axis name, optional
Align object with threshold along the given axis.

Returns clipped : same type as input

See also:
clip

pandas.DataFrame.corr

DataFrame.corr(method='pearson', min_periods=1)
Compute pairwise correlation of columns, excluding NA/null values

Parameters method : {'pearson', 'kendall', 'spearman'}

- pearson : standard correlation coefficient
- kendall : Kendall Tau correlation coefficient
- spearman : Spearman rank correlation

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** $y$ : DataFrame

**pandas.DataFrame.corrwith**

`DataFrame.corrwith(other, axis=0, drop=False)`  
Compute pairwise correlation between rows or columns of two DataFrame objects.

- **Parameters**
  - other : DataFrame  
  - axis : {0 or ‘index’, 1 or ‘columns’}, default 0  
    - 0 or ‘index’ to compute column-wise, 1 or ‘columns’ for row-wise  
  - drop : boolean, default False  
    - Drop missing indices from result, default returns union of all

- **Returns**  
  - correls : Series

**pandas.DataFrame.count**

`DataFrame.count(axis=0, level=None, numeric_only=False)`  
Return Series with number of non-NA/null observations over requested axis. Works with non-floating point data as well (detects NaN and None).

- **Parameters**
  - axis : {0 or ‘index’, 1 or ‘columns’}, default 0  
    - 0 or ‘index’ for row-wise, 1 or ‘columns’ for column-wise  
  - level : int or level name, default None  
    - If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame  
  - numeric_only : boolean, default False  
    - Include only float, int, boolean data

- **Returns**  
  - count : Series (or DataFrame if level specified)

**pandas.DataFrame.cov**

`DataFrame.cov(min_periods=None)`  
Compute pairwise covariance of columns, excluding NA/null values

- **Parameters**
  - min_periods : int, optional  
    - Minimum number of observations required per pair of columns to have a valid result.

- **Returns**  
  - y : DataFrame

**Notes**

$y$ contains the covariance matrix of the DataFrame’s time series. The covariance is normalized by N-1 (unbiased estimator).
pandas.DataFrame.cummax

DataFrame.cummax (axis=None, dtype=None, out=None, skipna=True, **kwargs)

Return cumulative max over requested axis.

Parameters axis : {index (0), columns (1)}
    skipna  : boolean, default True
        Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns max : Series

pandas.DataFrame.cummin

DataFrame.cummin (axis=None, dtype=None, out=None, skipna=True, **kwargs)

Return cumulative min over requested axis.

Parameters axis : {index (0), columns (1)}
    skipna  : boolean, default True
        Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns min : Series

pandas.DataFrame.cumprod

DataFrame.cumprod (axis=None, dtype=None, out=None, skipna=True, **kwargs)

Return cumulative prod over requested axis.

Parameters axis : {index (0), columns (1)}
    skipna  : boolean, default True
        Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns prod : Series

pandas.DataFrame.cumsum

DataFrame.cumsum (axis=None, dtype=None, out=None, skipna=True, **kwargs)

Return cumulative sum over requested axis.

Parameters axis : {index (0), columns (1)}
    skipna  : boolean, default True
        Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns sum : Series

pandas.DataFrame.describe

DataFrame.describe (percentiles=None, include=None, exclude=None)

Generate various summary statistics, excluding NaN values.

Parameters percentiles : array-like, optional
The percentiles to include in the output. Should all be in the interval [0, 1]. By default percentiles is [.25, .5, .75], returning the 25th, 50th, and 75th percentiles.

**include, exclude**: list-like, ‘all’, or None (default)

Specify the form of the returned result. Either:

- None to both (default). The result will include only numeric-typed columns or, if none are, only categorical columns.
- A list of dtypes or strings to be included/excluded. To select all numeric types use numpy numpy.number. To select categorical objects use type object. See also the select_dtypes documentation. eg. df.describe(include=['O'])
- If include is the string ‘all’, the output column-set will match the input one.

**Returns** summary: DataFrame of summary statistics

**See also:**

DataFrame.select_dtypes

**Notes**

The output DataFrame index depends on the requested dtypes:

For numeric dtypes, it will include: count, mean, std, min, max, and lower, 50, and upper percentiles.

For object dtypes (e.g. timestamps or strings), the index will include the count, unique, most common, and frequency of the most common. Timestamps also include the first and last items.

For mixed dtypes, the index will be the union of the corresponding output types. Non-applicable entries will be filled with NaN. Note that mixed-dtype outputs can only be returned from mixed-dtype inputs and appropriate use of the include/exclude arguments.

If multiple values have the highest count, then the count and most common pair will be arbitrarily chosen from among those with the highest count.

The include, exclude arguments are ignored for Series.

**pandas.DataFrame.diff**

DataFrame.diff(periods=1, axis=0)

1st discrete difference of object

**Parameters**

- **periods**: int, default 1
  
  Periods to shift for forming difference

- **axis**: {0 or ‘index’, 1 or ‘columns’}, default 0
  
  Take difference over rows (0) or columns (1).

**Returns**

diffed: DataFrame

**pandas.DataFrame.eval**

DataFrame.eval(expr, **kwargs)

Evaluate an expression in the context of the calling DataFrame instance.

**Parameters**

- **expr**: string
The expression string to evaluate.

**kwargs**: dict

See the documentation for `eval()` for complete details on the keyword arguments accepted by `query()`.

Returns **ret**: ndarray, scalar, or pandas object

See also:

- `pandas.DataFrame.query`
- `pandas.eval`

Notes

For more details see the API documentation for `eval()`. For detailed examples see *enhancing performance with eval*.

Examples

```python
>>> from numpy.random import randn
>>> from pandas import DataFrame
>>> df = DataFrame(randn(10, 2), columns=list('ab'))
>>> df.eval('a + b')
>>> df.eval('c = a + b')
```

**pandas.DataFrame.kurt**

DataFrame.kurt *(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)*

Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters

- **axis**: {index (0), columns (1)}
  - skipna : boolean, 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
  - numeric_only : boolean, default None
    - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **kurt**: Series or DataFrame (if level specified)

**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)}
  - skipna : boolean, 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

**numeric_only** : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**

* mad : Series or DataFrame (if level specified)

### pandas.DataFrame.max

*DataFrame.max*(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

This method returns the maximum of the values in the object. 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)}
- **skipna** : boolean, 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

- **numeric_only** : boolean, default None
  
  Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**

* max : Series or DataFrame (if level specified)

### 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)}
- **skipna** : boolean, 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

- **numeric_only** : boolean, default None
  
  Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**

* mean : 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)}

- skipna : boolean, 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

numeric_only : boolean, default None

  - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns

median : Series or DataFrame (if level specified)

pandas.DataFrame.min

DataFrame.min(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

This method returns the minimum of the values in the object. 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)}

- skipna : boolean, 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

numeric_only : boolean, default None

  - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns

min : Series or DataFrame (if level specified)

pandas.DataFrame.mode

DataFrame.mode(axis=0, numeric_only=False)

Gets the mode(s) of each element along the axis selected. Empty if nothing has 2+ occurrences. Adds a row for each mode per label, fills in gaps with nan.

Note that there could be multiple values returned for the selected axis (when more than one item share the maximum frequency), which is the reason why a dataframe is returned. If you want to impute missing values with the mode in a dataframe df, you can just do this: df.fillna(df.mode().iloc[0])

Parameters

axis : {0 or ‘index’, 1 or ‘columns’}, default 0

  - 0 or ‘index’ : get mode of each column
  - 1 or ‘columns’ : get mode of each row
**numeric_only**: boolean, default False

if True, only apply to numeric columns

**Returns modes**: DataFrame (sorted)

**Examples**

```python
>>> df = pd.DataFrame({'A': [1, 2, 1, 2, 1, 2, 3]})
>>> df.mode()
A
  0 1
  1 2
```

**pandas.DataFrame.pct_change**

DataFrame.pct_change(*periods=1, fill_method='pad', limit=None, freq=None, **kwargs*)

Percent change over given number of periods.

**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 offset alias string, optional
  - Increment to use from time series API (e.g. ‘M’ or BDay())

**Returns**

- **chg**: NDFrame

**Notes**

By default, the percentage change is calculated along the stat axis: 0, or Index, for DataFrame and 1, or minor for Panel. You can change this with the axis keyword argument.

**pandas.DataFrame.prod**

DataFrame.prod(*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the product of the values for the requested axis

**Parameters**

- **axis**: {index (0), columns (1)}
- **skipna**: boolean, 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
- **numeric_only**: boolean, default None
pandas: powerful Python data analysis toolkit, Release 0.17.0

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns prod : Series or DataFrame (if level specified)

pandas.DataFrame.quantile

DataFrame.quantile\( (q=0.5, \text{axis}=0, \text{numeric\_only}=True)\)

Return values at the given quantile over requested axis, a la numpy.percentile.

Parameters q : float or array-like, default 0.5 (50% quantile)

0 <= q <= 1, the quantile(s) to compute

axis : {0, 1, ‘index’, ‘columns’} (default 0)

0 or ‘index’ for row-wise, 1 or ‘columns’ for column-wise

Returns quantiles : 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.

Examples

```python
>>> df = DataFrame(np.array([[1, 1], [2, 10], [3, 100], [4, 100]]),
    columns=['a', 'b'])
>>> df.quantile(.1)
a  1.3
b  3.7
dtype: float64
>>> df.quantile([.1, .5])
    a   b
0.1  1.3  3.7
0.5  2.5  55.0
```

pandas.DataFrame.rank

DataFrame.rank\( (\text{axis}=0, \text{numeric\_only}=\text{None}, \text{method}=\text{‘average’}, \text{na\_option}=\text{‘keep’}, \text{ascending}=\text{True}, \text{pct}=\text{False})\)

Compute numerical data ranks (1 through n) along axis. 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

Ranks over columns (0) or rows (1)

numeric_only : boolean, default None

Include only float, int, boolean data


- 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

na_option : {'keep', 'top', 'bottom'}
• keep: leave NA values where they are
• top: smallest rank if ascending
• bottom: smallest rank if descending

ascending : boolean, default True
False for ranks by high (1) to low (N)

pct : boolean, default False
Computes percentage rank of data

Returns ranks : DataFrame

pandas.DataFrame.round

DataFrame.round (decimals=0, out=None)
Round a DataFrame to a variable number of decimal places.
New in version 0.17.0.

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.

Returns DataFrame object

Examples

>>> df = pd.DataFrame(np.random.random([3, 3]),
... columns=['A', 'B', 'C'], index=['first', 'second', 'third'])
>>> df
   A      B      C
first 0.028208 0.992815 0.173891
second 0.038683 0.645646 0.577595
third 0.877076 0.149370 0.491027
>>> df.round(2)
   A      B      C
first  0.03   0.99   0.17
second 0.04   0.65   0.58
third  0.88   0.15   0.49
>>> df.round({'A': 1, 'C': 2})
   A      B      C
first  0.0  0.992815  0.17
second 0.0  0.645646  0.58
third  0.9  0.149370  0.49
>>> decimals = pd.Series([1, 0, 2], index=['A', 'B', 'C'])
>>> df.round(decimals)
   A      B      C
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`: boolean, 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
- `numeric_only`: boolean, default None
  - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**
- `sem`: Series or DataFrame (if level specified)

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)}
- `skipna`: boolean, 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
- `numeric_only`: boolean, default None
  - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**
- `skew`: Series or DataFrame (if level specified)

pandas.DataFrame.sum

`DataFrame.sum(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return the sum of the values for the requested axis

**Parameters**
- `axis`: {index (0), columns (1)}
- `skipna`: boolean, 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

**numeric_only** : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns** sum : Series or DataFrame (if level specified)

### pandas.DataFrame.std

pandas.DataFrame.std

DataFrame.std(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)

Return unbiased 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** : boolean, 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

**numeric_only** : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns** std : Series or DataFrame (if level specified)

### pandas.DataFrame.var

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** : boolean, 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

**numeric_only** : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns** var : Series or DataFrame (if level specified)
34.4.8 Reindexing / Selection / Label manipulation

DataFrame.add_prefix(prefix)
Concatenate prefix string with panel items names.

DataFrame.add_suffix(suffix)
Concatenate suffix string with panel items names

DataFrame.align(other[, join, axis, level, ...])
Align two object on their axes with the

DataFrame.drop(labels[, axis, level, ...])
Return new object with labels in requested axis removed

DataFrame.drop_duplicates(*args, **kwargs)
Return DataFrame with duplicate rows removed, optionally only

DataFrame.equals(other)
Determines if two NDFrame objects contain the same elements.

DataFrame.first(offset)
Restrict the info axis to set of items or wildcard

DataFrame.head(n)
Convenience method for subsetting initial periods of time series data

DataFrame.idxmax(axis, skipna)
Returns first n rows

DataFrame.idxmin(axis, skipna)
Return index of first occurrence of maximum over requested axis.

DataFrame.last(offset)
Return index of first occurrence of minimum over requested axis.

DataFrame.reindex((index, columns))
Convenience method for subsetting final periods of time series data

DataFrame.reindex_axis(labels[, axis, ...])
Conform DataFrames to new index with optional filling logic, placing NA/Nan

DataFrame.reindex_like(other[, method, ...])
Conform input object to new index with optional filling logic, placing NA/Nan

DataFrame.first(offset)
return an object with matching indicies to myself

DataFrame.reset_index([level, drop, ...])
Alternate axes input function or functions.

DataFrame.sample([n, frac, replace, ...])
For DataFrame with multi-level index, return new DataFrame with labeling

DataFrame.set_index(keys[, drop, append, ...])
Returns a random sample of items from an axis of object.

DataFrame.select(crit[, axis])
Return data corresponding to axis labels matching criteria

DataFrame.tail(n)
Set the DataFrame index (row labels) using one or more existing columns.

DataFrame.take(indices[, axis, convert, is_copy])
Returns last n rows

DataFrame.truncate([before, after, axis, copy])
Analogous to ndarray.take

Truncates a sorted NDFrame before and/or after some particular dates.
**pandas**: powerful Python data analysis toolkit, Release 0.17.0

**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**: boolean, 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**: str, default None

**limit**: int, default None

**fill_axis**: {0, 1, ‘index’, ‘columns’}, default 0
   Filling axis, method and limit

**broadcast_axis**: {0, 1, ‘index’, ‘columns’}, default None
   Broadcast values along this axis, if aligning two objects of different dimensions
   New in version 0.17.0.

**Returns** (left, right): (DataFrame, type of other)
   Aligned objects

**pandas.DataFrame.drop**

DataFrame.drop(labels, axis=0, level=None, inplace=False, errors=’raise’)
   Return new object with labels in requested axis removed

**Parameters**

**labels**: single label or list-like

**axis**: int or axis name

**level**: int or level name, default None
   For MultiIndex

**inplace**: bool, default False
   If True, do operation inplace and return None.

**errors**: {‘ignore’, ‘raise’}, default ‘raise’
   If ‘ignore’, suppress error and existing labels are dropped.
   New in version 0.16.1.

**Returns**

**dropped**: type of caller

**pandas.DataFrame.drop_duplicates**

DataFrame.drop_duplicates(*args, **kwargs)
   Return DataFrame with duplicate rows removed, optionally only considering certain columns

**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’
- first : Drop duplicates except for the first occurrence.
- last : Drop duplicates except for the last occurrence.
- False : Drop all duplicates.

take_last : deprecated

inplace : boolean, default False
Whether to drop duplicates in place or to return a copy

cols : kwargs only argument of subset [deprecated]

Returns deduplicated : DataFrame

DataFrame.duplicated

DataFrame.duplicated(*args, **kwargs)
Return boolean Series denoting duplicate rows, optionally only considering certain columns

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’
- 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.
- take_last : deprecated
- cols : kwargs only argument of subset [deprecated]

Returns duplicated : Series

DataFrame.equals

DataFrame.equals(other)
Determines if two NDFrame objects contain the same elements. NaNs in the same location are considered equal.

DataFrame.filter

DataFrame.filter(items=None, like=None, regex=None, axis=None)
Restrict the info axis to set of items or wildcard

Parameters items : list-like
- List of info axis to restrict to (must not all be present)

like : string
- Keep info axis where “arg in col == True”
regex : string (regular expression)

Keep info axis with re.search(regex, col) == True

axis : int or None

The axis to filter on. By default this is the info axis. The “info axis” is the axis that
is used when indexing with []. For example, df = DataFrame({'a': [1, 2, 3, 4]}); df['a']. So, the DataFrame columns are the info axis.

Notes

Arguments are mutually exclusive, but this is not checked for

pandas.DataFrame.first

DataFrame.first(offset)

Convenience method for subsetting initial periods of time series data based on a date offset

Parameters offset : string, DateOffset, dateutil.relativedelta

Returns subset : type of caller

Examples

ts.last('10D') -> First 10 days

pandas.DataFrame.head

DataFrame.head(n=5)

Returns first n rows

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

0 or ‘index’ for row-wise, 1 or ‘columns’ for column-wise

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be first index.

Returns idxmax : Series

See also:

Series.idxmax

Notes

This method is the DataFrame version of ndarray.argmax.
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
0 or ‘index’ for row-wise, 1 or ‘columns’ for column-wise
skipna : boolean, default True
Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns
idxmin : Series

See also:
Series.idxmin

Notes
This method is the DataFrame version of ndarray.argmin.

pandas.DataFrame.last

DataFrame.last(offset)

Convenience method for subsetting final periods of time series data based on a date offset

Parameters
offset : string, DateOffset, dateutil.relativedelta

Returns
subset : type of caller

Examples

ts.last('5M') -> Last 5 months

pandas.DataFrame.reindex

DataFrame.reindex(index=None, columns=None, **kwargs)

Conform DataFrame to new index with optional filling logic, placing 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, columns : array-like, optional (can be specified in order, or as keywords) New labels / index to conform to. Preferably an Index object to avoid duplicating data

Method to use for filling holes in reindexed DataFrame:

• 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 : boolean, 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.

New in version 0.17.0.

Returns reindexed : DataFrame

Examples

>>> df.reindex(index=[date1, date2, date3], columns=['A', 'B', 'C'])

pandas.DataFrame.reindex_axis

DataFrame.reindex_axis(labels, axis=0, method=None, level=None, copy=True, limit=None, fill_value=nan)

Conform input object to new index with optional filling logic, placing 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 labels : array-like

New labels / index to conform to. Preferably an Index object to avoid duplicating data

axis : {0, 1, ‘index’, ‘columns’}


Method to use for filling holes in reindexed DataFrame:

• 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 : boolean, 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
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.

New in version 0.17.0.

Returns reindexed : DataFrame

See also:
reindex, reindex_like

Examples

>>> df.reindex_axis(['A', 'B', 'C'], axis=1)

pandas.DataFrame.reindex_like

DataFrame.reindex_like(other, method=None, copy=True, limit=None, tolerance=None)
return an object with matching indicies to myself

Parameters other : Object

method : string or None
copy : boolean, default True
limit : int, default None

Maximum number of consecutive labels to fill for inexact matches.
tolerance : optional

Maximum distance between labels of the other object and this object for inexact matches.

New in version 0.17.0.

Returns reindexed : same as input

Notes

Like calling s.reindex(index=other.index, columns=other.columns, method=...)

pandas.DataFrame.rename

DataFrame.rename(index=None, columns=None, **kwargs)
Alter axes input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters index, columns : dict-like or function, optional

Transformation to apply to that axis values
copy : boolean, default True
    Also copy underlying data

inplace : boolean, default False
    Whether to return a new DataFrame. If True then value of copy is ignored.

Returns renamed : DataFrame (new object)

pandas.DataFrame.reset_index

DataFrame.reset_index(level=None, drop=False, inplace=False, col_level=0, col_fill='')
For DataFrame with multi-level index, return new DataFrame with labeling information in the columns under
the index names, defaulting to ‘level_0’, ‘level_1’, etc. if any are None. For a standard index, the index name
will be used (if set), otherwise a default ‘index’ or ‘level_0’ (if ‘index’ is already taken) will be used.

Parameters level : int, str, tuple, or list, default None
    Only remove the given levels from the index. Removes all levels by default

drop : boolean, default False
    Do not try to insert index into dataframe columns. This resets the index to the default
    integer index.

inplace : boolean, 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 resetted : DataFrame

pandas.DataFrame.sample

DataFrame.sample(n=None, frac=None, replace=False, weights=None, random_state=None,
axis=None)
Returns a random sample of items from an axis of object.
New in version 0.16.1.

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 : boolean, optional
    Sample with or without replacement. Default = False.

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. inf and -inf values not allowed.

**random_state**: int or numpy.random.RandomState, optional

Seed for the random number generator (if int), or numpy RandomState object.

**axis**: int or string, optional

Axis to sample. Accepts axis number or name. Default is stat axis for given data type (0 for Series and DataFrames, 1 for Panels).

**Returns**
A new object of same type as caller.

### pandas.DataFrame.select

**DataFrame.select** *(crit, axis=0)*

Return data corresponding to axis labels matching criteria

**Parameters**

- **crit**: function
  - To be called on each index (label). Should return True or False
- **axis**: int

**Returns**
selection : type of caller

### pandas.DataFrame.set_index

**DataFrame.set_index** *(keys, drop=True, append=False, inplace=False, verify_integrity=False)*

Set the DataFrame index (row labels) using one or more existing columns. By default yields a new object.

**Parameters**

- **keys**: column label or list of column labels / arrays
- **drop**: boolean, default True
  - Delete columns to be used as the new index
- **append**: boolean, default False
  - Whether to append columns to existing index
- **inplace**: boolean, default False
  - Modify the DataFrame in place (do not create a new object)
- **verify_integrity**: boolean, 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 : DataFrame
Examples

```python
>>> indexed_df = df.set_index(['A', 'B'])
>>> indexed_df2 = df.set_index(['A', [0, 1, 2, 0, 1, 2]])
>>> indexed_df3 = df.set_index([[0, 1, 2, 0, 1, 2]])
```

**pandas.DataFrame.tail**

Dataframe.

```python
DataFrame.tail(n=5)
```

Returns last n rows

**pandas.DataFrame.take**

Dataframe.

```python
DataFrame.take(indices, axis=0, convert=True, is_copy=True)
```

Analogous to ndarray.take

Parameters

- **indices**: list / array of ints
- **axis**: int, default 0
- **convert**: translate neg to pos indices (default)
- **is_copy**: mark the returned frame as a copy

Returns

**taken**: type of caller

**pandas.DataFrame.truncate**

Dataframe.

```python
DataFrame.truncate(before=None, after=None, axis=None, copy=True)
```

Truncates a sorted NDFrame before and/or after some particular dates.

Parameters

- **before**: date
  - Truncate before date
- **after**: date
  - Truncate after date
- **axis**: the truncation axis, defaults to the stat axis
- **copy**: boolean, default is True,
  - return a copy of the truncated section

Returns

**truncated**: type of caller

### 34.4.9 Missing data handling

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>DataFrame.dropna()</code></td>
<td>Return object with labels on given axis omitted where alternately any</td>
</tr>
<tr>
<td><code>DataFrame.fillna()</code></td>
<td>Fill NA/NaN values using the specified method</td>
</tr>
</tbody>
</table>
| `DataFrame.replace()` | Replace values given in ‘to_replace’ with ‘value’.
pandas.DataFrame.dropna

DataFrame.dropna (axis=0, how=’any’, thresh=None, subset=None, inplace=False)

Return object with labels on given axis omitted where alternately any or all of the data are missing

Parameters

axis : {0 or ‘index’, 1 or ‘columns’}, or tuple/list thereof

Pass tuple or list to drop on multiple axes

how : {'any', 'all'}

- any : if any NA values are present, drop that label
- all : if all values are NA, drop that label

thresh : int, default None

int value : require that many non-NA values

subset : array-like

Labels along other axis to consider, e.g. if you are dropping rows these would be a list of columns to include

inplace : boolean, default False

If True, do operation inplace and return None.

Returns
dropped : DataFrame

pandas.DataFrame.fillna

DataFrame.fillna(value=None, method=None, axis=None, inplace=False, limit=None, downcast=None, **kwargs)

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, 1, ‘index’, ‘columns’}

inplace : boolean, 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.

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 filled : DataFrame

See also:
reindex, asfreq

pandas.DataFrame.replace

DataFrame.replace(to_replace=None, value=None, inplace=False, limit=None, regex=False, method='pad', axis=None)

Replace values given in ‘to_replace’ with ‘value’.

Parameters to_replace : str, regex, list, dict, Series, numeric, or None

• str or regex:
  – 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 regexes 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 and regex rules apply as above.

• dict:
  – Nested dictionaries, e.g., {'a': {'b': nan}}, are read as follows: look in column ‘a’ for the value ‘b’ and replace it with nan. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) cannot be regular expressions.
  – Keys map to column names and values map to substitution values. You can treat this as a special case of passing two lists except that you are specifying the column to search in.

• 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 use to fill holes (e.g. 0), alternately a dict of values specifying 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 : boolean, default False

If True, in place. Note: this will modify any other views on this object (e.g. a column form 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. Otherwise, `to_replace must` be None because this parameter will be interpreted as a regular expression or a list, dict, or array of regular expressions.

**method**: string, optional, {'pad', 'ffill', 'bfill'}

The method to use when for replacement, when `to_replace` is a list.

**Returns filled**: NDFrame

**Raises AssertionError**

- If regex is not a bool and to_replace is not None.

**TypeError**

- 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.

**ValueError**

- If `to_replace` and value are lists or ndarray, but they are not the same length.

**See also**:

NDFrame.reindex, NDFrame.asfreq, NDFrame.fillna

**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.

### 34.4.10 Reshaping, sorting, transposing

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataFrame.pivot([index, columns, values])</td>
<td>Reshape data (produce a “pivot” table) based on column values.</td>
</tr>
<tr>
<td>DataFrame.reorder_levels(order[, axis])</td>
<td>Rearrange index levels using input order.</td>
</tr>
<tr>
<td>DataFrame.sort_values(by[, axis, ascending, ...])</td>
<td>Sort by the values along either axis</td>
</tr>
<tr>
<td>DataFrame.sort_index(axis[, level, ...])</td>
<td>Sort object by labels (along an axis)</td>
</tr>
<tr>
<td>DataFrame.sortlevel([level, axis, ...])</td>
<td>Sort multilevel index by chosen axis and primary level.</td>
</tr>
<tr>
<td>DataFrame.nlargest(n, columns[, keep])</td>
<td>Get the rows of a DataFrame sorted by the n largest values of columns.</td>
</tr>
<tr>
<td>DataFrame.nsmallest(n, columns[, keep])</td>
<td>Get the rows of a DataFrame sorted by the n smallest values of columns.</td>
</tr>
<tr>
<td>DataFrame.swaplevel(i, j[, axis])</td>
<td>Swap levels i and j in a MultiIndex on a particular axis</td>
</tr>
<tr>
<td>DataFrame.stack([level, dropna])</td>
<td>Pivot a level of the (possibly hierarchical) column labels, returning a Data</td>
</tr>
<tr>
<td>DataFrame.unstack([level])</td>
<td>Pivot a level of the (necessarily hierarchical) index labels, returning a Data</td>
</tr>
<tr>
<td>DataFrame.T</td>
<td>Transpose index and columns</td>
</tr>
</tbody>
</table>
DataFrame.to_panel()  Transform long (stacked) format (DataFrame) into wide (3D, Panel) format.
DataFrame.transpose()  Transpose index and columns

pandas.DataFrame.pivot

DataFrame.pivot (index=None, columns=None, values=None)

Reshape data (produce a “pivot” table) based on column values. Uses unique values from index / columns to form axes and return either DataFrame or Panel, depending on whether you request a single value column (DataFrame) or all columns (Panel)

Parameters

index : string or object, optional
Column name to use to make new frame’s index. If None, uses existing index.

columns : string or object
Column name to use to make new frame’s columns

values : string or object, optional
Column name to use for populating new frame’s values

Returns

pivoted : DataFrame
If no values column specified, will have hierarchically indexed columns

Notes

For finer-tuned control, see hierarchical indexing documentation along with the related stack/unstack methods

Examples

```python
>>> df
     foo  bar  baz
0     one   A   1
1     one   B   2
2     one   C   3
3     two   A   4
4     two   B   5
5     two   C   6

>>> df.pivot('foo', 'bar', 'baz')
     A  B  C
one  1  2  3
two  4  5  6

>>> df.pivot('foo', 'bar')['baz']
     A  B  C
one  1  2  3
two  4  5  6
```

pandas.DataFrame.reorder_levels

DataFrame.reorder_levels (order, axis=0)

Rearrange index levels using input order. May not drop or duplicate levels
**pandas: powerful Python data analysis toolkit, Release 0.17.0**

**Parameters**

- **order**: list of int or list of str
  - List representing new level order. Reference level by number (position) or by key (label).

- **axis**: int
  - Where to reorder levels.

**Returns**

- type of caller (new object)

### pandas.DataFrame.sort_values

**DataFrame.sort_values(by, axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last')**

Sort by the values along either axis

New in version 0.17.0.

- **Parameters**
  - **by**: string name or list of names which refer to the axis items
  - **axis**: index, columns to direct sorting
  - **ascending**: bool or list of bool
    - 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
    - if True, perform operation in-place
  - **kind**: \{'quicksort', 'mergesort', 'heapsort'\}
    - 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'\}
    - *first* puts NaNs at the beginning, *last* puts NaNs at the end

**Returns**

- **sorted_obj**: DataFrame

### pandas.DataFrame.sort_index

**DataFrame.sort_index(axis=0, level=None, ascending=True, inplace=False, kind='quicksort', na_position='last', sort_remaining=True, by=None)**

Sort object by labels (along an axis)

- **Parameters**
  - **axis**: index, columns to direct sorting
  - **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**: boolean, default True
    - Sort ascending vs. descending
  - **inplace**: bool
    - if True, perform operation in-place
  - **kind**: \{'quicksort', 'mergesort', 'heapsort'\}
Choice of sorting algorithm. See also ndarray.

- **merge-sort** is the only stable algorithm. For DataFrames, this option is only applied when sorting on a single column or label.

**na_position**: {'first', 'last'}

- *first* puts NaNs at the beginning, *last* puts NaNs at the end

**sort_remaining**: bool

- If true and sorting by level and index is multilevel, sort by other levels too (in order)
- After sorting by specified level

**Returns**

- sorted_obj : DataFrame

---

**pandas.DataFrame.sortlevel**

DataFrame.sortlevel (level=0, axis=0, ascending=True, inplace=False, sort_remaining=True)

Sort multilevel index by chosen axis and primary level. Data will be lexicographically sorted by the chosen level followed by the other levels (in order)

**Parameters**

- **level**: int
- **axis**: {0 or 'index', 1 or 'columns'}, default 0
- **ascending**: boolean, default True
- **inplace**: boolean, default False

Sort the DataFrame without creating a new instance

**sort_remaining**: boolean, default True

- Sort by the other levels too.

**Returns**

- sorted : DataFrame

---

**See also:**

DataFrame.sort_index

---

**pandas.DataFrame.nlargest**

DataFrame.nlargest (n, columns, keep='first')

Get the rows of a DataFrame sorted by the *n* largest values of *columns*.

New in version 0.17.0.

**Parameters**

- **n**: int

- Number of items to retrieve

- **columns**: list or str

- Column name or names to order by

- **keep**: {'first', 'last', False}, default 'first'

- Where there are duplicate values: - *first*: take the first occurrence. - *last*: take the last occurrence.

**Returns**

- DataFrame
Examples

```python
>>> df = DataFrame({'a': [1, 10, 8, 11, -1],
... 'b': list('abdce'),
... 'c': [1.0, 2.0, np.nan, 3.0, 4.0]})
>>> df.nlargest(3, 'a')
   a  b  c
0  3  c  3
1  1  b  2
2  8  d  NaN
```

pandas.DataFrame.nsmallest

DataFrame.nsmallest(n, columns, keep='first')

Get the rows of a DataFrame sorted by the n smallest values of columns.

New in version 0.17.0.

Parameters

- **n**: int
  - Number of items to retrieve
- **columns**: list or str
  - Column name or names to order by
- **keep**: {'first', 'last', False}, default 'first'
  - Where there are duplicate values: - first: take the first occurrence. - last: take the last occurrence.

Returns **DataFrame**

Examples

```python
>>> df = DataFrame({'a': [1, 10, 8, 11, -1],
... 'b': list('abdce'),
... 'c': [1.0, 2.0, np.nan, 3.0, 4.0]})
>>> df.nsmallest(3, 'a')
   a  b  c
0  4  e  4
1  0  a  1
2  8  d  NaN
```

pandas.DataFrame.swaplevel

DataFrame.swaplevel(i, j, axis=0)

Swap levels i and j in a MultiIndex on a particular axis.

Parameters

- **i, j**: int, string (can be mixed)
  - Level of index to be swapped. Can pass level name as string.

Returns **swapped** : type of caller (new object)
pandas.DataFrame.stack

DataFrame.stack(level=-1, dropna=True)

Pivot a level of the (possibly hierarchical) column labels, returning a DataFrame (or Series in the case of an object with a single level of column labels) having a hierarchical index with a new inner-most level of row labels. The level involved will automatically get sorted.

**Parameters**

- **level**: int, string, or list of these, default last level
  - Level(s) to stack, can pass level name
- **dropna**: boolean, default True
  - Whether to drop rows in the resulting Frame/Series with no valid values

**Returns**

- **stacked**: DataFrame or Series

**Examples**

```python
>>> s
   a  b
one 1  2
two 3  4

>>> s.stack()
   a  1
   b  2
   a  3
   b  4
```

pandas.DataFrame.unstack

DataFrame.unstack(level=-1)

Pivot a level of the (necessarily hierarchical) index labels, returning 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). The level involved will automatically get sorted.

**Parameters**

- **level**: int, string, or list of these, default -1 (last level)
  - Level(s) of index to unstack, can pass level name

**Returns**

- **unstacked**: DataFrame or Series

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
   three a  3
```

34.4. DataFrame
>>> s.unstack(level=-1)
    a  b
one 1 2
two 3 4

>>> s.unstack(level=0)
    one  two
    a     1
          b
    b     2
          4

>>> df = s.unstack(level=0)
>>> df.unstack()
    one a 1.
          b 3.
    two a 2.
          b 4.

pandas.DataFrame.T

DataFrame.T
    Transpose index and columns

pandas.DataFrame.to_panel

DataFrame.to_panel()
    Transform long (stacked) format (DataFrame) into wide (3D, Panel) format.

    Currently the index of the DataFrame must be a 2-level MultiIndex. This may be generalized later

    Returns panel : Panel

pandas.DataFrame.transpose

DataFrame.transpose()
    Transpose index and columns

34.4.11 Combining / joining / merging

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataFrame.append</td>
<td>Append rows of other to the end of this frame, returning a new object.</td>
</tr>
<tr>
<td>DataFrame.assign</td>
<td>Assign new columns to a DataFrame, returning a new object (a copy) with all the Join columns with other DataFrame either on index or on a key column.</td>
</tr>
<tr>
<td>DataFrame.merge</td>
<td>Merge DataFrame objects by performing a database-style join operation by column.</td>
</tr>
<tr>
<td>DataFrame.update</td>
<td>Modify DataFrame in place using non-NA values from passed DataFrame.</td>
</tr>
</tbody>
</table>
**pandas.DataFrame.append**

Dataframe.append(other, ignore_index=False, verify_integrity=False)

Append rows of other to the end of this frame, returning a new object. Columns not in this frame are added as new columns.

- **other**: DataFrame or Series/dict-like object, or list of these
  - The data to append.
  - **ignore_index**: boolean, default False
    - If True, do not use the index labels.
  - **verify_integrity**: boolean, default False
    - If True, raise ValueError on creating index with duplicates.

- **Returns appended**: DataFrame

**See also:**

**pandas.concat** General function to concatenate DataFrame, Series or Panel 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.

**Examples**

```python
>>> df = pd.DataFrame([[1, 2], [3, 4]], columns=list('AB'))
>>> df
   A  B
0  1  2
1  3  4
>>> df2 = pd.DataFrame([[5, 6], [7, 8]], columns=list('AB'))
>>> df.append(df2)
   A  B
0  1  2
1  3  4
0  5  6
1  7  8

With ignore_index set to True:

```python
>>> df.append(df2, ignore_index=True)
   A  B
0  1  2
1  3  4
2  5  6
3  7  8
```

**pandas.DataFrame.assign**

Dataframe.assign(**kwargs)

Assign new columns to a DataFrame, returning a new object (a copy) with all the original columns in addition
to the new ones.

New in version 0.16.0.

Parameters **kwargs**: keyword, value pairs

- **kwargs** are the column names. If the values are callable, they are computed on the DataFrame and assigned to the new columns. If the values are not callable, (e.g. a Series, scalar, or array), they are simply assigned.

Returns **df**: DataFrame

- **df** is a new DataFrame with the new columns in addition to all the existing columns.

Notes

Since **kwargs** is a dictionary, the order of your arguments may not be preserved. The make things predictable, the columns are inserted in alphabetical order, at the end of your DataFrame. Assigning multiple columns within the same **assign** is possible, but you cannot reference other columns created within the same **assign** call.

Examples

```python
>>> df = DataFrame({'A': range(1, 11), 'B': np.random.randn(10)})
```

Where the value is a callable, evaluated on **df**:

```python
>>> df.assign(ln_A = lambda x: np.log(x.A))
```

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>ln_A</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>0.426905 0.000000</td>
</tr>
<tr>
<td>1</td>
<td>-0.780949 0.693147</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>-0.418711 1.098612</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>-0.269708 1.386294</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>-0.274002 1.609438</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>-0.500792 1.791759</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>1.649697 1.945910</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>-1.495604 2.079442</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>0.549296 2.197225</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>-0.758542 2.302585</td>
<td></td>
</tr>
</tbody>
</table>

Where the value already exists and is inserted:

```python
>>> newcol = np.log(df['A'])
>>> df.assign(ln_A=newcol)
```

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>ln_A</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>0.426905 0.000000</td>
</tr>
<tr>
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<td>-0.418711 1.098612</td>
<td></td>
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<td>7</td>
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</tr>
<tr>
<td>8</td>
<td>0.549296 2.197225</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>-0.758542 2.302585</td>
<td></td>
</tr>
</tbody>
</table>
pandas.DataFrame.join

DataFrame.join(other=None, on=None, how='left', lsuffix='', rsuffix='', sort=False)

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 with name field set, 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 : column name, tuple/list of column names, or array-like

Column(s) to use for joining, otherwise join on index. If multiples columns given, the passed DataFrame must have a MultiIndex. Can pass an array as the join key if not already contained in the calling DataFrame. Like an Excel VLOOKUP operation

how : {'left', 'right', 'outer', 'inner'}

How to handle indexes of the two objects. Default: ‘left’ for joining on index, None otherwise

- left: use calling frame’s index
- right: use input frame’s index
- outer: form union of indexes
- inner: use intersection of indexes

lsuffix : string

Suffix to use from left frame’s overlapping columns

rsuffix : string

Suffix to use from right frame’s overlapping columns

sort : boolean, default False

Order result DataFrame lexicographically by the join key. If False, preserves the index order of the calling (left) DataFrame

**Returns**

joined : DataFrame

**Notes**

on, lsuffix, and rsuffix options are not supported when passing a list of DataFrame objects

pandas.DataFrame.merge

DataFrame.merge(right=None, 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)

Merge DataFrame objects by performing a database-style join operation by 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

how : {'left', 'right', 'outer', 'inner'}, default ‘inner’
• 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)

on : label or list
  Field names to join on. Must be found in both DataFrames. If on is None and not merging on indexes, then it merges on the intersection of the columns by default.

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_index : boolean, 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 : boolean, default False
  Use the index from the right DataFrame as the join key. Same caveats as left_index

sort : boolean, default False
  Sort the join keys lexicographically in the result DataFrame

suffixes : 2-length sequence (tuple, list, ...)
  Suffix to apply to overlapping column names in the left and right side, respectively

copy : boolean, default True
  If False, do not copy data unnecessarily

indicator : boolean or string, default False
  If True, adds a column to output DataFrame called “_merge” with information on the source of each row. If string, column with information on source of each row will be added to output DataFrame, and column will be named value of string. Information column is Categorical-type and takes on a value of “left_only” for observations whose merge key only appears in ‘left’ DataFrame, “right_only” for observations whose merge key only appears in ‘right’ DataFrame, and “both” if the observation’s merge key is found in both.

New in version 0.17.0.

Returns merged : DataFrame
  The output type will be same as ‘left’, if it is a subclass of DataFrame.

Examples
>>> A
   lkey value
  0 foo 1
  1 bar 2
  2 baz 3
  3 foo 4

>>> B
   rkey value
  0 foo 5
  1 bar 6
  2 qux 7

>>> merge(A, B, left_on='lkey', right_on='rkey', how='outer')
   lkey value_x  rkey value_y
  0 foo 1        foo 5
  1 foo 4        foo 5
  2 bar 2        bar 6
  3 bar 2        bar 8
  4 baz 3        NaN  NaN
  5 NaN  NaN      qux  7

pandas.DataFrame.update

DataFrame.update(other, join='left', overwrite=True, filter_func=None, raise_conflict=False)
Modify DataFrame in place using non-NA values from passed DataFrame. Aligns on indices

Parameters

other : DataFrame, or object coercible into a DataFrame
join : {'left'}, default 'left'
overwrite : boolean, default True
If True then overwrite values for common keys in the calling frame
filter_func : callable(1d-array) -> 1d-array<boolean>, default None
Can choose to replace values other than NA. Return True for values that should be updated
raise_conflict : boolean
If True, will raise an error if the DataFrame and other both contain data in the same place.

34.4.12 Time series-related

DataFrame.asfreq(freq[, method, how, normalize]) Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.
DataFrame.shift([periods, freq, axis]) Shift index by desired number of periods with an optional time freq
DataFrame.first_valid_index() Return label for first non-NA/null value
DataFrame.last_valid_index() Return label for last non-NA/null value
DataFrame.resample(rule[, how, axis, ...]) Convenience method for frequency conversion and resampling of regular time series
DataFrame.to_period([freq, axis, copy]) Convert DataFrame from DatetimeIndex to PeriodIndex with desired
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(*args, **kwargs) Localize tz-naive TimeSeries to target time zone

pandas.DataFrame.asfreq

Dataframe.asfreq(freq=‘None’, how=‘None’, normalize=‘False’)
Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

34.4. Dataframe
pandas: powerful Python data analysis toolkit, Release 0.17.0

**Parameters**

<table>
<thead>
<tr>
<th>Name</th>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>freq</td>
<td>DateOffset object, or string</td>
<td>Parameters freq: DateOffset object, or string</td>
</tr>
<tr>
<td>method</td>
<td>{'backfill', 'bfill', 'pad', 'ffill', None}</td>
<td>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 method</td>
</tr>
<tr>
<td>how</td>
<td>{'start', 'end'}, default end</td>
<td>For PeriodIndex only, see PeriodIndex.asfreq</td>
</tr>
<tr>
<td>normalize</td>
<td>bool, default False</td>
<td>Whether to reset output index to midnight</td>
</tr>
</tbody>
</table>

**Returns**

<table>
<thead>
<tr>
<th>Name</th>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>converted</td>
<td>type of caller</td>
<td>Returns converted: type of caller</td>
</tr>
</tbody>
</table>

### pandas.DataFrame.shift

**DataFrame.shift**(periods=1, freq=None, axis=0)

Shift index by desired number of periods with an optional time freq

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>periods</td>
<td>int</td>
<td>Number of periods to move, can be positive or negative</td>
</tr>
<tr>
<td>freq</td>
<td>DateOffset, timedelta, or time rule string, optional</td>
<td>Increment to use from datetools module or time rule (e.g. ‘EOM’). See Notes.</td>
</tr>
<tr>
<td>axis</td>
<td>{0, 1, ‘index’, ‘columns’}</td>
<td></td>
</tr>
</tbody>
</table>

**Returns**

<table>
<thead>
<tr>
<th>Name</th>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>shifted</td>
<td>DataFrame</td>
<td>Returns shifted: DataFrame</td>
</tr>
</tbody>
</table>

**Notes**

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.

### pandas.DataFrame.first_valid_index

**DataFrame.first_valid_index**

Return label for first non-NA/null value

**DataFrame.last_valid_index**

Return label for last non-NA/null value

### pandas.DataFrame.resample

**DataFrame.resample**(rule, how=None, axis=0, fill_method=None, closed=None, label=None, convention='start', kind=None, loffset=None, limit=None, base=0)

Convenience method for frequency conversion and resampling of regular time-series data.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>rule</td>
<td>string</td>
<td>Parameters rule: string</td>
</tr>
</tbody>
</table>
the offset string or object representing target conversion

**how** : string
   method for down- or re-sampling, default to ‘mean’ for downsampling

**axis** : int, optional, default 0

**fill_method** : string, default None
   fill_method for upsampling

**closed** : {'right', 'left'}
   Which side of bin interval is closed

**label** : {'right', 'left'}
   Which bin edge label to label bucket with

**convention** : {'start', 'end', 's', 'e'}

**kind** : “period”/”timestamp”

**loffset** : timedelta
   Adjust the resampled time labels

**limit** : int, default None
   Maximum size gap to when reindexing with fill_method

**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

**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', how='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', how='sum', label='right')
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', how='sum', label='right', closed='right')
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')[0:5] # select first 5 rows
2000-01-01 00:00:00    0
2000-01-01 00:00:30   NaN
2000-01-01 00:01:00    1
2000-01-01 00:01:30   NaN
2000-01-01 00:02:00    2
Freq: 30S, dtype: float64
```

Upsample the series into 30 second bins and fill the NaN values using the pad method.

```python
>>> series.resample('30S', fill_method='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', fill_method='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 to how.

```python
>>> def custom_resampler(array_like):
...         return np.sum(array_like)+5

>>> series.resample('3T', how=custom_resampler)
2000-01-01 00:00:00    8
2000-01-01 00:03:00   17
```

Pass a custom function to how.
pandas.DataFrame.to_period

DataFrame.to_period(freq=None, axis=0, copy=True)
Convert DataFrame from DatetimeIndex to PeriodIndex with desired frequency (inferred from index if not passed)

Parameters:
- freq: string, default
- axis: {0 or 'index', 1 or 'columns'}, default 0
  The axis to convert (the index by default)
- copy: boolean, default True
  If False then underlying input data is not copied

Returns:
ts: TimeSeries with PeriodIndex

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: string, 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: boolean, default True
  If false then underlying input data is not copied

Returns:
df: DataFrame with DatetimeIndex

pandas.DataFrame.tz_convert

DataFrame.tz_convert(tz, axis=0, level=None, copy=True)
Convert tz-aware axis to target time zone.

Parameters:
- tz: string or pytz.timezone object
- axis: the axis to convert
- level: int, str, default None
  If axis ia a MultiIndex, convert a specific level. Otherwise must be None
- copy: boolean, default True
  Also make a copy of the underlying data

Raises:
TypeError
If the axis is tz-naive.

**pandas.DataFrame.tz_localize**

DataFrame.tz_localize(*args, **kwargs)

Localize tz-naive TimeSeries to target time zone

**Parameters**

- **tz**: string or pytz.timezone object
- **axis**: the axis to localize
- **level**: int, str, default None
  If axis is a MultiIndex, localize a specific level. Otherwise must be None
- **copy**: boolean, default True
  Also make a copy of the underlying data
- **ambiguous**: ‘infer’, bool-ndarray, ‘NaT’, default ‘raise’
  - ‘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
- **infer_dst**: boolean, default False (DEPRECATED)
  Attempt to infer fall dst-transition hours based on order

**Raises** **TypeError**

If the TimeSeries is tz-aware and tz is not None.

### 34.4.13 Plotting

DataFrame.plot is both a callable method and a namespace attribute for specific plotting methods of the form DataFrame.plot.<kind>.

```python
DataFrame.plot((x, y, kind, ax, ....))  # DataFrame plotting accessor and method
```

**pandas.DataFrame.plot**

DataFrame.plot(x=None, y=None, kind='line', ax=None, subplots=False, sharex=None, sharey=False, layout=None, figsize=None, use_index=True, title=None, grid=None, legend=True, style=None, logx=False, logy=False, loglog=False, xticks=None, yticks=None, xlim=None, ylim=None, rot=None, fontsize=None, colormap=None, table=False, yerr=None, xerr=None, secondary_y=False, sort_columns=False, **kwds)

Make plots of DataFrame using matplotlib / pylab.

**New in version 0.17.0**: Each plot kind has a corresponding method on the DataFrame.plot accessor: df.plot(kind='line') is equivalent to df.plot.line().

**Parameters**

- **data**: DataFrame
  - **x**: label or position, default None
y : label or position, default None
   Allows plotting of one column versus another

kind : str
   • ‘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

subplots : boolean, default False
   Make separate subplots for each column

sharex : boolean, 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 : boolean, 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

use_index : boolean, default True
   Use index as ticks for x axis

title : string
   Title to use for the plot

grid : boolean, default None (matlab style default)
   Axis grid lines

legend : False/True/’reverse’
   Place legend on axis subplots

style : list or dict
   matplotlib line style per column

logx : boolean, default False
Use log scaling on x axis

**logy** : boolean, default False

Use log scaling on y axis

**loglog** : boolean, default False

Use log scaling on both x and y axes

**xticks** : sequence

Values to use for the xticks

**yticks** : sequence

Values to use for the yticks

**xlim** : 2-tuple/list

**ylim** : 2-tuple/list

**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** : boolean, 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)

**layout** : tuple (optional)

(rows, columns) for the layout of the plot

**table** : boolean, 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** : same types as yerr.

**stacked** : boolean, default False in line and bar plots, and True in area plot. If True, create stacked plot.

**sort_columns** : boolean, default False

Sort column names to determine plot ordering

**secondary_y** : boolean 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** : boolean, default True

When using a secondary_y axis, automatically mark the column labels with “(right)” in the legend

**kwds** : keywords

Options to pass to matplotlib plotting method

**Returns** **axes** : matplotlib.AxesSubplot or np.array of them

**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)

•If **kind** = 'scatter' and the argument **c** is the name of a dataframe column, the values of that column are used to color each point.

•If **kind** = 'hexbin', you can control the size of the bins with the **gridsize** argument. 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**).

<table>
<thead>
<tr>
<th>pandas.DataFrame.plot.area([x, y])</th>
<th>Area plot</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataFrame.plot.bar([x, y])</td>
<td>Vertical bar plot</td>
</tr>
<tr>
<td>DataFrame.plot.barh([x, y])</td>
<td>Horizontal bar plot</td>
</tr>
<tr>
<td>DataFrame.plot.box([by])</td>
<td>Boxplot</td>
</tr>
<tr>
<td>DataFrame.plot.density(<strong>kwds</strong>)</td>
<td>Kernel Density Estimate plot</td>
</tr>
<tr>
<td>DataFrame.plot.hexbin(x, y[, C, ...])</td>
<td>Hexbin plot</td>
</tr>
<tr>
<td>DataFrame.plot.hist([by, bins])</td>
<td>Histogram</td>
</tr>
<tr>
<td>DataFrame.plot.kde(<strong>kwds</strong>)</td>
<td>Kernel Density Estimate plot</td>
</tr>
<tr>
<td>DataFrame.plot.line([x, bins])</td>
<td>Line plot</td>
</tr>
<tr>
<td>DataFrame.plot.pie([y])</td>
<td>Pie chart</td>
</tr>
<tr>
<td>DataFrame.plot.scatter(x, y[, s, c])</td>
<td>Scatter plot</td>
</tr>
</tbody>
</table>

**pandas.DataFrame.plot.area**

DataFrame.plot .area (**x=None, y=None, **kwds**)  
Area plot

New in version 0.17.0.

**Parameters** **x**, **y** : label or position, optional

Coordinates for each point.

**kwds** : optional

Keyword arguments to pass on to pandas.DataFrame.plot().

**Returns** **axes** : matplotlib.AxesSubplot or np.array of them
**pandas.DataFrame.plot.bar**

**DataFrame.plot.bar** *(x=None, y=None, **kwds)*

Vertical bar plot

New in version 0.17.0.

**Parameters**
- **x, y**: label or position, optional
  - Coordinates for each point.
- **kwds**: optional
  - Keyword arguments to pass on to *pandas.DataFrame.plot().*

**Returns**
- **axes**: matplotlib.AxesSubplot or np.array of them

**pandas.DataFrame.plot.barh**

**DataFrame.plot.barh** *(x=None, y=None, **kwds)*

Horizontal bar plot

New in version 0.17.0.

**Parameters**
- **x, y**: label or position, optional
  - Coordinates for each point.
- **kwds**: optional
  - Keyword arguments to pass on to *pandas.DataFrame.plot().*

**Returns**
- **axes**: matplotlib.AxesSubplot or np.array of them

**pandas.DataFrame.plot.box**

**DataFrame.plot.box** *(by=None, **kwds)*

Boxplot

New in version 0.17.0.

**Parameters**
- **by**: string or sequence
  - Column in the DataFrame to group by.
- **kwds**: optional
  - Keyword arguments to pass on to *pandas.DataFrame.plot().*

**Returns**
- **axes**: matplotlib.AxesSubplot or np.array of them

**pandas.DataFrame.plot.density**

**DataFrame.plot.density**( **kwds)**

Kernel Density Estimate plot

New in version 0.17.0.

**Parameters**
- **kwds**: optional
  - Keyword arguments to pass on to *pandas.DataFrame.plot().*

**Returns**
- **axes**: matplotlib.AxesSubplot or np.array of them
**pandas.DataFrame.plot.hexbin**

DataFrame.plot.hexbin(x, y, C=None, reduce_C_function=None, gridsize=None, **kwds)

Hexbin plot

New in version 0.17.0.

**Parameters**

- `x, y`: label or position, optional
  Coordinates for each point.
- `C`: label or position, optional
  The value at each `(x, y)` point.
- `reduce_C_function`: callable, optional
  Function of one argument that reduces all the values in a bin to a single number (e.g. mean, max, sum, std).
- `gridsize`: int, optional
  Number of bins.
- `**kwds`: optional
  Keyword arguments to pass on to pandas.DataFrame.plot().

**Returns**

`axes`: matplotlib.AxesSubplot or np.array of them

**pandas.DataFrame.plot.hist**

DataFrame.plot.hist(by=None, bins=10, **kwds)

Histogram

New in version 0.17.0.

**Parameters**

- `by`: string or sequence
  Column in the DataFrame to group by.
- `bins`: integer, default 10
  Number of histogram bins to be used
- `**kwds`: optional
  Keyword arguments to pass on to pandas.DataFrame.plot().

**Returns**

`axes`: matplotlib.AxesSubplot or np.array of them

**pandas.DataFrame.plot.kde**

DataFrame.plot.kde(**kwds)

Kernel Density Estimate plot

New in version 0.17.0.

**Parameters**

- `**kwds`: optional
  Keyword arguments to pass on to pandas.DataFrame.plot().

**Returns**

`axes`: matplotlib.AxesSubplot or np.array of them
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**pandas.DataFrame.plot.line**

DataFrame.plot.line(x=None, y=None, **kwds)

Line plot

New in version 0.17.0.

**Parameters**

- **x**, **y** : label or position, optional
  Coordinates for each point.

- **kwds** : optional
  Keyword arguments to pass on to pandas.DataFrame.plot().

**Returns**

- **axes** : matplotlib.AxesSubplot or np.array of them

**pandas.DataFrame.plot.pie**

DataFrame.plot.pie(y=None, **kwds)

Pie chart

New in version 0.17.0.

**Parameters**

- **y** : label or position, optional
  Column to plot.

- **kwds** : optional
  Keyword arguments to pass on to pandas.DataFrame.plot().

**Returns**

- **axes** : matplotlib.AxesSubplot or np.array of them

**pandas.DataFrame.plot.scatter**

DataFrame.plot.scatter(x, y, s=None, c=None, **kwds)

Scatter plot

New in version 0.17.0.

**Parameters**

- **x**, **y** : label or position, optional
  Coordinates for each point.

- **s** : scalar or array_like, optional
  Size of each point.

- **c** : label or position, optional
  Color of each point.

- **kwds** : optional
  Keyword arguments to pass on to pandas.DataFrame.plot().

**Returns**

- **axes** : matplotlib.AxesSubplot or np.array of them

**DataFrame.boxplot([column, by, ax, ...])**

Make a box plot from DataFrame column optionally grouped by some columns or

**DataFrame.hist(data[, column, by, grid, ...])**

Draw histogram of the DataFrame’s series using matplotlib / pylab.
pandas.DataFrame.boxplot

DataFrame.boxplot(column=None, by=None, ax=None, fontsize=None, rot=0, grid=True, figsize=None, layout=None, return_type=None, **kwds)

Make a box plot from DataFrame column optionally grouped by some columns or other inputs

Parameters
data : the pandas object holding the data

column : column name or list of names, or vector
Can be any valid input to groupby

by : string or sequence
Column in the DataFrame to group by

ax : Matplotlib axes object, optional

fontsize : int or string

rot : label rotation angle

figsize : A tuple (width, height) in inches

grid : Setting this to True will show the grid

layout : tuple (optional)
(rows, columns) for the layout of the plot

return_type : {'axes', 'dict', 'both'}, default ‘dict’
The kind of object to return. ‘dict’ returns a dictionary whose values are the matplotlib Lines of the boxplot; ‘axes’ returns the matplotlib axes the boxplot is drawn on; ‘both’ returns a namedtuple with the axes and dict.

When grouping with by, a dict mapping columns to return_type is returned.

kwds : other plotting keyword arguments to be passed to matplotlib boxplot

function

Returns
lines : dict

ax : matplotlib Axes

(ax, lines): namedtuple

Notes

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.

pandas.DataFrame.hist

DataFrame.hist(data, 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, **kwds)

Draw histogram of the DataFrame’s series using matplotlib / pylab.

Parameters
data : DataFrame

column : string 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**: boolean, 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

**ax**: matplotlib axes object, default None

**sharex**: boolean, 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 subplots in a figure!

**sharey**: boolean, default False

In case subplots=True, share y axis and set some y axis labels to invisible

**figsize**: tuple

The size of the figure to create in inches by default

**layout**: (optional) a tuple (rows, columns) for the layout of the histograms

**bins**: integer, default 10

Number of histogram bins to be used

**kwds**: other plotting keyword arguments

To be passed to hist function

### 34.4.14 Serialization / IO / Conversion

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataFrame.from_csv</td>
<td>Read CSV file (DISCOURAGED, please use pandas.read_csv())</td>
</tr>
<tr>
<td>DataFrame.from_dict</td>
<td>Construct DataFrame from dict of array-like or dicts</td>
</tr>
<tr>
<td>DataFrame.from_items</td>
<td>Convert (key, value) pairs to DataFrame.</td>
</tr>
<tr>
<td>DataFrame.from_records</td>
<td>Convert structured or record ndarray to DataFrame</td>
</tr>
<tr>
<td>DataFrame.info</td>
<td>Concise summary of a DataFrame.</td>
</tr>
<tr>
<td>DataFrame.to_pickle</td>
<td>Pickle (serialize) object to input file path</td>
</tr>
<tr>
<td>DataFrame.to_csv</td>
<td>Write DataFrame to a comma-separated values (csv) file</td>
</tr>
<tr>
<td>DataFrame.to_hdf</td>
<td>activate the HDFStore</td>
</tr>
<tr>
<td>DataFrame.to_sql</td>
<td>Write records stored in a DataFrame to a SQL database.</td>
</tr>
</tbody>
</table>

---

1358 Chapter 34. API Reference
**pandas: powerful Python data analysis toolkit, Release 0.17.0**

**Table 34.68 – continued from previous page**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataFrame.to_dict(*args, **kwargs)</td>
<td>Convert DataFrame to dictionary.</td>
</tr>
<tr>
<td>DataFrame.to_excel(excel_writer, ...)</td>
<td>Write DataFrame 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 string.</td>
</tr>
<tr>
<td>DataFrame.to_latex(buf, columns, ...)</td>
<td>Render a DataFrame to a tabular environment table.</td>
</tr>
<tr>
<td>DataFrame.to_stata(fname, convert_dates, ...)</td>
<td>A class for writing Stata binary dta files from array-like objects.</td>
</tr>
<tr>
<td>DataFrame.to_msgpack(path_or_buf)</td>
<td>msgpack (serialize) object to input file path.</td>
</tr>
<tr>
<td>DataFrame.to_gbq(destination_table, project_id)</td>
<td>Write a DataFrame to a Google BigQuery table.</td>
</tr>
<tr>
<td>DataFrame.to_records(index, convert_datetime64)</td>
<td>Convert DataFrame to record array.</td>
</tr>
<tr>
<td>DataFrame.to_sparse(fill_value, kind)</td>
<td>Convert to SparseDataFrame.</td>
</tr>
<tr>
<td>DataFrame.to_dense()</td>
<td>Return dense representation of NDFrame (as opposed to sparse).</td>
</tr>
<tr>
<td>DataFrame.to_string(buf, columns, ...)</td>
<td>Render a DataFrame to a console-friendly tabular output.</td>
</tr>
<tr>
<td>DataFrame.to_clipboard(excel, sep)</td>
<td>Attempt to write text representation of object to the system clipboard.</td>
</tr>
</tbody>
</table>

**pandas.DataFrame.from_csv**

**classmethod DataFrame.from_csv(path, header=0, sep=',', index_col=0, parse_dates=True, encoding=None, tupleize_cols=False, infer_datetime_format=False)**

Read CSV file (DISCOURAGED, please use pandas.read_csv() instead).

It is preferable to use the more powerful pandas.read_csv() for most general purposes, but from_csv makes for an easy roundtrip to and from a file (the exact counterpart of to_csv), especially with a DataFrame of time series data.

This method only differs from the preferred pandas.read_csv() in some defaults:

- **index_col** is 0 instead of None (take first column as index by default)
- **parse_dates** is True instead of False (try parsing the index as datetime by default)

So a pandas.DataFrame.from_csv(path) can be replaced by pandas.read_csv(path, index_col=0, parse_dates=True).

**Parameters**

- **path**: string file path or file handle / StringIO
- **header**: int, default 0
  - Row to use as header (skip prior rows)
- **sep**: string, default ‘,’
  - Field delimiter
- **index_col**: int or sequence, default 0
  - Column to use for index. If a sequence is given, a MultiIndex is used. Different default from read_table
- **parse_dates**: boolean, default True
  - Parse dates. Different default from read_table
- **tupleize_cols**: boolean, default False
  - Write multi_index columns as a list of tuples (if True) or new (expanded format) if False
  - infer_datetime_format: boolean, default False

  If True and parse_dates is True for a column, try to infer the datetime format based on the first datetime string. If the format can be inferred, there often will be a large parsing speed-up.
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**Returns** y : DataFrame

**See also:**

pandas.read_csv

**pandas.DataFrame.from_dict**

*classmethod* DataFrame.from_dict(data, orient='columns', dtype=None)*

Construct DataFrame from dict of array-like or dicts

**Parameters**

- **data**: dict
  - {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

**Returns** DataFrame

**pandas.DataFrame.from_items**

*classmethod* DataFrame.from_items(items, columns=None, orient='columns')*

Convert (key, value) pairs to DataFrame. The keys will be the axis index (usually the columns, but depends on the specified orientation). The values should be arrays or Series.

**Parameters**

- **items**: sequence of (key, value) pairs
  - Values should be arrays or Series.
- columns : sequence of column labels, optional
  - Must be passed if orient=’index’.
- orient : {'columns', 'index'}, default ‘columns’
  - The “orientation” of the data. If the keys of the input correspond to column labels, pass ‘columns’ (default). Otherwise if the keys correspond to the index, pass ‘index’.

**Returns** frame : DataFrame

**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

**Parameters**

- **data**: ndarray (structured dtype), list of tuples, dict, or DataFrame
- index : string, 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**: boolean, default False

Attempt to convert values to non-string, non-numeric objects (like decimal.Decimal) to floating point, useful for SQL result sets

**Returns** df : DataFrame

**pandas.DataFrame.info**

DataFrame.info(verbos=None, buf=None, max_cols=None, memory_usage=None, null_counts=None)

Concise summary of a DataFrame.

**Parameters**

**verbose**: {None, True, False}, optional

Whether to print the full summary. None follows the display.max_info_columns setting. True or False overrides the display.max_info_columns setting.

**buf** : writable buffer, defaults to sys.stdout

**max_cols** : int, default None

Determines whether full summary or short summary is printed. None follows the display.max_info_columns setting.

**memory_usage** : boolean, default None

Specifies whether total memory usage of the DataFrame elements (including index) should be displayed. None follows the display.memory_usage setting. True or False overrides the display.memory_usage setting. Memory usage is shown in human-readable units (base-2 representation).

**null_counts** : boolean, default None

Whether to show the non-null counts. If None, then only show if the frame is smaller than max_info_rows and max_info_columns. If True, always show counts. If False, never show counts.

**pandas.DataFrame.to_pickle**

DataFrame.to_pickle(path)

Pickle (serialize) object to input file path

**Parameters**

**path** : string

File path
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, quoting=None, quotechar='', line_terminator='
', chunksize=None, tupleize_cols=False, date_format=None, doublequote=True, escapechar=None, decimal='.', **kwds)

Write DataFrame to a comma-separated values (csv) file

**Parameters** path_or_buf : string or file handle, default None

- File path or object, if None is provided the result is returned as a string.

  sep : character, default ‘,’

  - Field delimiter for the output file.

  na_rep : string, default ‘’

  - Missing data representation

float_format : string, default None

- Format string for floating point numbers

columns : sequence, optional

- Columns to write

header : boolean or list of string, default True

- Write out column names. If a list of string is given it is assumed to be aliases for the column names

index : boolean, default True

- Write row names (index)

index_label : string 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 DataFrame uses MultiIndex. If False do not print fields for index names. Use index_label=False for easier importing in R

nanRep : None

- deprecated, use na_rep

mode : str

- Python write mode, default ‘w’

encoding : string, optional

- A string representing the encoding to use in the output file, defaults to ‘ascii’ on Python 2 and ‘utf-8’ on Python 3.

line_terminator : string, default ‘n’

- The newline character or character sequence to use in the output file

quoting : optional constant from csv module

- defaults to csv.QUOTE_MINIMAL

quotechar : string (length 1), default ‘’
character used to quote fields

doublequote : boolean, default True

Control quoting of quotechar inside a field

escapechar : string (length 1), default None

character used to escape sep and quotechar when appropriate

chunksize : int or None

rows to write at a time

tupleize_cols : boolean, default False

write multi_index columns as a list of tuples (if True) or new (expanded format) if False

date_format : string, default None

Format string for datetime objects

decimal: string, default ‘.’

Character recognized as decimal separator. E.g. use ‘,’ for European data

New in version 0.16.0.

**pandas.DataFrame.to_hdf**

DataFrame.to_hdf(path_or_buf, key, **kwargs)

activate the HDFStore

Parameters

path_or_buf : the path (string) or HDFStore object

key : string

identifier for the group in the store

mode : optional, {'a', 'w', 'r', 'r+'}, default ‘a’

‘r’ Read-only; no data can be modified.

‘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+’ It is similar to ‘a’, but the file must already exist.

format : ‘fixed(f)|table(t)’, default is ‘fixed’

fixed(f) [Fixed format] Fast writing/reading. Not-appendable, nor searchable

table(t) [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 : boolean, default False

For Table formats, append the input data to the existing

complevel : int, 1-9, default 0

If a complib is specified compression will be applied where possible
complib : {‘zlib’, ‘bzip2’, ‘lzo’, ‘blosc’, None}, default None

If complevel is > 0 apply compression to objects written in the store wherever possible

fletcher32 : bool, default False

If applying compression use the fletcher32 checksum

dropna : boolean, default False.

If true, ALL nan rows will not be written to store.

pandas.DataFrame.to_sql

DataFrame.to_sql(name, con, flavor='sqlite', schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None)

Write records stored in a DataFrame to a SQL database.

Parameters

name : string

Name of SQL table

con : SQLAlchemy engine or DBAPI2 connection (legacy mode)

Using SQLAlchemy makes it possible to use any DB supported by that library. If a
DBAPI2 object, only sqlite3 is supported.

flavor : {‘sqlite’, ‘mysql’}, default ‘sqlite’

The flavor of SQL to use. Ignored when using SQLAlchemy engine. ‘mysql’ is
deprecated and will be removed in future versions, but it will be further supported
through SQLAlchemy engines.

schema : string, default None

Specify the schema (if database flavor supports this). If None, use default schema.

if_exists : {‘fail’, ‘replace’, ‘append’}, default ‘fail’

• fail: If table exists, do nothing.
• replace: If table exists, drop it, recreate it, and insert data.
• append: If table exists, insert data. Create if does not exist.

index : boolean, default True

Write DataFrame index as a column.

index_label : string 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, default None

If not None, then rows will be written in batches of this size at a time. If None, all
rows will be written at once.

dtype : dict of column name to SQL type, default None

Optional specifying the datatype for columns. The SQL type should be a
SQLAlchemy type, or a string for sqlite3 fallback connection.
pandas.DataFrame.to_dict

DataFrame.to_dict(*args, **kwargs)
Convert DataFrame to dictionary.

**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}}

New in version 0.17.0.
Abbreviations are allowed. s indicates series and sp indicates split.

**Returns**

result : dict like {column -> {index -> value}}

pandas.DataFrame.to_excel

DataFrame.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)
Write DataFrame to a excel sheet

**Parameters**

- **excel_writer** : string or ExcelWriter object
  File path or existing ExcelWriter
- **sheet_name** : string, default ‘Sheet1’
  Name of sheet which will contain DataFrame
- **na_rep** : string, default ‘’
  Missing data representation
- **float_format** : string, default None
  Format string for floating point numbers
- **columns** : sequence, optional
  Columns to write
- **header** : boolean or list of string, default True
  Write out column names. If a list of string is given it is assumed to be aliases for the column names
- **index** : boolean, default True
  Write row names (index)
- **index_label** : string or sequence, 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 DataFrame uses MultiIndex.

**startrow:**
upper left cell row to dump data frame

**startcol:**
upper left cell column to dump data frame

**engine:** string, default None
write engine to use - you can also set this via the options io.excel.xlsx.writer, io.excel.xls.writer, and io.excel.xlsm.writer.

**merge_cells:** boolean, default True
Write MultiIndex and Hierarchical Rows as merged cells.

**encoding:** string, default None
encoding of the resulting excel file. Only necessary for xlwt, other writers support unicode natively.

**inf_rep:** string, default ‘inf’
Representation for infinity (there is no native representation for infinity in Excel)

**Notes**

If passing an existing ExcelWriter object, then the sheet will be added to the existing workbook. This can be used to save different DataFrames to one workbook:

```python
>>> writer = ExcelWriter('output.xlsx')
>>> df1.to_excel(writer,'Sheet1')
>>> df2.to_excel(writer,'Sheet2')
>>> writer.save()
```

For compatibility with to_csv, to_excel serializes lists and dicts to strings before writing.

**pandas.DataFrame.to_json**

DataFrame.to_json(path_or_buf=None, orient=None, date_format='epoch', double_precision=10, force_ascii=True, date_unit='ms', default_handler=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:** the path or buffer to write the result string
if this is None, return a StringIO of the converted string

**orient:** string
• Series
  – default is ‘index’
  – allowed values are: {'split','records','index'}
• **DataFrame**
  – default is ‘columns’
  – allowed values are: {'split', 'records', 'index', 'columns', 'values'}

• **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 -> {index -> value}}
  – **values** : just the values array

**date_format**: {‘epoch’, ‘iso’}  
Type of date conversion. *epoch* = epoch milliseconds, *iso* = ISO8601, default is *epoch*.

**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**: string, 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.

**Returns** same type as input object with filtered info axis

### pandas.DataFrame.to_html

DataFrame.to_html (buf=None, columns=None, col_space=None, colSpace=None, header=True, index=True, na_rep='NaN', formatters=None, float_format=None, sparsify=None, index_names=True, justify=None, bold_rows=True, classes=None, escape=True, max_rows=None, max_cols=None, show_dimensions=False, notebook=False)

Render a DataFrame as an HTML table.

**to_html**-specific options:

**bold_rows** [boolean, 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** [boolean, default True] Convert the characters <, >, and & to HTML-safe sequences.

**max_rows** [int, optional] Maximum number of rows to show before truncating. If None, show all.

**max_cols** [int, optional] Maximum number of columns to show before truncating. If None, show all.

**Parameters**

**buf** : StringIO-like, optional  
buffer to write to
pandas: powerful Python data analysis toolkit, Release 0.17.0

- `columns`: sequence, optional
  - the subset of columns to write; default None writes all columns
- `col_space`: int, optional
  - the minimum width of each column
- `header`: bool, optional
  - whether to print column labels, default True
- `index`: bool, optional
  - whether to print index (row) labels, default True
- `na_rep`: string, optional
  - string representation of NaN to use, default ‘NaN’
- `formatters`: list or dict of one-parameter functions, optional
  - formatter functions to apply to columns’ elements by position or name, default None. 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, optional
  - formatter function to apply to columns’ elements if they are floats, default None. The result of this function must be a unicode string.
- `sparsify`: bool, optional
  - Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row, default True
- `index_names`: bool, optional
  - Prints the names of the indexes, default True
- `justify`: {'left', 'right'}, default None
  - Left or right-justify the column labels. If None uses the option from the print configuration (controlled by set_option), ‘right’ out of the box.

Returns `formatted`: string (or unicode, depending on data and options)

**pandas.DataFrame.to_latex**

DataFrame.to_latex(buf=None, columns=None, col_space=None, colSpace=None, header=True, index=True, na_rep='NaN', formatters=None, float_format=None, sparsify=None, index_names=True, bold_rows=True, column_format=None, longtable=False, escape=True)

Render a DataFrame to a tabular environment table. You can splice this into a LaTeX document. Requires usepackage{booktabs}.

to_latex-specific options:

- `bold_rows` [boolean, default True] Make the row labels bold in the output
- `column_format` [str, default None] The columns format as specified in LaTeX table format e.g ‘rcl’ for 3 columns
- `longtable` [boolean, default False] Use a longtable environment instead of tabular. Requires adding a usepackage{longtable} to your LaTeX preamble.
**escape** [boolean, default True] When set to False prevents from escaping latex special characters in column names.

**Parameters**

- **buf**: StringIO-like, optional
  buffer to write to
- **columns**: sequence, optional
  the subset of columns to write; default None writes all columns
- **col_space**: int, optional
  the minimum width of each column
- **header**: bool, optional
  whether to print column labels, default True
- **index**: bool, optional
  whether to print index (row) labels, default True
- **na_rep**: string, optional
  string representation of NAN to use, default ‘NaN’
- **formatters**: list or dict of one-parameter functions, optional
  formatter functions to apply to columns’ elements by position or name, default None.
  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, optional
  formatter function to apply to columns’ elements if they are floats, default None.
  The result of this function must be a unicode string.
- **sparsify**: bool, optional
  Set to False for a DataFrame with a hierarchical index to print every multiindex key
  at each row, default True
- **index_names**: bool, optional
  Prints the names of the indexes, default True

**Returns**

- **formatted**: string (or unicode, depending on data and options)

**pandas.DataFrame.to_stata**

DataFrame.to_stata(fname, convert_dates=None, write_index=True, encoding='latin-1', byte-order=None, time_stamp=None, data_label=None)

A class for writing Stata binary dta files from array-like objects

**Parameters**

- **fname**: file path or buffer
  Where to save the dta file.
- **convert_dates**: dict
  Dictionary mapping column of datetime types to the stata internal format that you
  can be either a number or a name.
- **encoding**: str
Default is latin-1. Note that Stata does not support unicode.

byteorder : str
Can be “>”, “<”, “little”, or “big”. The default is None which uses sys.byteorder

Examples

```python
>>> writer = StataWriter('./data_file.dta', data)
>>> writer.write_file()

Or with dates

>>> writer = StataWriter('./date_data_file.dta', data, {2 : 'tw'})
>>> writer.write_file()
```

**pandas.DataFrame.to_msgpack**

DataFrame.to_msgpack(path_or_buf=None, **kwargs)
msgpack (serialize) object to input file path
THIS IS AN EXPERIMENTAL LIBRARY and the storage format may not be stable until a future release.

Parameters

- path : string File path, buffer-like, or None if None, return generated string
- append : boolean whether to append to an existing msgpack (default is False)
- compress : type of compressor (zlib or blosc), default to None (no compression)

**pandas.DataFrame.to_gbq**

DataFrame.to_gbq(destination_table, project_id, chunksize=10000, verbose=True, reauth=False, if_exists='fail')
Write a DataFrame to a Google BigQuery table.
THIS IS AN EXPERIMENTAL LIBRARY

Parameters

- dataframe : DataFrame DataFrame to be written
- destination_table : string Name of table to be written, in the form ‘dataset.tablename’
- project_id : str Google BigQuery Account project ID.
- chunksize : int (default 10000) Number of rows to be inserted in each chunk from the dataframe.
- verbose : boolean (default True) Show percentage complete
reauth : boolean (default False)
Force Google BigQuery to reauthenticate the user. This is useful if multiple accounts
are used.

if_exists : {'fail', 'replace', 'append'}, default 'fail'
'fail': If table exists, do nothing. 'replace': If table exists, drop it, recreate it, and
insert data. 'append': If table exists, insert data. Create if does not exist.
New in version 0.17.0.

pandas.DataFrame.to_records

DataFrame.to_records(index=True, convert_datetime64=True)
Convert DataFrame to record array. Index will be put in the ‘index’ field of the record array if requested

Parameters index : boolean, default True
Include index in resulting record array, stored in ‘index’ field

convert_datetime64 : boolean, default True
Whether to convert the index to datetime.datetime if it is a DatetimeIndex

Returns y : recarray

pandas.DataFrame.to_sparse

DataFrame.to_sparse(fill_value=None, kind='block')
Convert to SparseDataFrame

Parameters fill_value : float, default NaN
kind : {'block', 'integer'}

Returns y : SparseDataFrame

pandas.DataFrame.to_dense

DataFrame.to_dense()
Return dense representation of NDFrame (as opposed to sparse)

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, line_width=None, max_rows=None, max_cols=None, show_dimensions=False)
Render a DataFrame to a console-friendly tabular output.

Parameters buf : StringIO-like, optional
buffer to write to

columns : sequence, optional
the subset of columns to write; default None writes all columns

col_space : int, optional
the minimum width of each column

**header** : bool, optional
whether to print column labels, default True

**index** : bool, optional
whether to print index (row) labels, default True

**na_rep** : string, optional
string representation of NaN to use, default ‘NaN’

**formatters** : list or dict of one-parameter functions, optional
formatter functions to apply to columns’ elements by position or name, default None. 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, optional
formatter function to apply to columns’ elements if they are floats, default None. The result of this function must be a unicode string.

**sparsify** : bool, optional
Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row, default True

**index_names** : bool, optional
Prints the names of the indexes, default True

**justify** : {‘left’, ‘right’}, default None
Left or right-justify the column labels. If None uses the option from the print configuration (controlled by set_option), ‘right’ out of the box.

**Returns** **formatted** : string (or unicode, depending on data and options)

### pandas.DataFrame.to_clipboard

**DataFrame.to_clipboard** *(excel=None, sep=None, **kwargs)*

Attempt to write text representation of object to the system clipboard This can be pasted into Excel, for example.

**Parameters** **excel** : boolean, defaults to True
if True, use the provided separator, writing in a csv format for allowing easy pasting into excel. if False, write a string representation of the object to the clipboard

**sep** : optional, defaults to tab

**other keywords are passed to to_csv**

**Notes**

**Requirements for your platform**

- Linux: xclip, or xsel (with gtk or PyQt4 modules)
- Windows: none
- OS X: none
34.5 Panel

34.5.1 Constructor

```
Panel([data, items, major_axis, minor_axis, ...])  Represents wide format panel data, stored as 3-dimensional array
```

```
pandas.Panel
class pandas.Panel(data=None, items=None, major_axis=None, minor_axis=None, copy=False, dtype=None)
Represents wide format panel data, stored as 3-dimensional array
```

**Parameters**

- **data**: ndarray (items x major x minor), or dict of DataFrames
  - **items**: Index or array-like
    
  - **major_axis**: Index or array-like
    
  - **minor_axis**: Index or array-like

- **dtype**: dtype, default None
  - Data type to force, otherwise infer

- **copy**: boolean, default False
  - Copy data from inputs. Only affects DataFrame / 2d ndarray input

**Attributes**

- **at**: Fast label-based scalar accessor
- **axes**: Return index label(s) of the internal NDFrame
- **blocks**: Internal property, property synonym for as_blocks()
- **dtypes**: Return the dtypes in this object
- **empty**: True if NDFrame is entirely empty [no items]
- **ftypes**: Return the ftypes (indication of sparse/dense and dtype) in this object.
- **iat**: Fast integer location scalar accessor.
- **iloc**: Purely integer-location based indexing for selection by position.
- **is_copy**: A primarily label-location based indexer, with integer position fallback.
- **ix**: Purely label-location based indexer for selection by label.
- **ndim**: Number of axes / array dimensions
- **shape**: Return a tuple of axis dimensions
- **size**: number of elements in the NDFrame
- **values**: Numpy representation of NDFrame
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**pandas.Panel.at**

Panel.at
Fast label-based scalar accessor
Similarly to loc, at provides label based scalar lookups. You can also set using these indexers.

**pandas.Panel.axes**

Panel.axes
Return index label(s) of the internal NDFrame

**pandas.Panel.blocks**

Panel.blocks
Internal property, property synonym for as_blocks()

**pandas.Panel.dtypes**

Panel.dtypes
Return the dtypes in this object

**pandas.Panel.empty**

Panel.empty
True if NDFrame is entirely empty [no items]

**pandas.Panel.ftypes**

Panel.ftypes
Return the ftypes (indication of sparse/dense and dtype) in this object.

**pandas.Panel.iat**

Panel.iat
Fast integer location scalar accessor.
Similarly to iloc, iat provides integer based lookups. You can also set using these indexers.

**pandas.Panel.iloc**

Panel.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.

.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

pandas.Panel.is_copy

Panel.is_copy = None

pandas.Panel.ix

Panel.ix
A primarily label-location based indexer, with integer position fallback.

.ix[] supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type.

.ix is the most general indexer and will support any of the inputs in .loc and .iloc. .ix also supports floating point label schemes. .ix is exceptionally useful when dealing with mixed positional and label based hierarchical indexes.

However, when an axis is integer based, ONLY label based access and not positional access is supported. Thus, in such cases, it's usually better to be explicit and use .iloc or .loc.

See more at Advanced Indexing.

pandas.Panel.loc

Panel.loc
Purely label-location based indexer for selection by label.

.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' (note that contrary to usual python slices, both the start and the stop are included!).
• A boolean array.

.loc will raise a KeyError when the items are not found.

See more at Selection by Label
pandas.Panel.ndim

```python
Panel.ndim
Number of axes / array dimensions
```

pandas.Panel.shape

```python
Panel.shape
Return a tuple of axis dimensions
```

pandas.Panel.size

```python
Panel.size
number of elements in the NDFrame
```

pandas.Panel.values

```python
Panel.values
Numpy representation of NDFrame
```

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 upcase to int32.

Methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>abs()</td>
<td>Return an object with absolute value taken.</td>
</tr>
<tr>
<td>add(other[, axis])</td>
<td>Addition of series and other, element-wise (binary operator add).</td>
</tr>
<tr>
<td>add_prefix(prefix)</td>
<td>Concatenate prefix string with panel items names.</td>
</tr>
<tr>
<td>add_suffix(suffix)</td>
<td>Concatenate suffix string with panel items names.</td>
</tr>
<tr>
<td>align(other, **kwargs)</td>
<td>Synonym for NDFrame.fillna(method='bfill').</td>
</tr>
<tr>
<td>all([axis, bool_only, skipna, level])</td>
<td>Return whether all elements are True over requested axis</td>
</tr>
<tr>
<td>any([axis, bool_only, skipna, level])</td>
<td>Return whether any element is True over requested axis</td>
</tr>
<tr>
<td>apply(func[, axis])</td>
<td>Applies function along input axis of the Panel</td>
</tr>
<tr>
<td>as_blocks([copy])</td>
<td>Convert the frame to a dict of dtype -&gt; Constructor Types that each has a homogeneous dtype.</td>
</tr>
<tr>
<td>as_matrix()</td>
<td>Cast object to input numpy.dtype</td>
</tr>
<tr>
<td>asfreq(freq[, method, how, normalize])</td>
<td>Convert all TimeSeries inside to specified frequency using DateOffset objects.</td>
</tr>
<tr>
<td>at_time(time[, asof])</td>
<td>Select values at particular time of day (e.g.</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 NDFrame.fillna(method='bfill')</td>
</tr>
<tr>
<td>bool()</td>
<td>Return the bool of a single element PandasObject</td>
</tr>
<tr>
<td>clip([lower, upper, out, axis])</td>
<td>Trim values at input threshold(s)</td>
</tr>
<tr>
<td>Function</td>
<td>Description</td>
</tr>
<tr>
<td>-------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td><code>clip_lower</code></td>
<td>Return copy of the input with values below given value(s) truncated</td>
</tr>
<tr>
<td><code>clip_upper</code></td>
<td>Return copy of input with values above given value(s) truncated</td>
</tr>
<tr>
<td><code>compound</code></td>
<td>Return the compound percentage of the values for the requested axis</td>
</tr>
<tr>
<td><code>conform</code></td>
<td>Conform input DataFrame to align with chosen axis pair.</td>
</tr>
<tr>
<td><code>consolidate</code></td>
<td>Compute NDataFrame with “consolidated” internals (data of each dtype grouped to</td>
</tr>
<tr>
<td><code>clip_upper</code></td>
<td>Attempt to infer better dtype for object columns</td>
</tr>
<tr>
<td><code>clip_lower</code></td>
<td>Make a copy of this object</td>
</tr>
<tr>
<td><code>count</code></td>
<td>Return number of observations over requested axis</td>
</tr>
<tr>
<td><code>cummax</code></td>
<td>Return cumulative max over requested axis</td>
</tr>
<tr>
<td><code>cummin</code></td>
<td>Return cumulative min over requested axis</td>
</tr>
<tr>
<td><code>cumprod</code></td>
<td>Return cumulative prod over requested axis</td>
</tr>
<tr>
<td><code>cumsum</code></td>
<td>Return cumulative sum over requested axis</td>
</tr>
<tr>
<td><code>describe</code></td>
<td>Generate various summary statistics, excluding NaN values.</td>
</tr>
<tr>
<td><code>divide</code></td>
<td>Floating division of series and other, element-wise (binary operator truediv).</td>
</tr>
<tr>
<td><code>div</code></td>
<td>Floating division of series and other, element-wise (binary operator truediv).</td>
</tr>
<tr>
<td><code>drop</code></td>
<td>Return new object with labels in requested axis removed</td>
</tr>
<tr>
<td><code>dropna</code></td>
<td>Drop 2D from panel, holding passed axis constant</td>
</tr>
<tr>
<td><code>eq</code></td>
<td>Wrapper for comparison method eq</td>
</tr>
<tr>
<td><code>equals</code></td>
<td>Determines if two NDataFrame objects contain the same elements.</td>
</tr>
<tr>
<td><code>ffill</code></td>
<td>Synonym for NDataFrame.fillna(method='ffill')</td>
</tr>
<tr>
<td><code>fillna</code></td>
<td>Fill NA/NaN values using the specified method</td>
</tr>
<tr>
<td><code>filter</code></td>
<td>Restrict the info axis to set of items or wildcard</td>
</tr>
<tr>
<td><code>first</code></td>
<td>Convenience method for subsetting initial periods of time series data</td>
</tr>
<tr>
<td><code>floordiv</code></td>
<td>Integer division of series and other, element-wise (binary operator floordiv).</td>
</tr>
<tr>
<td><code>fromDict</code></td>
<td>Construct Panel from dict of DataFrame objects</td>
</tr>
<tr>
<td><code>from_dict</code></td>
<td>Construct Panel from dict of DataFrame objects</td>
</tr>
<tr>
<td><code>get</code></td>
<td>Wrapper for comparison method ge</td>
</tr>
<tr>
<td><code>getitem</code></td>
<td>Get item from object for given key (DataFrame column, Panel slice, etc.).</td>
</tr>
<tr>
<td><code>get_dtypes</code></td>
<td>Return the counts of dtypes in this object</td>
</tr>
<tr>
<td><code>get_fdoes</code></td>
<td>Return the counts of ftypes in this object</td>
</tr>
<tr>
<td><code>get_value</code></td>
<td>Quickly retrieve single value at (item, major, minor) location</td>
</tr>
<tr>
<td><code>interp</code></td>
<td>same as values (but handles sparseness conversions)</td>
</tr>
<tr>
<td><code>interpolate</code></td>
<td>Group data on given axis, returning GroupBy object</td>
</tr>
<tr>
<td><code>iteritems</code></td>
<td>Wrapper for comparison method gt</td>
</tr>
<tr>
<td><code>isnull</code></td>
<td>Interpolate values according to different methods.</td>
</tr>
<tr>
<td><code>iterkeys</code></td>
<td>Return a boolean same-sized object indicating if the values are null</td>
</tr>
<tr>
<td><code>iteritems</code></td>
<td>Iterate over (label, values) on info axis</td>
</tr>
<tr>
<td><code>keys</code></td>
<td>iteritems alias used to get around 2to3. Deprecated</td>
</tr>
<tr>
<td><code>kurt</code></td>
<td>Join items with other Panel either on major and minor axes column</td>
</tr>
<tr>
<td><code>kurtosis</code></td>
<td>Get the ’info axis’ (see Indexing for more)</td>
</tr>
<tr>
<td><code>last</code></td>
<td>Return unbiased kurtosis over requested axis using Fishers definition of kurtosis.</td>
</tr>
<tr>
<td><code>le</code></td>
<td>Convenience method for subsetting final periods of time series data</td>
</tr>
<tr>
<td><code>lt</code></td>
<td>Wrapper for comparison method le</td>
</tr>
<tr>
<td><code>max</code></td>
<td>Wrapper for comparison method lt</td>
</tr>
<tr>
<td><code>mad</code></td>
<td>Return the mean absolute deviation of the values for the requested axis</td>
</tr>
<tr>
<td><code>major_xs</code></td>
<td>Return slice of panel along major axis</td>
</tr>
<tr>
<td><code>mask</code></td>
<td>Return an object of same shape as self and whose corresponding entries are from</td>
</tr>
</tbody>
</table>
Table 34.71 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>min()</code></td>
<td>Return the minimum of the values in the object.</td>
</tr>
<tr>
<td><code>minor_xs(key[, copy])</code></td>
<td>Return slice of panel along minor axis.</td>
</tr>
<tr>
<td><code>mod(other[, axis])</code></td>
<td>Modulo of series and other, element-wise (binary operator <code>%</code>).</td>
</tr>
<tr>
<td><code>multiply(other[, axis])</code></td>
<td>Multiplication of series and other, element-wise (binary operator <code>*</code>).</td>
</tr>
<tr>
<td><code>ne(other)</code></td>
<td>Wraps a comparison method for element-wise comparison.</td>
</tr>
<tr>
<td><code>pct_change([periods, fill_method, limit, freq])</code></td>
<td>Percent change over given number of periods.</td>
</tr>
<tr>
<td><code>pipe(func, *args, **kwargs)</code></td>
<td>Apply a function to a DataFrame.</td>
</tr>
<tr>
<td><code>pop(item)</code></td>
<td>Return item and drop from frame.</td>
</tr>
<tr>
<td><code>pow(other[, axis])</code></td>
<td>Exponential power of series and other, element-wise (binary operator <code>**</code>).</td>
</tr>
<tr>
<td><code>prod([axis, skipna, level, numeric_only])</code></td>
<td>Return the product of the values for the requested axis.</td>
</tr>
<tr>
<td><code>radd(other[, axis])</code></td>
<td>Addition of series and other, element-wise (binary operator <code>+</code>).</td>
</tr>
<tr>
<td><code>rdiv(other[, axis])</code></td>
<td>Floating division of series and other, element-wise (binary operator <code>/</code>).</td>
</tr>
<tr>
<td><code>rfloddiv(other[, axis])</code></td>
<td>Conform Panel to new index with optional filling logic, placing NA/NaN in locations.</td>
</tr>
<tr>
<td><code>rmul(other[, axis])</code></td>
<td>Conform input object to new index with optional filling logic, placing NA/NaN in locations.</td>
</tr>
<tr>
<td><code>rpow(other[, axis])</code></td>
<td>Exponential power of series and other, element-wise (binary operator <code>**</code>).</td>
</tr>
<tr>
<td><code>rsub(other[, axis])</code></td>
<td>Subtraction of series and other, element-wise (binary operator <code>-</code>).</td>
</tr>
<tr>
<td><code>rtruediv(other[, axis])</code></td>
<td>Equivalent to divide without copying data.</td>
</tr>
<tr>
<td>`replace(Io_replace, value, inplace, limit, ...)</td>
<td>Return an object with matching indicies to myself.</td>
</tr>
<tr>
<td><code>resample(rule[, how, axis, fill_method, ...])</code></td>
<td>Alter axes input function or functions.</td>
</tr>
<tr>
<td><code>rfloordiv(other[, axis])</code></td>
<td>Replace values given in ‘to_replace’ with ‘value’.</td>
</tr>
<tr>
<td><code>rmod(other[, axis])</code></td>
<td>Convenience method for frequency conversion and resampling of regular time-series.</td>
</tr>
<tr>
<td><code>rmul(other[, axis])</code></td>
<td>Integer division of series and other, element-wise (binary operator <code>//</code>).</td>
</tr>
<tr>
<td><code>rpow(other[, axis])</code></td>
<td>Modulo of series and other, element-wise (binary operator <code>%</code>).</td>
</tr>
<tr>
<td><code>rsbdiv(other[, axis])</code></td>
<td>Multiplication of series and other, element-wise (binary operator <code>*</code>).</td>
</tr>
<tr>
<td><code>rtruevdiv(other[, axis])</code></td>
<td>Exponential power of series and other, element-wise (binary operator <code>**</code>).</td>
</tr>
<tr>
<td><code>sample([n, frac, replace, weights, ...])</code></td>
<td>Floating division of series and other, element-wise (binary operator <code>/</code>).</td>
</tr>
<tr>
<td><code>select(crit[, axis])</code></td>
<td>Returns a random sample of items from an axis of object.</td>
</tr>
<tr>
<td><code>sem([axis, skipna, level, numeric_only])</code></td>
<td>Return unbiased standard error of the mean over requested axis.</td>
</tr>
<tr>
<td><code>set_axis(axis, labels)</code></td>
<td>public version of axis assignment</td>
</tr>
<tr>
<td><code>set_value(*args, **kwargs)</code></td>
<td>Quickly set single value at (item, major, minor) location.</td>
</tr>
<tr>
<td><code>shift(*args, **kwargs)</code></td>
<td>Shift index by desired number of periods with an optional time freq.</td>
</tr>
<tr>
<td><code>skew([axis, skipna, level, numeric_only])</code></td>
<td>Return unbiased skew over requested axis.</td>
</tr>
<tr>
<td><code>slice_shift([periods, axis])</code></td>
<td>Equivalent to shift without copying data.</td>
</tr>
<tr>
<td><code>sort_index([axis, level, ascending, ...])</code></td>
<td>Sort object by labels (along an axis)</td>
</tr>
<tr>
<td><code>sort_values(by[, axis, ascending, inplace, ...])</code></td>
<td>Sort object by labels (along an axis)</td>
</tr>
<tr>
<td><code>squeeze()</code></td>
<td>Squeeze length 1 dimensions.</td>
</tr>
<tr>
<td><code>std([axis, skipna, level, numeric_only])</code></td>
<td>Return unbiased standard deviation over requested axis.</td>
</tr>
<tr>
<td><code>sub(other[, axis])</code></td>
<td>Subtraction of series and other, element-wise (binary operator <code>-</code>).</td>
</tr>
<tr>
<td><code>subtract(other[, axis])</code></td>
<td>Subtraction of series and other, element-wise (binary operator <code>-</code>).</td>
</tr>
<tr>
<td><code>sum([axis, skipna, level, numeric_only])</code></td>
<td>Return the sum of the values for the requested axis.</td>
</tr>
<tr>
<td><code>swapaxes(axis1, axis2[, copy])</code></td>
<td>Interchange axes and swap values axes appropriately.</td>
</tr>
<tr>
<td><code>swaplevel(i, j[, axis])</code></td>
<td>Swap levels i and j in a MultiIndex on a particular axis.</td>
</tr>
<tr>
<td><code>tail([n])</code></td>
<td>Analogous to ndarray.take</td>
</tr>
<tr>
<td><code>take(indices[, axis, convert, is_copy])</code></td>
<td>Attempt to write text representation of object to the system clipboard This can be used instead of <code>to_csv</code></td>
</tr>
<tr>
<td><code>toLong(*args, **kwargs)</code></td>
<td>Write each DataFrame in Panel to a separate excel sheet</td>
</tr>
<tr>
<td><code>to_clipboard([excel, sep])</code></td>
<td>Transform wide format into long (stacked) format as DataFrame whose columns</td>
</tr>
<tr>
<td><code>to_dense()</code></td>
<td>Write each DataFrame in Panel to a separate excel sheet</td>
</tr>
<tr>
<td><code>to_excel(path[, na_rep, engine])</code></td>
<td>Transform wide format into long (stacked) format as DataFrame whose columns</td>
</tr>
<tr>
<td><code>to_frame([filter_observations])</code></td>
<td>Transform wide format into long (stacked) format as DataFrame whose columns</td>
</tr>
</tbody>
</table>
Table 34.71 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>to_hdf(path_or_buf, key, **kwargs)</code></td>
<td>activate the HDFStore</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_long(*args, **kwargs)</code></td>
<td>msgpack (serialize) object to input file path</td>
</tr>
<tr>
<td><code>to_msgpack(path_or_buf)</code></td>
<td>Pickle (serialize) object to input file path</td>
</tr>
<tr>
<td><code>to_sparse(fill_value, kind)</code></td>
<td>Convert to SparsePanel</td>
</tr>
<tr>
<td><code>to_sql(name, con[, flavor, schema, ...])</code></td>
<td>Write records stored in a DataFrame to a SQL database.</td>
</tr>
<tr>
<td><code>transpose(*args, **kwargs)</code></td>
<td>Permute the dimensions of the Panel</td>
</tr>
<tr>
<td><code>truediv(other[, axis])</code></td>
<td>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>Truncates a sorted DataFrame before and/or after some particular dates.</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(*args, **kwargs)</code></td>
<td>Localize tz-naive TimeSeries to target time zone</td>
</tr>
<tr>
<td><code>update(other[, join, overwrite, ...])</code></td>
<td>Modify Panel in place using non-NA values from passed Panel, or object coercible to Panel.</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>Return an object of same shape as self and whose corresponding entries are from other.</td>
</tr>
<tr>
<td><code>xs(key[, axis, copy])</code></td>
<td>Return slice of panel along selected axis</td>
</tr>
</tbody>
</table>

---

**pandas.Panel.abs**

Panel.abs()  
Return an object with absolute value taken. Only applicable to objects that are all numeric  

**Returns**  
abs: type of caller

**pandas.Panel.add**

Panel.add(other, axis=0)  
Addition of series and other, element-wise (binary operator `add`). Equivalent to `panel + other`.  

**Parameters**  
other: DataFrame or Panel  
axis: {items, major_axis, minor_axis}  

**Returns**  
Panel

**See also:**  
Panel.radd

**pandas.Panel.add_prefix**

Panel.add_prefix(prefix)  
Concatenate prefix string with panel items names.  

**Parameters**  
prefix: string

**Returns**  
with_prefix: type of caller
pandas.Panel.add_suffix

```
Panel.add_suffix(suffix)
Concateenate suffix string with panel items names
```

**Parameters**

- `suffix` : string
  
**Returns**

- `with_suffix` : type of caller

pandas.Panel.align

```
Panel.align(other, **kwargs)
```

pandas.Panel.all

```
Panel.all(axis=None, bool_only=None, skipna=None, level=None, **kwargs)
```

Return whether all elements are True over requested axis

**Parameters**

- `axis` : {items (0), major_axis (1), minor_axis (2)}
  
- `skipna` : boolean, 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 DataFrame

- `bool_only` : boolean, default None
  
  Include only boolean data. If None, will attempt to use everything, then use only boolean data

**Returns**

- `all` : DataFrame or Panel (if level specified)

pandas.Panel.any

```
Panel.any(axis=None, bool_only=None, skipna=None, level=None, **kwargs)
```

Return whether any element is True over requested axis

**Parameters**

- `axis` : {items (0), major_axis (1), minor_axis (2)}
  
- `skipna` : boolean, 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 DataFrame

- `bool_only` : boolean, default None
  
  Include only boolean data. If None, will attempt to use everything, then use only boolean data

**Returns**

- `any` : DataFrame or Panel (if level specified)
pandas.Panel.apply

Panel.apply(func, axis='major', **kwargs)
Applies function along input axis of the Panel

Parameters  
func : function
Function to apply to each combination of ‘other’ axes e.g. if axis = ‘items’, then the combination of major_axis/minor_axis will be passed a Series
axis : {'major', 'minor', 'items'}

Additional keyword arguments will be passed as keywords to the function

Returns  
result : Pandas Object

Examples

>>> p.apply(numpy.sqrt)  # returns a Panel
>>> p.apply(lambda x: x.sum(), axis=0)  # equiv to p.sum(0)
>>> p.apply(lambda x: x.sum(), axis=1)  # equiv to p.sum(1)
>>> p.apply(lambda x: x.sum(), axis=2)  # equiv to p.sum(2)

pandas.Panel.as_blocks

Panel.as_blocks(copy=True)
Convert the frame to a dict of dtype -> Constructor Types that each has a homogeneous dtype.

NOTE: the dtypes of the blocks WILL BE PRESERVED HERE (unlike in as_matrix)

Parameters  
copy : boolean, default True

Returns  
values : a dict of dtype -> Constructor Types

pandas.Panel.as_matrix

Panel.as_matrix()

pandas.Panel.asfreq

Panel.asfreq(freq, method=None, how=None, normalize=False)
Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

Parameters  
freq : DateOffset object, or string
method : {'backfill', 'bfill', 'pad', 'ffill', None}
how : {'start', 'end'}, default end

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 method

how : {'start', 'end'}, default end
For PeriodIndex only, see PeriodIndex.asfreq

normalize : bool, default False
Whether to reset output index to midnight

Returns converted : type of caller

pandas.Panel.astype

Panel.astype(dtype, copy=True, raise_on_error=True, **kwargs)
Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

Parameters dtype : numpy.dtype or Python type
raise_on_error : raise on invalid input
kwargs : keyword arguments to pass on to the constructor

Returns casted : type of caller

pandas.Panel.at_time

Panel.at_time(time, asof=False)
Select values at particular time of day (e.g. 9:30AM)

Parameters time : datetime.time or string

Returns values_at_time : type of caller

pandas.Panel.between_time

Panel.between_time(start_time, end_time, include_start=True, include_end=True)
Select values between particular times of the day (e.g., 9:00-9:30 AM)

Parameters start_time : datetime.time or string
end_time : datetime.time or string
include_start : boolean, default True
include_end : boolean, default True

Returns values_between_time : type of caller

pandas.Panel.bfill

Panel.bfill(axis=None, inplace=False, limit=None, downcast=None)
Synonym for NDFrame.fillna(method='bfill')

pandas.Panel.bool

Panel.bool()
Return the bool of a single element PandasObject This must be a boolean scalar value, either True or False
Raise a ValueError if the PandasObject does not have exactly 1 element, or that element is not boolean
pandas.Panel.clip

Panel.clip(lower=None, upper=None, out=None, axis=None)
Trim values at input threshold(s)

Parameters lower : float or array_like, default None
upper : float or array_like, default None
axis : int or string axis name, optional

Align object with lower and upper along the given axis.

Returns clipped : Series

Examples

```python
def df
0 1
0 0.335232 -1.256177
1 -1.367855 0.746646
2 0.027753 -1.176076
3 0.230930 -0.679613
4 1.261967 0.570967
def.clip(-1.0, 0.5)
0 1
0 0.335232 -1.000000
1 -1.000000 0.500000
2 0.027753 -1.000000
3 0.230930 -0.679613
4 0.500000 0.500000
t
0 -0.3
1 -0.2
2 -0.1
3 0.0
4 0.1
dtype: float64
def.clip(t, t + 1, axis=0)
0 1
0 0.335232 -0.300000
1 -0.200000 0.746646
2 0.027753 -0.100000
3 0.230930 0.000000
4 1.100000 0.570967
```

pandas.Panel.clip_lower

Panel.clip_lower(threshold, axis=None)
Return copy of the input with values below given value(s) truncated

Parameters threshold : float or array_like
axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns clipped : same type as input
See also:
clip

pandas.Panel.clip_upper

Panel.clip_upper (threshold, axis=None)
Return copy of input with values above given value(s) truncated

Parameters threshold : float or array_like
axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns clipped : same type as input

See also:
clip

pandas.Panel.compound

Panel.compound (axis=None, skipna=None, level=None)
Return the compound percentage of the values for the requested axis

Parameters axis : {items (0), major_axis (1), minor_axis (2)}
skipna : boolean, 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 DataFrame
numeric_only : boolean, default None
Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns compounded : DataFrame or Panel (if level specified)

pandas.Panel.conform

Panel.conform (frame, axis='items')
Conform input DataFrame to align with chosen axis pair.

Parameters frame : DataFrame
axis : {'items', 'major', 'minor'}

Axis the input corresponds to. E.g., if axis='major', then the frame's columns would be items, and the index would be values of the minor axis

Returns DataFrame
**pandas.Panel.consolidate**

Panel.consolidate(inplace=False)

Compute NDFrame with “consolidated” internals (data of each dtype grouped together in a single ndarray). Mainly an internal API function, but available here to the savvy user.

**Parameters**

- **inplace**: boolean, default False
  
  If False return new object, otherwise modify existing object.

**Returns**

- **consolidated**: type of caller

**pandas.Panel.convert_objects**

Panel.convert_objects(convert_dates=True, convert_numeric=False, convert_timedeltas=True, copy=True)

Attempt to infer better dtype for object columns.

**Parameters**

- **convert_dates**: boolean, default True
  
  If True, convert to date where possible. If ‘coerce’, force conversion, with unconvertible values becoming NaT.

- **convert_numeric**: boolean, default False
  
  If True, attempt to coerce to numbers (including strings), with unconvertible values becoming NaN.

- **convert_timedeltas**: boolean, default True
  
  If True, convert to timedelta where possible. If ‘coerce’, force conversion, with unconvertible values becoming NaT.

- **copy**: boolean, default True
  
  If True, return a copy even if no copy is necessary (e.g. no conversion was done). Note: This is meant for internal use, and should not be confused with inplace.

**Returns**

- **converted**: same as input object

**pandas.Panel.copy**

Panel.copy(deep=True)

Make a copy of this object.

**Parameters**

- **deep**: boolean or string, default True
  
  Make a deep copy, i.e. also copy data.

**Returns**

- **copy**: type of caller

**pandas.Panel.count**

Panel.count(axis='major')

Return number of observations over requested axis.

**Parameters**

- **axis**: {‘items’, ‘major’, ‘minor’} or {0, 1, 2}

**Returns**

- **count**: DataFrame
pandas.Panel.cummax

```
Panel.cummax (axis=None, dtype=None, out=None, skipna=True, **kwargs)
Return cumulative max over requested axis.
```

**Parameters**

- `axis` : {items (0), major_axis (1), minor_axis (2)}
- `skipna` : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**Returns**

- `max` : DataFrame

pandas.Panel.cummin

```
Panel.cummin (axis=None, dtype=None, out=None, skipna=True, **kwargs)
Return cumulative min over requested axis.
```

**Parameters**

- `axis` : {items (0), major_axis (1), minor_axis (2)}
- `skipna` : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**Returns**

- `min` : DataFrame

pandas.Panel.cumprod

```
Panel.cumprod (axis=None, dtype=None, out=None, skipna=True, **kwargs)
Return cumulative prod over requested axis.
```

**Parameters**

- `axis` : {items (0), major_axis (1), minor_axis (2)}
- `skipna` : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**Returns**

- `prod` : DataFrame

pandas.Panel.cumsum

```
Panel.cumsum (axis=None, dtype=None, out=None, skipna=True, **kwargs)
Return cumulative sum over requested axis.
```

**Parameters**

- `axis` : {items (0), major_axis (1), minor_axis (2)}
- `skipna` : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**Returns**

- `sum` : DataFrame

pandas.Panel.describe

```
Panel.describe (percentiles=None, include=None, exclude=None)
Generate various summary statistics, excluding NaN values.
```

**Parameters**

- `percentiles` : array-like, optional
The percentiles to include in the output. Should all be in the interval [0, 1]. By default percentiles is [.25, .5, .75], returning the 25th, 50th, and 75th percentiles.

**include, exclude** : list-like, ‘all’, or None (default)

Specify the form of the returned result. Either:

- None to both (default). The result will include only numeric-typed columns or, if none are, only categorical columns.
- A list of dtypes or strings to be included/excluded. To select all numeric types use numpy number. To select categorical objects use type object. See also the select_dtypes documentation. eg. df.describe(include=['O'])
- If include is the string ‘all’, the output column-set will match the input one.

**Returns** summary: NDFrame of summary statistics

**See also:**

*DataFrame.select_dtypes*

**Notes**

The output DataFrame index depends on the requested dtypes:

For numeric dtypes, it will include: count, mean, std, min, max, and lower, 50, and upper percentiles.

For object dtypes (e.g. timestamps or strings), the index will include the count, unique, most common, and frequency of the most common. Timestamps also include the first and last items.

For mixed dtypes, the index will be the union of the corresponding output types. Non-applicable entries will be filled with NaN. Note that mixed-dtype outputs can only be returned from mixed-dtype inputs and appropriate use of the include/exclude arguments.

If multiple values have the highest count, then the count and most common pair will be arbitrarily chosen from among those with the highest count.

The include, exclude arguments are ignored for Series.

**pandas.Panel.div**

**Panel.div(other, axis=0)**

Floating division of series and other, element-wise (binary operator truediv). Equivalent to panel / other.

**Parameters**

- other : DataFrame or Panel
- axis : [items, major_axis, minor_axis]

Axis to broadcast over

**Returns** Panel

**See also:**

*Panel.rtruediv*
**pandas.Panel.divide**

Panel.divide(*other*, *axis=0*)

Floating division of series and other, element-wise (binary operator `truediv`). Equivalent to `panel / other`.

**Parameters**

- **other**: DataFrame or Panel
- **axis**: {items, major_axis, minor_axis}

**Returns**

Panel

**See also:**

Panel.rtruediv

**pandas.Panel.drop**

Panel.drop(*labels*, *axis=0*, *level=None*, *inplace=False*, *errors=`raise`*)

Return new object with labels in requested axis removed.

**Parameters**

- **labels**: single label or list-like
- **axis**: int or axis name
- **level**: int or level name, default None
  - For MultiIndex
- **inplace**: bool, default False
  - If True, do operation inplace and return None.
- **errors**: {‘ignore’, ‘raise’}, default ‘raise’
  - If ‘ignore’, suppress error and existing labels are dropped.
  - New in version 0.16.1.

**Returns**

dropped : type of caller

**pandas.Panel.dropna**

Panel.dropna(*axis=0*, *how=’any’*, *inplace=False*)

Drop 2D from panel, holding passed axis constant.

**Parameters**

- **axis**: int, default 0
  - Axis to hold constant. E.g. `axis=1` will drop major_axis entries having a certain amount of NA data
- **how**: {‘all’, ‘any’}, default ‘any’
  - ‘any’: one or more values are NA in the DataFrame along the axis. For ‘all’ they all must be.
- **inplace**: bool, default False
  - If True, do operation inplace and return None.

**Returns**

dropped : Panel
pandas.Panel.eq

Panel.eq(other)
   Wrapper for comparison method eq

pandas.Panel.equals

Panel.equals(other)
   Determines if two NDFrame objects contain the same elements. NaNs in the same location are considered equal.

pandas.Panel.ffill

Panel.ffill(axis=None, inplace=False, limit=None, downcast=None)
   Synonym for NDFrame.fillna(method='ffill')

pandas.Panel.fillna

Panel.fillna(value=None, method=None, axis=None, inplace=False, limit=None, downcast=None, **kwargs)
   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, 1, 2, 'items', 'major_axis', 'minor_axis'}
      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).

   inplace : boolean, default False
      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.

   limit : int, default 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
   filled : Panel
See also:

reindex, asfreq

pandas.Panel.filter

Panel.filter(items=None, like=None, regex=None, axis=None)
Restrict the info axis to set of items or wildcard

Parameters:

- **items**: list-like
  - List of info axis to restrict to (must not all be present)
- **like**: string
  - Keep info axis where “arg in col == True”
- **regex**: string (regular expression)
  - Keep info axis with re.search(regex, col) == True
- **axis**: int or None
  - The axis to filter on. By default this is the info axis. The “info axis” is the axis that is used when indexing with[]. For example, df = DataFrame({'a': [1, 2, 3, 4]}); df['a']. So, the DataFrame columns are the info axis.

Notes

Arguments are mutually exclusive, but this is not checked for

pandas.Panel.first

Panel.first(offset)
Convenience method for subsetting initial periods of time series data based on a date offset

Parameters:

- **offset**: string, DateOffset, dateutil.relativedelta

Returns:

- **subset**: type of caller

Examples

ts.last('10D') -> First 10 days

pandas.Panel.floordiv

Panel.floordiv(other, axis=0)
Integer division of series and other, element-wise (binary operator floordiv). Equivalent to panel // other.

Parameters:

- **other**: DataFrame or Panel
- **axis**: {'items', 'major_axis', 'minor_axis'}
  - Axis to broadcast over
Returns  Panel

See also:

Panel.rfloordiv

pandas.Panel.fromDict
classmethod Panel.fromDict (data, intersect=False, orient='items', dtype=None)
Construct Panel from dict of DataFrame objects

Parameters  data : dict
            {field : DataFrame}

intersect : boolean
    Intersect indexes of input DataFrames

orient : {'items', 'minor'}, default 'items'
    The “orientation” of the data. If the keys of the passed dict should be the items of
the result panel, pass ‘items’ (default). Otherwise if the columns of the values of
the passed DataFrame objects should be the items (which in the case of mixed-
dtype data you should do), instead pass ‘minor’

dtype : dtype, default None
    Data type to force, otherwise infer

Returns  Panel

pandas.Panel.from_dict
classmethod Panel.from_dict (data, intersect=False, orient='items', dtype=None)
Construct Panel from dict of DataFrame objects

Parameters  data : dict
            {field : DataFrame}

intersect : boolean
    Intersect indexes of input DataFrames

orient : {'items', 'minor'}, default 'items'
    The “orientation” of the data. If the keys of the passed dict should be the items of
the result panel, pass ‘items’ (default). Otherwise if the columns of the values of
the passed DataFrame objects should be the items (which in the case of mixed-
dtype data you should do), instead pass ‘minor’

dtype : dtype, default None
    Data type to force, otherwise infer

Returns  Panel
pandas.Panel.ge

Panel.ge(other)
Wrapper for comparison method ge

pandas.Panel.get

Panel.get(key, default=None)
Get item from object for given key (DataFrame column, Panel slice, etc.). Returns default value if not found

Parameters key : object

Returns value : type of items contained in object

pandas.Panel.get_dtype_counts

Panel.get_dtype_counts()
Return the counts of dtypes in this object

pandas.Panel.get_ftype_counts

Panel.get_ftype_counts()
Return the counts of ftypes in this object

pandas.Panel.get_value

Panel.get_value(*args, **kwargs)
Quickly retrieve single value at (item, major, minor) location

Parameters item : item label (panel item)

major : major axis label (panel item row)

minor : minor axis label (panel item column)

takeable : interpret the passed labels as indexers, default False

Returns value : scalar value

pandas.Panel.get_values

Panel.get_values()
same as values (but handles sparseness conversions)

pandas.Panel.groupby

Panel.groupby(function, axis='major')
Group data on given axis, returning GroupBy object

Parameters function : callable

Mapping function for chosen access
axis : {'major', 'minor', 'items'}, default 'major'

Returns grouped : PanelGroupBy

pandas.Panel.gt

Panel.gt (other)
Wrapper for comparison method gt

pandas.Panel.head

Panel.head (n=5)

pandas.Panel.interpolate

Panel.interpolate (method='linear', axis=0, limit=None, inplace=False, limit_direction='forward', downcast=None, **kwargs)
Interpolate values according to different methods.
Please note that only method='linear' is supported for DataFrames/Series with a MultiIndex.

Parameters method : {'linear', 'time', 'index', 'values', 'nearest', 'zero',
'slinear', 'quadratic', 'cubic', 'barycentric', 'krogh', 'polynomial', 'spline'
'piecewise_polynomial', 'pchip'}

• ‘linear’: ignore the index and treat the values as equally spaced. This is the only method supported on MultiIndexes. default
• ‘time’: interpolation works on daily and higher resolution data to interpolate given length of interval
• ‘index’, ‘values’: use the actual numerical values of the index
• ‘nearest’, ‘zero’, ‘slinear’, ‘quadratic’, ‘cubic’, ‘barycentric’, ‘polynomial’ is passed to scipy.interpolate.interp1d. Both ‘polynomial’ and ‘spline’ require that you also specify an order (int), e.g. df.interpolate(method='polynomial', order=4). These use the actual numerical values of the index.
• ‘krogh’, ‘piecewise_polynomial’, ‘spline’, and ‘pchip’ are all wrappers around the scipy interpolation methods of similar names. These use the actual numerical values of the index. See the scipy documentation for more on their behavior here and here

axis : {0, 1}, default 0
• 0: fill column-by-column
• 1: fill row-by-row

limit : int, default None.
Maximum number of consecutive NaNs to fill.

limit_direction : {'forward', 'backward', 'both'}, defaults to ‘forward’
If limit is specified, consecutive NaNs will be filled in this direction.

New in version 0.17.0.

inplace : bool, default False
    Update the NDFrame in place if possible.

downcast : optional, ‘infer’ or None, defaults to None
    Downcast dtypes if possible.

kwarg : keyword arguments to pass on to the interpolating function.

Returns
    Series or DataFrame of same shape interpolated at the NaNs

See also:
    reindex, replace, fillna

Examples

Filling in NaNs

```python
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s.interpolate()
0   0
1   1
2   2
3   3
dtype: float64
```

pandas.Panel.isnull

Panel.isnull()
    Return a boolean same-sized object indicating if the values are null

See also:
    notnull boolean inverse of isnull

pandas.Panel.iteritems

Panel.iteritems()
    Iterate over (label, values) on info axis

    This is index for Series, columns for DataFrame, major_axis for Panel, and so on.

pandas.Panel.iterkv

Panel.iterkv(*args, **kwargs)
    iteritems alias used to get around 2to3. Deprecated
pandas.Panel.join

Panel.join(other, how='left', lsuffix='', rsuffix='')
Join items with other Panel either on major and minor axes column

Parameters
other : Panel or list of Panels
   Index should be similar to one of the columns in this one
how : {'left', 'right', 'outer', 'inner'}
   How to handle indexes of the two objects. Default: ‘left’ for joining on index,
   None otherwise * left: use calling frame’s index * right: use input frame’s index
   * outer: form union of indexes * inner: use intersection of indexes
lsuffix : string
   Suffix to use from left frame’s overlapping columns
rsuffix : string
   Suffix to use from right frame’s overlapping columns

Returns
joined : Panel

pandas.Panel.keys

Panel.keys()
Get the ‘info axis’ (see Indexing for more)
   This is index for Series, columns for DataFrame and major_axis for Panel.

pandas.Panel.kurt

Panel.kurt(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)
Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal ==
0.0). Normalized by N-1

Parameters
axis : {items (0), major_axis (1), minor_axis (2)}
skipna : boolean, 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 DataFrame
numeric_only : boolean, default None
   Include only float, int, boolean data. If None, will attempt to use everything, then
   use only numeric data

Returns kurt : DataFrame or Panel (if level specified)
pandas.Panel.kurtosis

Panel.kurtosis(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)
Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters

- **axis**: {items (0), major_axis (1), minor_axis (2)}
- **skipna**: boolean, 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 DataFrame
- **numeric_only**: boolean, default None
  Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns

- **kurt**: DataFrame or Panel (if level specified)

pandas.Panel.last

Panel.last(offset)
Convenience method for subsetting final periods of time series data based on a date offset

Parameters

- **offset**: string, DateOffset, dateutil.relativedelta

Returns

- **subset**: type of caller

Examples

ts.last('5M') -> Last 5 months

pandas.Panel.le

Panel.le(other)
Wrapper for comparison method le

pandas.Panel.lt

Panel.lt(other)
Wrapper for comparison method lt

pandas.Panel.mad

Panel.mad(axis=None, skipna=None, level=None)
Return the mean absolute deviation of the values for the requested axis

Parameters

- **axis**: {items (0), major_axis (1), minor_axis (2)}
- **skipna**: boolean, 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 DataFrame

**numeric_only**: boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns mad**: DataFrame or Panel (if level specified)

### pandas.Panel.major_xs

**Panel.major_xs(key, copy=None)**

Return slice of panel along major axis

**Parameters**

- **key**: object
  - Major axis label
- **copy**: boolean [deprecated]
  - Whether to make a copy of the data

**Returns**

- **y**: DataFrame
  - index -> minor axis, columns -> items

**Notes**

major_xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of major_xs functionality, see [MultiIndex Slicers](#)

### pandas.Panel.mask

**Panel.mask(cond, other=nan, inplace=False, axis=None, level=None, try_cast=False, raise_on_error=True)**

Return an object of same shape as self and whose corresponding entries are from self where cond is False and otherwise are from other.

**Parameters**

- **cond**: boolean NDFrame or array
- **other**: scalar or NDFrame
- **inplace**: boolean, default False
  - Whether to perform the operation in place on the data
- **axis**: alignment axis if needed, default None
- **level**: alignment level if needed, default None
- **try_cast**: boolean, default False
  - try to cast the result back to the input type (if possible),
- **raise_on_error**: boolean, default True
Whether to raise on invalid data types (e.g. trying to where on strings)

**Returns**

- `wh`: same type as caller

**pandas.Panel.max**

```
pandas.Panel.max
```

Panel.max (axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

This method returns the maximum of the values in the object. If you want the index of the maximum, use idxmax. This is the equivalent of the numpy.ndarray method argmax.

**Parameters**

- `axis`: {items (0), major_axis (1), minor_axis (2)}
- `skipna`: boolean, 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 DataFrame
- `numeric_only`: boolean, default None
  - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**

- `max`: DataFrame or Panel (if level specified)

**pandas.Panel.mean**

```
pandas.Panel.mean
```

Panel.mean (axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

Return the mean of the values for the requested axis

**Parameters**

- `axis`: {items (0), major_axis (1), minor_axis (2)}
- `skipna`: boolean, 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 DataFrame
- `numeric_only`: boolean, default None
  - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**

- `mean`: DataFrame or Panel (if level specified)

**pandas.Panel.median**

```
pandas.Panel.median
```

Panel.median (axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

Return the median of the values for the requested axis

**Parameters**

- `axis`: {items (0), major_axis (1), minor_axis (2)}
- `skipna`: boolean, 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 DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then
use only numeric data

Returns median : DataFrame or Panel (if level specified)

pandas.Panel.min

Panel.min(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

This method returns the minimum of the values in the object. If you want the index of the minimum, use idxmin. This is the equivalent of the numpy.ndarray method argmin.

Parameters axis : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, 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 DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then
use only numeric data

Returns min : DataFrame or Panel (if level specified)

pandas.Panel.minor_xs

Panel.minor_xs(key, copy=None)

Return slice of panel along minor axis

Parameters key : object

Minor axis label

copy : boolean [deprecated]

Whether to make a copy of the data

Returns y : DataFrame

index -> major axis, columns -> items

Notes

minor_xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of minor_xs functionality, see MultiIndex Slicers
pandas: powerful Python data analysis toolkit, Release 0.17.0

pandas.Panel.mod

Panel.mod(other, axis=0)
Modulo of series and other, element-wise (binary operator mod). Equivalent to panel % other.

Parameters  
other : DataFrame or Panel
axis : {items, major_axis, minor_axis}

Returns  Panel

See also:  Panel.rmod

pandas.Panel.mul

Panel.mul(other, axis=0)
Multiplication of series and other, element-wise (binary operator mul). Equivalent to panel * other.

Parameters  
other : DataFrame or Panel
axis : {items, major_axis, minor_axis}

Returns  Panel

See also:  Panel.rmul

pandas.Panel.multiply

Panel.multiply(other, axis=0)
Multiplication of series and other, element-wise (binary operator mul). Equivalent to panel * other.

Parameters  
other : DataFrame or Panel
axis : {items, major_axis, minor_axis}

Returns  Panel

See also:  Panel.rmul

pandas.Panel.ne

Panel.ne(other)
Wrapper for comparison method ne
**pandas.Panel.notnull**

Panel.notnull()

Return a boolean same-sized object indicating if the values are not null

**See also:**

isnull boolean inverse of notnull

**pandas.Panel.pct_change**

Panel.pct_change(periods=1, fill_method='pad', limit=None, freq=None, **kwargs)

Percent change over given number of periods.

**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 offset alias string, optional
  - Increment to use from time series API (e.g. ‘M’ or BDay())

**Returns**

- **chg**: NDFrame

**Notes**

By default, the percentage change is calculated along the stat axis: 0, or Index, for DataFrame and 1, or minor for Panel. You can change this with the axis keyword argument.

**pandas.Panel.pipe**

Panel.pipe(func, *args, **kwargs)

Apply func(self, *args, **kwargs)

New in version 0.16.2.

**Parameters**

- **func**: function
  - function to apply to the NDFrame. 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 NDFrame.

- **args**: positional arguments passed into func.

- **kwargs**: a dictionary of keyword arguments passed into func.

**Returns**

- **object**: the return type of func.

**See also:**

pandas.DataFrame.apply, pandas.DataFrame.applymap, pandas.Series.map
Notes

Use .pipe when chaining together functions that expect on Series or DataFrames. Instead of writing

```python
>>> f(g(h(df), arg1=a), arg2=b, arg3=c)
```

You can write

```python
>>> (df.pipe(h)
...   .pipe(g, arg1=a)
...   .pipe(f, 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((f, 'arg2'), arg1=a, arg3=c)
... )
```

**pandas.Panel.pop**

Panel.pop(item)

Return item and drop from frame. Raise KeyError if not found.

**pandas.Panel.pow**

Panel.pow(other, axis=0)

Exponential power of series and other, element-wise (binary operator pow). Equivalent to panel ** other.

Parameters

- other : DataFrame or Panel
- axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

See also:

Panel.rpow

**pandas.Panel.prod**

Panel.prod(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

Return the product of the values for the requested axis

Parameters

- axis : {items (0), major_axis (1), minor_axis (2)}
- skipna : boolean, 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 DataFrame

**numeric_only**: boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns** **prod**: DataFrame or Panel (if level specified)

**pandas.Panel.product**

Panel.product(*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the product of the values for the requested axis

**Parameters**

- **axis**: {items (0), major_axis (1), minor_axis (2)}
- **skipna**: boolean, 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 DataFrame
- **numeric_only**: boolean, default None
  - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns** **prod**: DataFrame or Panel (if level specified)

**pandas.Panel.radd**

Panel.radd(*other*, *axis=0*)

Addition of series and other, element-wise (binary operator radd). Equivalent to other + panel.

**Parameters**

- **other**: DataFrame or Panel
- **axis**: {items, major_axis, minor_axis}
  - Axis to broadcast over

**Returns** Panel

See also:

Panel.add

**pandas.Panel.rdiv**

Panel.rdiv(*other*, *axis=0*)

Floating division of series and other, element-wise (binary operator rtruediv). Equivalent to other / panel.

**Parameters**

- **other**: DataFrame or Panel
- **axis**: {items, major_axis, minor_axis}
  - Axis to broadcast over
Returns Panel

See also:

Panel.truediv

pandas.Panel.reindex

Panel.reindex(items=None, major_axis=None, minor_axis=None, **kwargs)
Conform Panel to new index with optional filling logic, placing 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 items, major_axis, minor_axis : array-like, optional (can be specified in order, or as keywords) New labels / index to conform to. Preferably an Index object to avoid duplicating data


Method to use for filling holes in reindexed DataFrame:
• 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 : boolean, 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.

New in version 0.17.0.

Returns reindexed : Panel

Examples

```python
>>> df.reindex(index=[date1, date2, date3], columns=['A', 'B', 'C'])
```
pandas.Panel.reindex_axis

Panel.reindex_axis(labels, axis=0, method=None, level=None, copy=True, limit=None, fill_value=np.nan)

Conform input object to new index with optional filling logic, placing 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

labels : array-like
    New labels / index to conform to. Preferably an Index object to avoid duplicating data

axis : {0, 1, 2, ‘items’, ‘major_axis’, ‘minor_axis’}

    Method to use for filling holes in reindexed DataFrame:
    • 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 : boolean, 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

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 \( \text{abs}(\text{index}[\text{indexer}] - \text{target}) \leq \text{tolerance} \).
    New in version 0.17.0.

Returns

reindexed : Panel

See also:
reindex, reindex_like

Examples

>>> df.reindex_axis(['A', 'B', 'C'], axis=1)

pandas.Panel.reindex_like

Panel.reindex_like(other, method=None, copy=True, limit=None, tolerance=None)

return an object with matching indicies to myself
Parameters  

other : Object
  
method : string or None
  
copy : boolean, default True
  
limit : int, default None
    Maximum number of consecutive labels to fill for inexact matches.

tolerance : optional
    Maximum distance between labels of the other object and this object for inexact matches.
    
    New in version 0.17.0.

Returns reindexed : same as input

Notes

Like calling s.reindex(index=other.index, columns=other.columns, method=...)
Panel.replace

Panel.replace(to_replace=None, value=None, inplace=False, limit=None, regex=False, method='pad', axis=None)
Replace values given in ‘to_replace’ with ‘value’.

Parameters to_replace : str, regex, list, dict, Series, numeric, or None
- str or regex:
  - 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 and regex rules apply as above.
- dict:
  - Nested dictionaries, e.g., {'a': {'b': nan}}, are read as follows: look in column 'a' for the value 'b' and replace it with nan. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) cannot be regular expressions.
  - Keys map to column names and values map to substitution values. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
- 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 use to fill holes (e.g. 0), alternately a dict of values specifying which value to use for each column (columns not in the dict will not be filled). Regular expressions, strings and lists or dict s of such objects are also allowed.

inplace : boolean, default False
If True, in place. Note: this will modify any other views on this object (e.g. a column form 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. Otherwise, to_replace must be None because this parameter will be interpreted as a regular expression or a list, dict, or array of regular expressions.
method: string, optional, {'pad', 'ffill', 'bfill'}

The method to use when for replacement, when to_replace is a list.

Returns filled: NDFrame

Raises AssertionError

- If regex is not a bool and to_replace is not None.

TypeError

- 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.

ValueError

- If to_replace and value are lists or ndarrays, but they are not the same length.

See also:

NDFrame.reindex, NDFrame.asfreq, NDFrame.fillna

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.

pandas.Panel.resample

Panel.resample(rule, how=None, axis=0, fill_method=None, closed=None, label=None, convention='start', kind=None, loffset=None, limit=None, base=0)

Convenience method for frequency conversion and resampling of regular time-series data.

Parameters rule: string

the offset string or object representing target conversion

how: string

method for down- or re-sampling, default to ‘mean’ for downsampling

axis: int, optional, default 0

fill_method: string, default None

fill_method for upsampling

closed: {'right', 'left'}

Which side of bin interval is closed

label: {'right', 'left'}
Which bin edge label to label bucket with

**convention** : {'start', 'end', 's', 'e'}

**kind** : “period”/“timestamp”

**loffset** : timedelta

Adjust the resampled time labels

**limit** : int, default None

Maximum size gap to when reindexing with fill_method

**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

**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', how='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', how='sum', label='right')
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.
>>> series.resample('3T', how='sum', label='right', closed='right')
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.

>>> series.resample('30S')[0:5]  # select first 5 rows
2000-01-01 00:00:00    0
2000-01-01 00:00:30   NaN
2000-01-01 00:01:00    1
2000-01-01 00:01:30   NaN
2000-01-01 00:02:00    2
Freq: 30S, dtype: float64

Upsample the series into 30 second bins and fill the NaN values using the pad method.

>>> series.resample('30S', fill_method='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.

>>> series.resample('30S', fill_method='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 to how.

>>> def custom_resampler(array_like):
...     return np.sum(array_like)+5

>>> series.resample('3T', how=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

pandas.Panel.rfloordiv

Panel.rfloordiv(other, axis=0)

Integer division of series and other, element-wise (binary operator rfloordiv). Equivalent to other // panel.

Parameters

other : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over
**Returns** Panel

**See also:**

Panel.floordiv

---

**pandas.Panel.rmod**

Panel.rmod(\textit{other, axis=0})

Modulo of series and other, element-wise (binary operator \textit{rmod}). Equivalent to \textit{other} % panel.

**Parameters**

- \textit{other} : DataFrame or Panel
- \textit{axis} : \{items, major_axis, minor_axis\}

  Axis to broadcast over

**Returns** Panel

**See also:**

Panel.mod

---

**pandas.Panel.rmul**

Panel.rmul(\textit{other, axis=0})

Multiplication of series and other, element-wise (binary operator \textit{rmul}). Equivalent to \textit{other} * panel.

**Parameters**

- \textit{other} : DataFrame or Panel
- \textit{axis} : \{items, major_axis, minor_axis\}

  Axis to broadcast over

**Returns** Panel

**See also:**

Panel.mul

---

**pandas.Panel.rpow**

Panel.rpow(\textit{other, axis=0})

Exponential power of series and other, element-wise (binary operator \textit{rpow}). Equivalent to \textit{other} ** panel.

**Parameters**

- \textit{other} : DataFrame or Panel
- \textit{axis} : \{items, major_axis, minor_axis\}

  Axis to broadcast over

**Returns** Panel

**See also:**

Panel.pow
pandas.Panel.rsub

Panel.rsub(other, axis=0)
Subtraction of series and other, element-wise (binary operator rsub). Equivalent to other - panel.

Parameters other : DataFrame or Panel
axis : {items, major_axis, minor_axis}
Axis to broadcast over

Returns Panel

See also:
Panel.sub

pandas.Panel.rtruediv

Panel.rtruediv(other, axis=0)
Floating division of series and other, element-wise (binary operator rtruediv). Equivalent to other / panel.

Parameters other : DataFrame or Panel
axis : {items, major_axis, minor_axis}
Axis to broadcast over

Returns Panel

See also:
Panel.truediv

pandas.Panel.sample

Panel.sample(n=None, frac=None, replace=False, weights=None, random_state=None, axis=None)
Returns a random sample of items from an axis of object.
New in version 0.16.1.

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 : boolean, optional
Sample with or without replacement. Default = False.
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. inf and -inf
values not allowed.

**random_state** : int or numpy.random.RandomState, optional
   Seed for the random number generator (if int), or numpy RandomState object.

**axis** : int or string, optional
   Axis to sample. Accepts axis number or name. Default is stat axis for given data
type (0 for Series and DataFrames, 1 for Panels).

**Returns**
A new object of same type as caller.

**pandas.Panel.select**

Panel.select(*crit*, axis=0)
   Return data corresponding to axis labels matching criteria

   **Parameters**
   *crit* : function
      To be called on each index (label). Should return True or False

   *axis* : int

   **Returns**
   selection : type of caller

**pandas.Panel.sem**

Panel.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* : {items (0), major_axis (1), minor_axis (2)}

   *skipna* : boolean, 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 DataFrame

   *numeric_only* : boolean, default None
      Include only float, int, boolean data. If None, will attempt to use everything, then
      use only numeric data

   **Returns**
   sem : DataFrame or Panel (if level specified)

**pandas.Panel.set_axis**

Panel.set_axis(*axis*, labels)
   public version of axis assignment
pandas.Panel.set_value

```
Panel.set_value(*args, **kwargs)
```

Quickly set single value at (item, major, minor) location

**Parameters**

* item : item label (panel item)
  * major : major axis label (panel item row)
  * minor : minor axis label (panel item column)
  * value : scalar
  * takeable : interpret the passed labels as indexers, default False

**Returns**

* panel : Panel
  
  If label combo is contained, will be reference to calling Panel, otherwise a new object

pandas.Panel.shift

```
Panel.shift(*args, **kwargs)
```

Shift index by desired number of periods with an optional time freq. The shifted data will not include the dropped periods and the shifted axis will be smaller than the original. This is different from the behavior of DataFrame.shift()

**Parameters**

* periods : int
  
  Number of periods to move, can be positive or negative
  
  * freq : DateOffset, timedelta, or time rule string, optional
  
  * axis : {'items', 'major', 'minor'} or {0, 1, 2}

**Returns**

* shifted : Panel

pandas.Panel.skew

```
Panel.skew(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)
```

Return unbiased skew over requested axis Normalized by N-1

**Parameters**

* axis : {items (0), major_axis (1), minor_axis (2)}

  * skipna : boolean, 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 DataFrame

  * numeric_only : boolean, default None

    Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**

* skew : DataFrame or Panel (if level specified)
pandas.Panel.slice_shift

Panel.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.Panel.sort_index

Panel.sort_index(axis=0, level=None, ascending=True, inplace=False, kind='quicksort', na_position='last', sort_remaining=True)
Sort object by labels (along an axis)

Parameters axis : axes to direct sorting
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 : boolean, default True
        Sort ascending vs. descending
inplace : bool
        if True, perform operation in-place
kind : {quicksort, mergesort, heapsort}
        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'}
        first puts NaNs at the beginning, last puts NaNs at the end
sort_remaining : bool
        if true and sorting by level and index is multilevel, sort by other levels too (in order) after sorting by specified level

Returns sorted_obj : NDFrame

pandas.Panel.sort_values

Panel.sort_values(by, axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last')
pandas.Panel.squeeze

Panel.squeeze()
    squeeze length 1 dimensions

pandas.Panel.std

Panel.std(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)
    Return unbiased standard deviation over requested axis.
    Normalized by N-1 by default. This can be changed using the ddof argument

Parameters

axis : {items (0), major_axis (1), minor_axis (2)}
    skipna : boolean, 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 DataFrame
    numeric_only : boolean, default None
        Include only float, int, boolean data. If None, will attempt to use everything, then
        use only numeric data

Returns std : DataFrame or Panel (if level specified)

pandas.Panel.sub

Panel.sub(other, axis=0)
    Subtraction of series and other, element-wise (binary operator sub). Equivalent to panel - other.

Parameters

other : DataFrame or Panel
    axis : {items, major_axis, minor_axis}
        Axis to broadcast over

Returns Panel

See also:

Panel.rsub

pandas.Panel.subtract

Panel.subtract(other, axis=0)
    Subtraction of series and other, element-wise (binary operator sub). Equivalent to panel - other.

Parameters

other : DataFrame or Panel
    axis : {items, major_axis, minor_axis}
        Axis to broadcast over

Returns Panel
See also:

Panel.rsub

pandas.Panel.sum

Panel.sum(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)
Return the sum of the values for the requested axis

Parameters axis : {items (0), major_axis (1), minor_axis (2)}
skipna : boolean, 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 DataFrame
numeric_only : boolean, default None
   Include only float, int, boolean data. If None, will attempt to use everything, then
   use only numeric data

Returns sum : DataFrame or Panel (if level specified)

pandas.Panel.swapaxes

Panel.swapaxes(axis1, axis2, copy=True)
Interchange axes and swap values axes appropriately

Returns y : same as input

pandas.Panel.swaplevel

Panel.swaplevel(i, j, axis=0)
Swap levels i and j in a MultiIndex on a particular axis

Parameters i, j : int, string (can be mixed)
   Level of index to be swapped. Can pass level name as string.

Returns swapped : type of caller (new object)

pandas.Panel.tail

Panel.tail(n=5)

pandas.Panel.take

Panel.take(indices, axis=0, convert=True, is_copy=True)
Analogous to ndarray.take
Parameters indices: list / array of ints
  axis : int, default 0
  convert : translate neg to pos indices (default)
  is_copy : mark the returned frame as a copy

Returns taken : type of caller

pandas.Panel.toLong

Panel.toLong(*args, **kwargs)

pandas.Panel.to_clipboard

Panel.to_clipboard(excel=None, sep=None, **kwargs)

Attempt to write text representation of object to the system clipboard This can be pasted into Excel, for example.

Parameters excel : boolean, defaults to True
  if True, use the provided separator, writing in a csv format for allowing easy pasting into excel. if False, write a string representation of the object to the clipboard
  sep : optional, defaults to tab
  other keywords are passed to to_csv

Notes

Requirements for your platform

- Linux: xclip, or xsel (with gtk or PyQt4 modules)
- Windows: none
- OS X: none

pandas.Panel.to_dense

Panel.to_dense()

Return dense representation of NDFrame (as opposed to sparse)

pandas.Panel.to_excel

Panel.to_excel(path, na_rep='', engine=None, **kwargs)

Write each DataFrame in Panel to a separate excel sheet

Parameters path : string or ExcelWriter object
  File path or existing ExcelWriter
  na_rep : string, default ‘’
  Missing data representation
**Engine**

Write engine to use - you can also set this via the options `io.excel.xlsx.writer`, `io.excel.xls.writer`, and `io.excel.xlsm.writer`.

**Other Parameters**

- **float_format**: string, default None
  
  Format string for floating point numbers

- **cols**: sequence, optional
  
  Columns to write

- **header**: boolean or list of string, default True
  
  Write out column names. If a list of string is given it is assumed to be aliases for the column names

- **index**: boolean, default True
  
  Write row names (index)

- **index_label**: string or sequence, 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 DataFrame uses MultiIndex.

- **startrow**: upper left cell row to dump data frame

- **startcol**: upper left cell column to dump data frame

**Notes**

Keyword arguments (and na_rep) are passed to the `to_excel` method for each DataFrame written.

**pandas.Panel.to_frame**

Panel.to_frame(filter_observations=True)

Transform wide format into long (stacked) format as DataFrame whose columns are the Panel’s items and whose index is a MultiIndex formed of the Panel’s major and minor axes.

**Parameters**

- **filter_observations**: boolean, default True
  
  Drop (major, minor) pairs without a complete set of observations across all the items

**Returns**

- **y**: DataFrame

**pandas.Panel.to_hdf**

Panel.to_hdf(path_or_buf, key, **kwargs)

Activate the HDFStore

**Parameters**

- **path_or_buf**: the path (string) or HDFStore object

- **key**: string
  
  Identifier for the group in the store
mode : optional, {'a', 'w', 'r', 'r+'}, default 'a’

'r'  Read-only; no data can be modified.

'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+'  It is similar to 'a’, but the file must already exist.

format : ‘fixed(f)table(t)’, default is ‘fixed’

 fixed(f)  [Fixed format] Fast writing/reading. Not-appendable, nor searchable

table(t)  [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 : boolean, default False

For Table formats, append the input data to the existing

complevel : int, 1-9, default 0

If a complib is specified compression will be applied where possible

complib : {'zlib', 'bzip2', 'Izo', 'blosc', None}, default None

If complevel is > 0 apply compression to objects written in the store wherever possible

fletcher32 : bool, default False

If applying compression use the fletcher32 checksum

dropna : boolean, default False.

If true, ALL nan rows will not be written to store.

pandas.Panel.to_json

Panel.to_json(path_or_buf=None, orient=None, date_format='epoch’, double_precision=10, force_ascii=True, date_unit='ms’, default_handler=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 : the path or buffer to write the result string

if this is None, return a StringIO of the converted string

orient : string

• Series
  – default is ‘index’
  – allowed values are: {'split','records','index’}

• DataFrame
  – default is ‘columns’
  – allowed values are: {'split','records','index','columns','values’}
• 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 -> {index -> value}}
  – values : just the values array

```json
'date_format' : {'epoch', 'iso'}
```

Type of date conversion. `epoch` = epoch milliseconds, `iso` = ISO8601, default is epoch.

```json
'double_precision' : The number of decimal places to use when encoding
```

floating point values, default 10.

```json
'force_ascii' : force encoded string to be ASCII, default True.
```

```json
'date_unit' : string, 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 re-

spectively.

```json
'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.

Returns same type as input object with filtered info axis

```python
pandas.Panel.to_long
```

```python
Panel.to_long(*args, **kwargs)
```

```python
pandas.Panel.to_msgpack
```

```python
Panel.to_msgpack(path_or_buf=None, **kwargs)
```

msgpack (serialize) object to input file path

THIS IS AN EXPERIMENTAL LIBRARY and the storage format may not be stable until a future release.

Parameters path : string File path, buffer-like, or None

if None, return generated string

append : boolean whether to append to an existing msgpack

(default is False)

compress : type of compressor (zlib or blosc), default to None (no

compression)
pandas.Panel.to_pickle

Panel.to_pickle(path)
   Pickle (serialize) object to input file path

   Parameters
   path : string
      File path

pandas.Panel.to_sparse

Panel.to_sparse(fill_value=None, kind='block')
   Convert to SparsePanel

   Parameters
   fill_value : float, default NaN
      kind : {'block', 'integer'}

   Returns
   y : SparseDataFrame

pandas.Panel.to_sql

Panel.to_sql(name, con, flavor='sqlite', schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None)
   Write records stored in a DataFrame to a SQL database.

   Parameters
   name : string
      Name of SQL table
   con : SQLAlchemy engine or DBAPI2 connection (legacy mode)
      Using SQLAlchemy makes it possible to use any DB supported by that library. If a
      DBAPI2 object, only sqlite3 is supported.
   flavor : {'sqlite', 'mysql'}, default 'sqlite'
      The flavor of SQL to use. Ignored when using SQLAlchemy engine. ‘mysql’ is
      deprecated and will be removed in future versions, but it will be further supported
      through SQLAlchemy engines.
   schema : string, default None
      Specify the schema (if database flavor supports this). If None, use default schema.
   if_exists : {'fail', 'replace', 'append'}, default ‘fail’
      • fail: If table exists, do nothing.
      • replace: If table exists, drop it, recreate it, and insert data.
      • append: If table exists, insert data. Create if does not exist.
   index : boolean, default True
      Write DataFrame index as a column.
   index_label : string 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, default None
    If not None, then rows will be written in batches of this size at a time. If None, all rows will be written at once.

dtype : dict of column name to SQL type, default None
    Optional specifying the datatype for columns. The SQL type should be a SQLAlchemy type, or a string for sqlite3 fallback connection.

pandas.Panel.transpose

Panel.transpose(*args, **kwargs)
    Permute the dimensions of the Panel

    Parameters args : three positional arguments: each one of
        {0, 1, 2, ‘items’, ‘major_axis’, ‘minor_axis’}
    copy : boolean, default False
        Make a copy of the underlying data. Mixed-dtype data will always result in a copy

    Returns y : same as input

Examples

>>> p.transpose(2, 0, 1)
>>> p.transpose(2, 0, 1, copy=True)

pandas.Panel.truediv

Panel.truediv(other, axis=0)
    Floating division of series and other, element-wise (binary operator truediv). Equivalent to panel / other.

    Parameters other : DataFrame or Panel
        axis : {items, major_axis, minor_axis}
            Axis to broadcast over

    Returns Panel

See also:
            Panel.rtruediv

pandas.Panel.truncate

Panel.truncate(before=None, after=None, axis=None, copy=True)
    Truncates a sorted DataFrame before and/or after some particular dates.

    Parameters before : date
        Truncate before date
after : date
    Truncate after date
axis : the truncation axis, defaults to the stat axis
copy : boolean, default is True,
    return a copy of the truncated section

Returns truncated : type of caller

pandas.Panel.tshift

Panel.tshift (periods=1, freq=None, axis='major')

pandas.Panel.tz_convert

Panel.tz_convert (tz, axis=0, level=None, copy=True)
    Convert tz-aware axis to target time zone.

Parameters tz : string or pytz.timezone object
    axis : the axis to convert
    level : int, str, default None
        If axis ia a MultiIndex, convert a specific level. Otherwise must be None
    copy : boolean, default True
        Also make a copy of the underlying data

Raises TypeError
    If the axis is tz-naive.

pandas.Panel.tz_localize

Panel.tz_localize (*args, **kwargs)
    Localize tz-naive TimeSeries to target time zone

Parameters tz : string or pytz.timezone object
    axis : the axis to localize
    level : int, str, default None
        If axis ia a MultiIndex, localize a specific level. Otherwise must be None
    copy : boolean, default True
        Also make a copy of the underlying data
ambiguous : ‘infer’, bool-ndarray, ‘NaT’, default ‘raise’
    • ‘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

**infer_dst** : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

**Raises** **TypeError**

If the TimeSeries is tz-aware and tz is not None.

**pandas.Panel.update**

**Panel.update**(other, join=’left’, overwrite=True, filter_func=None, raise_conflict=False)

Modify Panel in place using non-NA values from passed Panel, or object coercible to Panel. Aligns on items

**Parameters** **other** : Panel, or object coercible to Panel

**join** : How to join individual DataFrames

{‘left’, ‘right’, ‘outer’, ‘inner’}, default ‘left’

**overwrite** : boolean, default True

If True then overwrite values for common keys in the calling panel

**filter_func** : callable(1d-array) -> 1d-array<boolean>, default None

Can choose to replace values other than NA. Return True for values that should be updated

**raise_conflict** : bool

If True, will raise an error if a DataFrame and other both contain data in the same place.

**pandas.Panel.var**

**Panel.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** : {items (0), major_axis (1), minor_axis (2)}

**skipna** : boolean, 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 DataFrame

**numeric_only** : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns** **var** : DataFrame or Panel (if level specified)
pandas.Panel.where

**Panel.where** *(cond, other=nan, inplace=False, axis=None, level=None, try_cast=False, raise_on_error=True)*

Return an object of same shape as self and whose corresponding entries are from self where cond is True and otherwise are from other.

**Parameters**

- **cond**: boolean NDFrame or array
- **other**: scalar or NDFrame
- **inplace**: boolean, default False
  - Whether to perform the operation in place on the data
- **axis**: alignment axis if needed, default None
- **level**: alignment level if needed, default None
- **try_cast**: boolean, default False
  - try to cast the result back to the input type (if possible),
- **raise_on_error**: boolean, default True
  - Whether to raise on invalid data types (e.g. trying to where on strings)

**Returns**

- **wh**: same type as caller

pandas.Panel.xs

**Panel.xs** *(key, axis=1, copy=None)*

Return slice of panel along selected axis

**Parameters**

- **key**: object
  - Label
- **axis**: {'items', 'major', 'minor'}, default 1/'major'
- **copy**: boolean [deprecated]
  - Whether to make a copy of the data

**Returns**

- **y**: ndim(self)-1

**Notes**

xs is only for getting, not setting values.

MultIndex Slicers is a generic way to get/set values on any level or levels it is a superset of xs functionality, see *MultIndex Slicers*

### 34.5.2 Attributes and underlying data

**Axes**

- **items**: axis 0; each item corresponds to a DataFrame contained inside
- **major_axis**: axis 1; the index (rows) of each of the DataFrames
- **minor_axis**: axis 2; the columns of each of the DataFrames
Panel.values  Numpy representation of NDFrame
Panel.axes  Return index label(s) of the internal NDFrame
Panel.ndim  Number of axes / array dimensions
Panel.size  number of elements in the NDFrame
Panel.shape  Return a tuple of axis dimensions
Panel.dtypes  Return the dtypes in this object
Panel.ftypes  Return the ftypes (indication of sparse/dense and dtype) in this object.
Panel.get_dtype_counts()  Return the counts of dtypes in this object
Panel.get_ftype_counts()  Return the counts of ftypes in this object

pandas.Panel.values

Panel.values
Numpy representation of NDFrame

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 upcase to int32.

pandas.Panel.axes

Panel.axes
Return index label(s) of the internal NDFrame

pandas.Panel.ndim

Panel.ndim
Number of axes / array dimensions

pandas.Panel.size

Panel.size
number of elements in the NDFrame

pandas.Panel.shape

Panel.shape
Return a tuple of axis dimensions

pandas.Panel.dtypes

Panel.dtypes
Return the dtypes in this object
pandas.Panel.ftypes

Panel.ftypes
Return the ftypes (indication of sparse/dense and dtype) in this object.

pandas.Panel.get_dtype_counts

Panel.get_dtype_counts()
Return the counts of dtypes in this object

pandas.Panel.get_ftype_counts

Panel.get_ftype_counts()
Return the counts of ftypes in this object

34.5.3 Conversion

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel.astype(dtype[, copy, raise_on_error])</td>
<td>Cast object to input numpy.dtype</td>
</tr>
<tr>
<td>Panel.copy([deep])</td>
<td>Make a copy of this object</td>
</tr>
<tr>
<td>Panel.isnull()</td>
<td>Return a boolean same-sized object indicating if the values are null</td>
</tr>
<tr>
<td>Panel.notnull()</td>
<td>Return a boolean same-sized object indicating if the values are null</td>
</tr>
</tbody>
</table>

pandas.Panel.astype

Panel.astype (dtype[, copy, raise_on_error]) Cast object to input numpy.dtype
Return a copy when copy = True (be really careful with this!)

Parameters
dtype : numpy.dtype or Python type
raise_on_error : raise on invalid input
kwarg : keyword arguments to pass on to the constructor

Returns
casted : type of caller

pandas.Panel.copy

Panel.copy (deep=True)
Make a copy of this object

Parameters
deep : boolean or string, default True
Make a deep copy, i.e. also copy data

Returns
copy : type of caller

pandas.Panel.isnull

Panel.isnull()
Return a boolean same-sized object indicating if the values are null

See also:
**notnull** boolean inverse of isnull

**pandas.Panel.null**

Panel.null()  
Return a boolean same-sized object indicating if the values are not null

See also:

**isnull** boolean inverse of notnull

### 34.5.4 Getting and setting

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel.get_value</strong>(*args, <strong>kwargs)</strong></td>
<td>Quickly retrieve single value at (item, major, minor) location</td>
</tr>
<tr>
<td><strong>Panel.set_value</strong>(*args, <strong>kwargs)</strong></td>
<td>Quickly set single value at (item, major, minor) location</td>
</tr>
</tbody>
</table>

**pandas.Panel.get_value**

Panel.get_value(*args, **kwargs)*  
Quickly retrieve single value at (item, major, minor) location

**Parameters**

- **item**: item label (panel item)
- **major**: major axis label (panel item row)
- **minor**: minor axis label (panel item column)
- **takeable**: interpret the passed labels as indexers, default False

**Returns**

- **value**: scalar value

**pandas.Panel.set_value**

Panel.set_value(*args, **kwargs)*  
Quickly set single value at (item, major, minor) location

**Parameters**

- **item**: item label (panel item)
- **major**: major axis label (panel item row)
- **minor**: minor axis label (panel item column)
- **value**: scalar
- **takeable**: interpret the passed labels as indexers, default False

**Returns**

- **panel**: Panel

  If label combo is contained, will be reference to calling Panel, otherwise a new object

### 34.5.5 Indexing, iteration, slicing

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel.at</strong></td>
<td>Fast label-based scalar accessor</td>
</tr>
<tr>
<td><strong>Panel.iat</strong></td>
<td>Fast integer location scalar accessor.</td>
</tr>
</tbody>
</table>
Table 34.75 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel.ix</td>
<td>A primarily label-location based indexer, with integer position fallback.</td>
</tr>
<tr>
<td>Panel.loc</td>
<td>Purely label-location based indexer for selection by label.</td>
</tr>
<tr>
<td>Panel.iloc</td>
<td>Purely integer-location based indexing for selection by position.</td>
</tr>
<tr>
<td>Panel.<strong>iter</strong></td>
<td>Iterate over info axis</td>
</tr>
<tr>
<td>Panel.iteritems()</td>
<td>Iterate over (label, values) on info axis</td>
</tr>
<tr>
<td>Panel.pop(item)</td>
<td>Return item and drop from frame.</td>
</tr>
<tr>
<td>Panel.xr(key[, axis, copy])</td>
<td>Return slice of panel along selected axis</td>
</tr>
<tr>
<td>Panel.major_xr(key[, copy])</td>
<td>Return slice of panel along major axis</td>
</tr>
<tr>
<td>Panel.minor_xr(key[, copy])</td>
<td>Return slice of panel along minor axis</td>
</tr>
</tbody>
</table>

pandas.Panel.at

Panel.at
Fast label-based scalar accessor

Similarly to loc, at provides label based scalar lookups. You can also set using these indexers.

pandas.Panel.iat

Panel.iat
Fast integer location scalar accessor.

Similarly to iloc, iat provides integer based lookups. You can also set using these indexers.

pandas.Panel.ix

Panel.ix
A primarily label-location based indexer, with integer position fallback.

.ix[] supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type.

.ix is the most general indexer and will support any of the inputs in .loc and .iloc. .ix also supports floating point label schemes. .ix is exceptionally useful when dealing with mixed positional and label based hierarchical indexes.

However, when an axis is integer based, ONLY label based access and not positional access is supported. Thus, in such cases, it’s usually better to be explicit and use .iloc or .loc.

See more at Advanced Indexing.

pandas.Panel.loc

Panel.loc
Purely label-location based indexer for selection by label.

.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’ (note that contrary to usual python slices, both the start and the stop are included!).
• A boolean array.
  `.loc` will raise a `KeyError` when the items are not found.

See more at Selection by Label

**pandas.Panel.iloc**

Panel.**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.

`.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

**pandas.Panel.__iter__**

Panel.**__iter__**()

Iterate over infor axis

**pandas.Panel.iteritems**

Panel.**iteritems**()

Iterate over (label, values) on info axis

This is index for Series, columns for DataFrame, major_axis for Panel, and so on.

**pandas.Panel.pop**

Panel.**pop**(item)

Return item and drop from frame. Raise `KeyError` if not found.

**pandas.Panel.xs**

Panel.**xs**(key, axis=1, copy=None)

Return slice of panel along selected axis

**Parameters**

`key` : object

Label
axis : {'items', 'major', 'minor'}, default 1/major

copy : boolean [deprecated]
    Whether to make a copy of the data

Returns y : ndim(self)-1

Notes

xs is only for getting, not setting 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

pandas.Panel.major_xs

Panel.major_xs (key, copy=None)
    Return slice of panel along major axis

Parameters key : object
    Major axis label

copy : boolean [deprecated]
    Whether to make a copy of the data

Returns y : DataFrame
    index -> minor axis, columns -> items

Notes

major_xs is only for getting, not setting values.
MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of major_xs functionality, see MultiIndex Slicers

pandas.Panel.minor_xs

Panel.minor_xs (key, copy=None)
    Return slice of panel along minor axis

Parameters key : object
    Minor axis label

copy : boolean [deprecated]
    Whether to make a copy of the data

Returns y : DataFrame
    index -> major axis, columns -> items
Notes

minor_xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of minor_xs functionality, see MultiIndex Slicers

For more information on .at, .iat, .ix, .loc, and .iloc, see the indexing documentation.

34.5.6 Binary operator functions

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel.add(其他[, axis])</td>
<td>Addition of series and other, element-wise (binary operator add).</td>
</tr>
<tr>
<td>Panel.sub(其他[, axis])</td>
<td>Subtraction of series and other, element-wise (binary operator sub).</td>
</tr>
<tr>
<td>Panel.mul(其他[, axis])</td>
<td>Multiplication of series and other, element-wise (binary operator mul).</td>
</tr>
<tr>
<td>Panel.div(其他[, axis])</td>
<td>Floating division of series and other, element-wise (binary operator truediv).</td>
</tr>
<tr>
<td>Panel.truediv(其他[, axis])</td>
<td>Floating division of series and other, element-wise (binary operator truediv).</td>
</tr>
<tr>
<td>Panel.floordiv(其他[, axis])</td>
<td>Integer division of series and other, element-wise (binary operator floordiv).</td>
</tr>
<tr>
<td>Panel.mod(其他[, axis])</td>
<td>Modulo of series and other, element-wise (binary operator mod).</td>
</tr>
<tr>
<td>Panel.pow(其他[, axis])</td>
<td>Exponential power of series and other, element-wise (binary operator pow).</td>
</tr>
<tr>
<td>Panel.radd(其他[, axis])</td>
<td>Addition of series and other, element-wise (binary operator radd).</td>
</tr>
<tr>
<td>Panel.rsub(其他[, axis])</td>
<td>Subtraction of series and other, element-wise (binary operator rsub).</td>
</tr>
<tr>
<td>Panel.rmul(其他[, axis])</td>
<td>Multiplication of series and other, element-wise (binary operator rmul).</td>
</tr>
<tr>
<td>Panel.rdiv(其他[, axis])</td>
<td>Floating division of series and other, element-wise (binary operator rtruediv).</td>
</tr>
<tr>
<td>Panel.rtruediv(其他[, axis])</td>
<td>Floating division of series and other, element-wise (binary operator rtruediv).</td>
</tr>
<tr>
<td>Panel.rfloordiv(其他[, axis])</td>
<td>Integer division of series and other, element-wise (binary operator rfloordiv).</td>
</tr>
<tr>
<td>Panel.rmod(其他[, axis])</td>
<td>Modulo of series and other, element-wise (binary operator rfloordiv).</td>
</tr>
<tr>
<td>Panel.rpow(其他[, axis])</td>
<td>Exponential power of series and other, element-wise (binary operator rpow).</td>
</tr>
<tr>
<td>Panel.lt(其他)</td>
<td>Wrapper for comparison method lt</td>
</tr>
<tr>
<td>Panel.gt(其他)</td>
<td>Wrapper for comparison method gt</td>
</tr>
<tr>
<td>Panel.le(其他)</td>
<td>Wrapper for comparison method le</td>
</tr>
<tr>
<td>Panel.ge(其他)</td>
<td>Wrapper for comparison method ge</td>
</tr>
<tr>
<td>Panel.ne(其他)</td>
<td>Wrapper for comparison method ne</td>
</tr>
<tr>
<td>Panel.eq(其他)</td>
<td>Wrapper for comparison method eq</td>
</tr>
</tbody>
</table>

pandas.Panel.add

Panel.add(other, axis=0)
Addition of series and other, element-wise (binary operator add). Equivalent to panel + other.

Parameters other : DataFrame or Panel

axis : {items, major_axis, minor_axis}
Axis to broadcast over

Returns Panel

See also:
Panel.radd

pandas.Panel.sub

Panel.sub(other, axis=0)
Subtraction of series and other, element-wise (binary operator sub). Equivalent to panel - other.
Parameters  

other : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns  Panel

See also:
Panel.rsub

**pandas.Panel.mul**

Panel.mul(other, axis=0)

Multiplication of series and other, element-wise (binary operator mul). Equivalent to panel * other.

Parameters  

other : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns  Panel

See also:
Panel.rmul

**pandas.Panel.div**

Panel.div(other, axis=0)

Floating division of series and other, element-wise (binary operator truediv). Equivalent to panel / other.

Parameters  

other : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns  Panel

See also:
Panel.rtruediv

**pandas.Panel.truediv**

Panel.truediv(other, axis=0)

Floating division of series and other, element-wise (binary operator truediv). Equivalent to panel / other.

Parameters  

other : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns  Panel

See also:
Panel.rtruediv
**pandas.Panel.floordiv**

`Panel.floordiv(other, axis=0)`  
Integer division of series and other, element-wise (binary operator `floordiv`). Equivalent to `panel // other`.

- **Parameters**
  - `other`: DataFrame or Panel
  - `axis`: `{items, major_axis, minor_axis}`
    
  - Axis to broadcast over

- **Returns**
  - Panel

- **See also:**
  - `Panel.rfloordiv`

**pandas.Panel.mod**

`Panel.mod(other, axis=0)`  
Modulo of series and other, element-wise (binary operator `mod`). Equivalent to `panel % other`.

- **Parameters**
  - `other`: DataFrame or Panel
  - `axis`: `{items, major_axis, minor_axis}`
    
  - Axis to broadcast over

- **Returns**
  - Panel

- **See also:**
  - `Panel.rmod`

**pandas.Panel.pow**

`Panel.pow(other, axis=0)`  
Exponential power of series and other, element-wise (binary operator `pow`). Equivalent to `panel ** other`.

- **Parameters**
  - `other`: DataFrame or Panel
  - `axis`: `{items, major_axis, minor_axis}`
    
  - Axis to broadcast over

- **Returns**
  - Panel

- **See also:**
  - `Panel.rpow`

**pandas.Panel.radd**

`Panel.radd(other, axis=0)`  
Addition of series and other, element-wise (binary operator `radd`). Equivalent to `other + panel`.

- **Parameters**
  - `other`: DataFrame or Panel
  - `axis`: `{items, major_axis, minor_axis}`
    
  - Axis to broadcast over

- **Returns**
  - Panel
See also:

Panel.add

**pandas.Panel.rsub**

Panel.rsub(other, axis=0)
Subtraction of series and other, element-wise (binary operator rsub). Equivalent to other - panel.

**Parameters**
- **other**: DataFrame or Panel
- **axis**: {items, major_axis, minor_axis}
  - Axis to broadcast over

**Returns**
Panel

See also:
Panel.sub

**pandas.Panel.rmul**

Panel.rmul(other, axis=0)
Multiplication of series and other, element-wise (binary operator rmul). Equivalent to other * panel.

**Parameters**
- **other**: DataFrame or Panel
- **axis**: {items, major_axis, minor_axis}
  - Axis to broadcast over

**Returns**
Panel

See also:
Panel.mul

**pandas.Panel.rdiv**

Panel.rdiv(other, axis=0)
Floating division of series and other, element-wise (binary operator rtruediv). Equivalent to other / panel.

**Parameters**
- **other**: DataFrame or Panel
- **axis**: {items, major_axis, minor_axis}
  - Axis to broadcast over

**Returns**
Panel

See also:
Panel.truediv

**pandas.Panel.rtruediv**

Panel.rtruediv(other, axis=0)
Floating division of series and other, element-wise (binary operator rtruediv). Equivalent to other / panel.
pandas: powerful Python data analysis toolkit, Release 0.17.0

**Parameters**

- **other**: DataFrame or Panel
  - **axis**: {items, major_axis, minor_axis}
    - Axis to broadcast over

**Returns**

Panel

**See also:**

Panel.truediv

### pandas.Panel.rfloordiv

**Panel.rfloordiv**(other, axis=0)

Integer division of series and other, element-wise (binary operator `rfloordiv`). Equivalent to `other // panel`.

**Parameters**

- **other**: DataFrame or Panel
  - **axis**: {items, major_axis, minor_axis}
    - Axis to broadcast over

**Returns**

Panel

**See also:**

Panel.floordiv

### pandas.Panel.rmod

**Panel.rmod**(other, axis=0)

Modulo of series and other, element-wise (binary operator `rmod`). Equivalent to `other % panel`.

**Parameters**

- **other**: DataFrame or Panel
  - **axis**: {items, major_axis, minor_axis}
    - Axis to broadcast over

**Returns**

Panel

**See also:**

Panel.mod

### pandas.Panel.rpow

**Panel.rpow**(other, axis=0)

Exponential power of series and other, element-wise (binary operator `rpow`). Equivalent to `other ** panel`.

**Parameters**

- **other**: DataFrame or Panel
  - **axis**: {items, major_axis, minor_axis}
    - Axis to broadcast over

**Returns**

Panel

**See also:**

Panel.pow
pandas.Panel.lt

Panel.lt(other)
Wrapper for comparison method lt

pandas.Panel.gt

Panel.gt(other)
Wrapper for comparison method gt

pandas.Panel.le

Panel.le(other)
Wrapper for comparison method le

pandas.Panel.ge

Panel.ge(other)
Wrapper for comparison method ge

pandas.Panel.ne

Panel.ne(other)
Wrapper for comparison method ne

pandas.Panel.eq

Panel.eq(other)
Wrapper for comparison method eq

34.5.7 Function application, GroupBy

Panel.apply(func[, axis]) Applies function along input axis of the Panel
Panel.groupby(function[, axis]) Group data on given axis, returning GroupBy object

pandas.Panel.apply

Panel.apply(func, axis='major', **kwargs)
Applies function along input axis of the Panel

Parameters  func : function

Function to apply to each combination of ‘other’ axes e.g. if axis = ‘items’, then the
combination of major_axis/minor_axis will be passed a Series

axis : {'major', 'minor', 'items'}

Additional keyword arguments will be passed as keywords to the function

Returns  result : Pandas Object
Examples

```python
>>> p.apply(numpy.sqrt)  # returns a Panel
>>> p.apply(lambda x: x.sum(), axis=0)  # equiv to p.sum(0)
>>> p.apply(lambda x: x.sum(), axis=1)  # equiv to p.sum(1)
>>> p.apply(lambda x: x.sum(), axis=2)  # equiv to p.sum(2)
```

**pandas.Panel.groupby**

`Panel.groupby(function, axis='major')`

Group data on given axis, returning GroupBy object

**Parameters**
- `function`: callable
  - Mapping function for chosen access
- `axis`: {'major', 'minor', 'items'}, default 'major'

**Returns**
- `grouped`: PanelGroupBy

### 34.5.8 Computations / Descriptive Stats

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Panel.abs()</code></td>
<td>Return an object with absolute value taken.</td>
</tr>
<tr>
<td><code>Panel.clip(lower, upper, out, axis)</code></td>
<td>Trim values at input threshold(s)</td>
</tr>
<tr>
<td><code>Panel.clip_lower(threshold[, axis])</code></td>
<td>Return copy of the input with values below given value(s) truncated</td>
</tr>
<tr>
<td><code>Panel.clip_upper(threshold[, axis])</code></td>
<td>Return copy of input with values above given value(s) truncated</td>
</tr>
<tr>
<td><code>Panel.count([axis])</code></td>
<td>Return number of observations over requested axis.</td>
</tr>
<tr>
<td><code>Panel.cummax([axis, dtype, out, skipna])</code></td>
<td>Return cumulative max over requested axis.</td>
</tr>
<tr>
<td><code>Panel.cummin([axis, dtype, out, skipna])</code></td>
<td>Return cumulative min over requested axis.</td>
</tr>
<tr>
<td><code>Panel.cumprod([axis, dtype, out, skipna])</code></td>
<td>Return cumulative prod over requested axis.</td>
</tr>
<tr>
<td><code>Panel.cumsum([axis, dtype, out, skipna])</code></td>
<td>Return cumulative sum over requested axis.</td>
</tr>
<tr>
<td><code>Panel.max([axis, skipna, level, numeric_only])</code></td>
<td>This method returns the maximum of the values in the object.</td>
</tr>
<tr>
<td><code>Panel.mean([axis, skipna, level, numeric_only])</code></td>
<td>Return the mean of the values for the requested axis</td>
</tr>
<tr>
<td><code>Panel.median([axis, skipna, level, numeric_only])</code></td>
<td>Return the median of the values for the requested axis</td>
</tr>
<tr>
<td><code>Panel.min([axis, skipna, level, numeric_only])</code></td>
<td>Return the minimum of the values in the object.</td>
</tr>
<tr>
<td><code>Panel.pct_change(periods, fill_method, ...)</code></td>
<td>Percent change over given number of periods.</td>
</tr>
<tr>
<td><code>Panel.prod([axis, skipna, level, numeric_only])</code></td>
<td>Return the product of the values for the requested axis</td>
</tr>
<tr>
<td><code>Panel.sem([axis, skipna, level, ddof, ...])</code></td>
<td>Return unbiased standard error of the mean over requested axis.</td>
</tr>
<tr>
<td><code>Panel.skew([axis, skipna, level, numeric_only])</code></td>
<td>Return unbiased skew over requested axis</td>
</tr>
<tr>
<td><code>Panel.sum([axis, skipna, level, numeric_only])</code></td>
<td>Return the sum of the values for the requested axis</td>
</tr>
<tr>
<td><code>Panel.var([axis, skipna, level, ddof, ...])</code></td>
<td>Return unbiased standard deviation over requested axis.</td>
</tr>
</tbody>
</table>

**pandas.Panel.abs**

`Panel.abs()`  
Return an object with absolute value taken. Only applicable to objects that are all numeric

**Returns**
- `abs`: type of caller
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**pandas.Panel.clip**

Panel.clip(lower=None, upper=None, out=None, axis=None)

Trim values at input threshold(s)

**Parameters**

- **lower** : float or array_like, default None
- **upper** : float or array_like, default None
- **axis** : int or string axis name, optional

Align object with lower and upper along the given axis.

**Returns**

clipped : Series

**Examples**

```python
>>> df
   0  1
0  0.335232 -1.256177
1 -1.367855  0.746646
2  0.027753 -1.176076
3  0.230930 -0.679613
4  1.261967  0.570967
>>> df.clip(-1, 0.5)
   0  1
0  0.335232 -1.000000
1 -1.000000  0.500000
2  0.027753 -1.000000
3  0.230930 -0.679613
4  0.500000  0.500000
```

**pandas.Panel.clip_lower**

Panel.clip_lower(threshold, axis=None)

Return copy of the input with values below given value(s) truncated

**Parameters**

- **threshold** : float or array_like
- **axis** : int or string axis name, optional

Align object with threshold along the given axis.

**Returns**

clipped : same type as input
See also:
clip

pandas.Panel.clip_upper

Panel.clip_upper (threshold, axis=None)
Return copy of input with values above given value(s) truncated

Parameters
- threshold : float or array_like
- axis : int or string axis name, optional
  Align object with threshold along the given axis.

Returns clipped : same type as input

See also:
clip

pandas.Panel.count

Panel.count (axis='major')
Return number of observations over requested axis.

Parameters
- axis : {'items', 'major', 'minor'} or {0, 1, 2}

Returns count : DataFrame

pandas.Panel.cummax

Panel.cummax (axis=None, dtype=None, out=None, skipna=True, **kwargs)
Return cumulative max over requested axis.

Parameters
- axis : {items (0), major_axis (1), minor_axis (2)}
  skipna : boolean, default True
    Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns max : DataFrame

pandas.Panel.cummin

Panel.cummin (axis=None, dtype=None, out=None, skipna=True, **kwargs)
Return cumulative min over requested axis.

Parameters
- axis : {items (0), major_axis (1), minor_axis (2)}
  skipna : boolean, default True
    Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns min : DataFrame
pandas: powerful Python data analysis toolkit, Release 0.17.0

**pandas.Panel.cumprod**

Panel.cumprod(\textit{axis}=None, \textit{dtype}=None, \textit{out}=None, \textit{skipna}=True, **\textit{kwargs})

Return cumulative prod over requested axis.

- **Parameters**
  - \textit{axis} : \{items (0), major_axis (1), minor_axis (2)\}
  - \textit{skipna} : boolean, default True
    - Exclude NA/null values. If an entire row/column is NA, the result will be NA

- **Returns**
  - \textit{prod} : DataFrame

**pandas.Panel.cumsum**

Panel.cumsum(\textit{axis}=None, \textit{dtype}=None, \textit{out}=None, \textit{skipna}=True, **\textit{kwargs})

Return cumulative sum over requested axis.

- **Parameters**
  - \textit{axis} : \{items (0), major_axis (1), minor_axis (2)\}
  - \textit{skipna} : boolean, default True
    - Exclude NA/null values. If an entire row/column is NA, the result will be NA

- **Returns**
  - \textit{sum} : DataFrame

**pandas.Panel.max**

Panel.max(\textit{axis}=None, \textit{skipna}=None, \textit{level}=None, \textit{numeric_only}=None, **\textit{kwargs})

This method returns the maximum of the values in the object. If you want the \textit{index} of the maximum, use \textit{idxmax}. This is the equivalent of the \texttt{numpy.ndarray} method \texttt{argmax}.

- **Parameters**
  - \textit{axis} : \{items (0), major_axis (1), minor_axis (2)\}
  - \textit{skipna} : boolean, default True
    - Exclude NA/null values. If an entire row/column is NA, the result will be NA
  - \textit{level} : int or level name, default None
    - If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame
  - \textit{numeric_only} : boolean, default None
    - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

- **Returns**
  - \textit{max} : DataFrame or Panel (if level specified)

**pandas.Panel.mean**

Panel.mean(\textit{axis}=None, \textit{skipna}=None, \textit{level}=None, \textit{numeric_only}=None, **\textit{kwargs})

Return the mean of the values for the requested axis

- **Parameters**
  - \textit{axis} : \{items (0), major_axis (1), minor_axis (2)\}
  - \textit{skipna} : boolean, default True
    - Exclude NA/null values. If an entire row/column is NA, the result will be NA
  - \textit{level} : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

**numeric_only** : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **mean** : DataFrame or Panel (if level specified)

### pandas.Panel.median

**Panel.median** *(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)*)

Return the median of the values for the requested axis

**Parameters**

- **axis** : {items (0), major_axis (1), minor_axis (2)}
- **skipna** : boolean, 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 DataFrame
- **numeric_only** : boolean, default None
  - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **median** : DataFrame or Panel (if level specified)

### pandas.Panel.min

**Panel.min** *(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)*)

This method returns the minimum of the values in the object. If you want the index of the minimum, use **idxmin**. This is the equivalent of the numpy.ndarray method argmin.

**Parameters**

- **axis** : {items (0), major_axis (1), minor_axis (2)}
- **skipna** : boolean, 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 DataFrame
- **numeric_only** : boolean, default None
  - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **min** : DataFrame or Panel (if level specified)
pandas.Panel.pct_change

Panel.pct_change(periods=1, fill_method='pad', limit=None, freq=None, **kwargs)

Percent change over given number of periods.

**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 offset alias string, optional
  - Increment to use from time series API (e.g. ‘M’ or BDay())

**Returns**
- **chg**: NDFrame

**Notes**

By default, the percentage change is calculated along the stat axis: 0, or Index, for DataFrame and 1, or minor for Panel. You can change this with the axis keyword argument.

pandas.Panel.prod

Panel.prod(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

Return the product of the values for the requested axis.

**Parameters**
- **axis**: {items (0), major_axis (1), minor_axis (2)}
- **skipna**: boolean, 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 DataFrame
- **numeric_only**: boolean, default None
  - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**
- **prod**: DataFrame or Panel (if level specified)

pandas.Panel.sem

Panel.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**: {items (0), major_axis (1), minor_axis (2)}
- **skipna**: boolean, 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 DataFrame

**numeric_only** : boolean, default None

    Include only float, int, boolean data. If None, will attempt to use everything, then
    use only numeric data

**Returns**

  **sem** : DataFrame or Panel (if level specified)

---

**pandas.Panel.skew**

`Panel.skew(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

    Return unbiased skew over requested axis Normalized by N-1

**Parameters**

  **axis** : {items (0), major_axis (1), minor_axis (2)}

  **skipna** : boolean, 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 DataFrame

  **numeric_only** : boolean, default None

    Include only float, int, boolean data. If None, will attempt to use everything, then
    use only numeric data

**Returns**

  **skew** : DataFrame or Panel (if level specified)

---

**pandas.Panel.sum**

`Panel.sum(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

    Return the sum of the values for the requested axis

**Parameters**

  **axis** : {items (0), major_axis (1), minor_axis (2)}

  **skipna** : boolean, 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 DataFrame

  **numeric_only** : boolean, default None

    Include only float, int, boolean data. If None, will attempt to use everything, then
    use only numeric data

**Returns**

  **sum** : DataFrame or Panel (if level specified)
### pandas.Panel.std

**`DataFrame.std(axis..., skipna..., level..., ddof..., numeric_only..., **kwargs)`**

Return unbiased standard deviation over requested axis.

Normalized by N-1 by default. This can be changed using the `ddof` argument.

**Parameters**
- `axis`: {items (0), major_axis (1), minor_axis (2)}
- `skipna`: boolean, 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 DataFrame
- `numeric_only`: boolean, default None
  - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**
- `std`: DataFrame or Panel (if level specified)

### pandas.Panel.var

**`DataFrame.var(axis..., skipna..., level..., ddof..., numeric_only..., **kwargs)`**

Return unbiased variance over requested axis.

Normalized by N-1 by default. This can be changed using the `ddof` argument.

**Parameters**
- `axis`: {items (0), major_axis (1), minor_axis (2)}
- `skipna`: boolean, 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 DataFrame
- `numeric_only`: boolean, default None
  - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**
- `var`: DataFrame or Panel (if level specified)

#### 34.5.9 Reindexing / Selection / Label manipulation

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>add_prefix(prefix)</code></td>
<td>Concatenate prefix string with panel items names.</td>
</tr>
<tr>
<td><code>add_suffix(suffix)</code></td>
<td>Concatenate suffix string with panel items names.</td>
</tr>
<tr>
<td><code>drop(labels[, axis, level, inplace, ...])</code></td>
<td>Return new object with labels in requested axis removed</td>
</tr>
<tr>
<td><code>equals(other)</code></td>
<td>Determines if two DataFrame objects contain the same elements.</td>
</tr>
<tr>
<td><code>filter([items, like, regex, axis])</code></td>
<td>Restrict the info axis to set of items or wildcard</td>
</tr>
<tr>
<td><code>first(offset)</code></td>
<td>Convenience method for subsetting initial periods of time series data</td>
</tr>
<tr>
<td><code>last(offset)</code></td>
<td>Convenience method for subsetting final periods of time series data</td>
</tr>
<tr>
<td><code>reindex([items, major_axis, minor_axis])</code></td>
<td>Conform Panel to new index with optional filling logic, placing NA/NaN in lost locations</td>
</tr>
</tbody>
</table>
### pandas.Panel

#### pandas.Panel.add_prefix

**Panel.add_prefix** *(prefix)*  
Concatenate prefix string with panel items names.  

**Parameters**  
- **prefix**: string  
  
**Returns**  
- **with_prefix**: type of caller

#### pandas.Panel.add_suffix

**Panel.add_suffix** *(suffix)*  
Concatenate suffix string with panel items names  

**Parameters**  
- **suffix**: string  
  
**Returns**  
- **with_suffix**: type of caller

#### pandas.Panel.drop

**Panel.drop** *(labels, axis=0, level=None, inplace=False, errors='raise')*  
Return new object with labels in requested axis removed  

**Parameters**  
- **labels**: single label or list-like  
- **axis**: int or axis name  
- **level**: int or level name, default None  
  
For MultiIndex  
- **inplace**: bool, default False  
  
If True, do operation inplace and return None.  
- **errors**: {'ignore', 'raise'}, default 'raise'  
  
If 'ignore', suppress error and existing labels are dropped.  
  
New in version 0.16.1.  

**Returns**  
- **dropped**: type of caller

#### pandas.Panel.equals

**Panel.equals** *(other)*  
Determines if two NDFrame objects contain the same elements. NaNs in the same location are considered equal.
pandas.Panel.filter

Panel.filter(items=None, like=None, regex=None, axis=None)
Restrict the info axis to set of items or wildcard

Parameters:
- **items**: list-like
  List of info axis to restrict to (must not all be present)
- **like**: string
  Keep info axis where “arg in col == True”
- **regex**: string (regular expression)
  Keep info axis with re.search(regex, col) == True
- **axis**: int or None
  The axis to filter on. By default this is the info axis. The “info axis” is the axis that is used when indexing with []. For example, df = DataFrame({'a': [1, 2, 3, 4]}); df['a']. So, the DataFrame columns are the info axis.

Notes
Arguments are mutually exclusive, but this is not checked for

pandas.Panel.first

Panel.first(offset)
Convenience method for subsetting initial periods of time series data based on a date offset

Parameters:
- **offset**: string, DateOffset, dateutil.relativedelta

Returns:
- **subset**: type of caller

Examples

ts.last('10D') -> First 10 days

pandas.Panel.last

Panel.last(offset)
Convenience method for subsetting final periods of time series data based on a date offset

Parameters:
- **offset**: string, DateOffset, dateutil.relativedelta

Returns:
- **subset**: type of caller

Examples

ts.last('5M') -> Last 5 months
**pandas.Panel.reindex**

Panel.reindex(items=None, major_axis=None, minor_axis=None, **kwargs)

Conform Panel to new index with optional filling logic, placing 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**
- **items**, **major_axis**, **minor_axis**: array-like, optional (can be specified in order, or as keywords) New labels / index to conform to. Preferably an Index object to avoid duplicating data
- **method**: {None, ‘backfill’/’bfill’, ‘pad’/’ffill’, ‘nearest’}, optional
  Method to use for filling holes in reindexed DataFrame:
  - 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**: boolean, 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.

New in version 0.17.0.

**Returns**
- **reindexed**: Panel

**Examples**

```python
>>> df.reindex(index=[date1, date2, date3], columns=['A', 'B', 'C'])
```

**pandas.Panel.reindex_axis**

Panel.reindex_axis(labels, axis=0, method=None, level=None, copy=True, limit=None, fill_value=np.nan)

Conform input object to new index with optional filling logic, placing 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**
- **labels**: array-like
New labels / index to conform to. Preferably an Index object to avoid duplicating data

**axis** : {0, 1, 2, ‘items’, ‘major_axis’, ‘minor_axis’}

**method** : {None, ‘backfill’/’bfill’, ‘pad’/’ffill’, ‘nearest’}, optional

**Method to use for filling holes in reindexed DataFrame:**
- 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** : boolean, 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

**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 must satisfy the equation

\[
\text{abs(index[indexer] - target)} \leq \text{tolerance}
\]

New in version 0.17.0.

**Returns reindexed** : Panel

**See also:**

reindex, reindex_like

**Examples**

```python
>>> df.reindex_axis(['A', 'B', 'C'], axis=1)
```

**pandas.Panel.reindex_like**

Panel.reindex_like(other, method=None, copy=True, limit=None, tolerance=None)

return an object with matching indicies to myself

**Parameters other** : Object

**method** : string or None

**copy** : boolean, default True

**limit** : int, default None

Maximum number of consecutive labels to fill for inexact matches.

**tolerance** : optional
Maximum distance between labels of the other object and this object for inexact matches.

New in version 0.17.0.

**Returns** reindexed : same as input

**Notes**

Like calling `s.reindex(index=other.index, columns=other.columns, method=...)`

**pandas.Panel.rename**

Panel.rename(items=None, major_axis=None, minor_axis=None, **kwargs)

Alter axes input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

**Parameters**

- **items**, **major_axis**, **minor_axis** : dict-like or function, optional
  
  Transformation to apply to that axis values

- **copy** : boolean, default True
  
  Also copy underlying data

- **inplace** : boolean, default False
  
  Whether to return a new Panel. If True then value of copy is ignored.

**Returns** renamed : Panel (new object)

**pandas.Panel.sample**

Panel.sample(n=None, frac=None, replace=False, weights=None, random_state=None, axis=None)

Returns a random sample of items from an axis of object.

New in version 0.16.1.

**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** : boolean, optional
  
  Sample with or without replacement. Default = False.

- **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. inf and -inf values not allowed.
random_state : int or numpy.random.RandomState, optional
    Seed for the random number generator (if int), or numpy RandomState object.

axis : int or string, optional
    Axis to sample. Accepts axis number or name. Default is stat axis for given data
type (0 for Series and DataFrames, 1 for Panels).

Returns A new object of same type as caller.

pandas.Panel.select

Panel.select (crit, axis=0)
    Return data corresponding to axis labels matching criteria

Parameters crit : function
    To be called on each index (label). Should return True or False

axis : int

Returns selection : type of caller

pandas.Panel.take

Panel.take (indices, axis=0, convert=True, is_copy=True)
    Analogous to ndarray.take

Parameters indices : list / array of ints
    axis : int, default 0
    convert : translate neg to pos indices (default)
    is_copy : mark the returned frame as a copy

Returns taken : type of caller

pandas.Panel.truncate

Panel.truncate (before=None, after=None, axis=None, copy=True)
    Truncates a sorted NDFrame before and/or after some particular dates.

Parameters before : date
    Truncate before date

after : date
    Truncate after date

axis : the truncation axis, defaults to the stat axis

copy : boolean, default is True,
    return a copy of the truncated section

Returns truncated : type of caller
34.5.10 Missing data handling
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| **Panel.dropna**(axis, how, inplace) | Drop 2D from panel, holding passed axis constant |
| **Panel.fillna**(value, method, axis, inplace, ...) | Fill NA/NaN values using the specified method |

**pandas.Panel.dropna**

Panel.dropna(axis=0, how='any', inplace=False)
Drop 2D from panel, holding passed axis constant

**Parameters**
- **axis**: int, default 0
  - Axis to hold constant. E.g. axis=1 will drop major_axis entries having a certain amount of NA data
- **how**: {'all', 'any'}, default 'any'
  - 'any': one or more values are NA in the DataFrame along the axis. For 'all' they all must be.
- **inplace**: bool, default False
  - If True, do operation inplace and return None.

**Returns**
- **dropped**: Panel

**pandas.Panel.fillna**

Panel.fillna(value=None, method=None, axis=None, inplace=False, limit=None, downcast=None, **kwargs)
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, 1, 2, ‘items’, ‘major_axis’, ‘minor_axis’}
- **inplace**: boolean, 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.
- **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)

1454 Chapter 34. API Reference
Returns filled : Panel

See also:
reindex, asfreq

34.5.11 Reshaping, sorting, transposing

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel.sort_index(*args, **kw)</td>
<td>Sort object by labels (along an axis)</td>
</tr>
<tr>
<td>Panel.swaplevel(i, j, axis)</td>
<td>Swap levels i and j in a MultiIndex on a particular axis</td>
</tr>
<tr>
<td>Panel.transpose(*args, **kwargs)</td>
<td>Permute the dimensions of the Panel</td>
</tr>
<tr>
<td>Panel.swapaxes(axis1, axis2, copy)</td>
<td>Interchange axes and swap values axes appropriately</td>
</tr>
<tr>
<td>Panel.conform(frame, axis)</td>
<td>Conform input DataFrame to align with chosen axis pair.</td>
</tr>
</tbody>
</table>

pandas.Panel.sort_index

Panel.sort_index(axis=0, level=None, ascending=True, inplace=False, kind='quicksort', na_position='last', sort_remaining=True)

Sort object by labels (along an axis)

Parameters
axis : axes to direct sorting
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 : boolean, default True
Sort ascending vs. descending
inplace : bool
if True, perform operation in-place
kind : {'quicksort', 'mergesort', 'heapsort'}
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'}
first puts NaNs at the beginning, last puts NaNs at the end
sort_remaining : bool
if true and sorting by level and index is multilevel, sort by other levels too (in order) after sorting by specified level

Returns sorted_obj : NDFrame

pandas.Panel.swaplevel

Panel.swaplevel(i, j, axis=0)

Swap levels i and j in a MultiIndex on a particular axis

Parameters
i, j : int, string (can be mixed)
Level of index to be swapped. Can pass level name as string.

Returns swapped : type of caller (new object)
pandas.Panel.transpose

Panel.transpose(*args, **kwargs)

Permute the dimensions of the Panel

Parameters:
- **args**: three positional arguments: each one of
  
  - `0, 1, 2, 'items', 'major_axis', 'minor_axis'`

- **copy**: boolean, default False
  
  Make a copy of the underlying data. Mixed-dtype data will always result in a copy

Returns:
- **y**: same as input

Examples

```python
>>> p.transpose(2, 0, 1)
>>> p.transpose(2, 0, 1, copy=True)
```

pandas.Panel.swapaxes

Panel.swapaxes(axis1, axis2, copy=True)

Interchange axes and swap values axes appropriately

Returns:
- **y**: same as input

pandas.Panel.conform

Panel.conform(frame, axis='items')

Conform input DataFrame to align with chosen axis pair.

Parameters:
- **frame**: DataFrame

- **axis**: {'items', 'major', 'minor'}
  
  Axis the input corresponds to. E.g., if axis='major', then the frame’s columns would be items, and the index would be values of the minor axis

Returns:
- DataFrame

34.5.12 Combining / joining / merging

Panel.join(other[, how, lsuffix, rsuffix])

Join items with other Panel either on major and minor axes column

Panel.update(other[, join, overwrite, ...])

Modify Panel in place using non-NA values from passed Panel, or object coercible to
How to handle indexes of the two objects. Default: ‘left’ for joining on index, None otherwise.

* left: use calling frame’s index
* right: use input frame’s index
* outer: form union of indexes
* inner: use intersection of indexes

**lsuffix**: string

Suffix to use from left frame’s overlapping columns

**rsuffix**: string

Suffix to use from right frame’s overlapping columns

Returns **joined**: Panel

**pandas.Panel.update**

Panel.update(other, join='left', overwrite=True, filter_func=None, raise_conflict=False)

Modify Panel in place using non-NA values from passed Panel, or object coercible to Panel. Aligns on items

**Parameters**

**other**: Panel, or object coercible to Panel

**join**: How to join individual DataFrames

{'left', 'right', 'outer', 'inner'}, default ‘left’

**overwrite**: boolean, default True

If True then overwrite values for common keys in the calling panel

**filter_func**: callable(1d-array) -> 1d-array<boolean>, default None

Can choose to replace values other than NA. Return True for values that should be updated

**raise_conflict**: bool

If True, will raise an error if a DataFrame and other both contain data in the same place.

### 34.5.13 Time series-related

**Panel.asfreq**(freq[, method, how, normalize])

Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

**Parameters**

**freq**: DateOffset object, or string

**method**: {'backfill', 'bfill', 'pad', 'ffill', 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 method

**Panel.shift**(args, **kwargs)

Shift index by desired number of periods with an optional time freq.

**Panel.resample**(rule[, how, axis, ...])

Convenience method for frequency conversion and resampling of regular time-series data.

**Panel.tz_convert**(tz[, axis, level, copy])

Convert tz-aware axis to target time zone.

**Panel.tz_localize**(args, **kwargs)

Localize tz-naive TimeSeries to target time zone

**pandas.Panel.asfreq**

Panel.asfreq(freq=None, method=None, how=None, normalize=False)

Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

**Parameters**

**freq**: DateOffset object, or string

**method**: {'backfill', 'bfill', 'pad', 'ffill', 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 method
how : {'start', 'end'}, default end

For PeriodIndex only, see PeriodIndex.asfreq

normalize : bool, default False

Whether to reset output index to midnight

Returns converted : type of caller

pandas.Panel.shift

Panel.shift(*args, **kwargs)
Shift index by desired number of periods with an optional time freq. The shifted data will not include the dropped periods and the shifted axis will be smaller than the original. This is different from the behavior of DataFrame.shift()

Parameters periods : int
Number of periods to move, can be positive or negative

freq : DateOffset, timedelta, or time rule string, optional
axis : {'items', 'major', 'minor'} or {0, 1, 2}

Returns shifted : Panel

pandas.Panel.resample

Panel.resample(rule, how=None, axis=0, fill_method=None, closed=None, label=None, convention='start', kind=None, loffset=None, limit=None, base=0)
Convenience method for frequency conversion and resampling of regular time-series data.

Parameters rule : string
the offset string or object representing target conversion

how : string
method for down- or re-sampling, default to 'mean' for downsampling

axis : int, optional, default 0

fill_method : string, default None
fill_method for upsampling

closed : {'right', 'left'}
Which side of bin interval is closed

label : {'right', 'left'}
Which bin edge label to label bucket with

convention : {'start', 'end', 's', 'e'}

kind : “period”/”timestamp”

loffset : timedelta
Adjust the resampled time labels

limit : int, default None
Maximum size gap to when reindexing with fill_method
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

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', how='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', how='sum', label='right')
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', how='sum', label='right', closed='right')
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')[0:5] #select first 5 rows
2000-01-01 00:00:00     0
2000-01-01 00:00:30   NaN
2000-01-01 00:01:00     1
```
Upsample the series into 30 second bins and fill the NaN values using the **pad** method.

```python
>>> series.resample('30S', fill_method='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', fill_method='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 to **how**.

```python
>>> def custom_resampler(array_like):
...     return np.sum(array_like)+5

>>> series.resample('3T', how=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
```

**pandas.Panel.tz_convert**

**Panel.tz_convert**(tz, axis=0, level=None, copy=True)
Convert tz-aware axis to target time zone.

- **tz**: string or pytz.timezone object
- **axis**: the axis to convert
- **level**: int, str, default None
  - If axis ia a MultiIndex, convert a specific level. Otherwise must be None
- **copy**: boolean, default True
  - Also make a copy of the underlying data

**Raises** **TypeError**
If the axis is tz-naive.

**pandas.Panel.tz_localize**

**Panel.tz_localize**(args, **kwargs)
Localize tz-naive TimeSeries to target time zone
Parameters **tz**: string or pytz.timezone object

**axis**: the axis to localize

**level**: int, str, default None

If axis ia a MultiIndex, localize a specific level. Otherwise must be None

**copy**: boolean, default True

Also make a copy of the underlying data

**ambiguous**: ‘infer’, bool-ndarray, ‘NaT’, default ‘raise’

- ‘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

**infer_dst**: boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

**Raises** **TypeError**

If the TimeSeries is tz-aware and tz is not None.

### 34.5.14 Serialization / IO / Conversion

*Panel.from_dict*(data[, intersect, orient, dtype]) Construct Panel from dict of DataFrame objects

*Panel.to_pickle*(path) Pickle (serialize) object to input file path

*Panel.to_excel*(path[, na_rep, engine]) Write each DataFrame in Panel to a separate excel sheet

*Panel.to_hdf*(path_or_buf, key, **kwargs) activate the HDFStore

*Panel.to_json*([path_or_buf, orient, ...]) Convert the object to a JSON string.

*Panel.to_sparse*[fill_value, kind]) Convert to SparsePanel

*Panel.to_frame*[filter_observations]) Transform wide format into long (stacked) format as DataFrame whose columns are the Panel’s items and whose index is a MultiIndex formed of the Panel’s major and minor axes.

*Panel.to_clipboard*[excel, sep]) Attempt to write text representation of object to the system clipboard This can be pasted into Excel, for example.

**pandas.Panel.from_dict**

classmethod **Panel.from_dict** (data, intersect=False, orient=’items’, dtype=None)

Construct Panel from dict of DataFrame objects

**Parameters** **data**: dict

{field : DataFrame}

**intersect**: boolean

Intersect indexes of input DataFrames

**orient**: {‘items’, ‘minor’}, default ‘items’

The “orientation” of the data. If the keys of the passed dict should be the items of the result panel, pass ‘items’ (default). Otherwise if the columns of the values of the passed DataFrame objects should be the items (which in the case of mixed-dtype data you should do), instead pass ‘minor’
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- **dtype**: dtype, default None
  Data type to force, otherwise infer

**Returns** Panel

**pandas.Panel.to_pickle**

Panel.to_pickle(path)

Pickle (serialize) object to input file path

Parameters:
- **path**: string
  File path

**pandas.Panel.to_excel**

Panel.to_excel(path, na_rep='', engine=None, **kwargs)

Write each DataFrame in Panel to a separate excel sheet

Parameters:
- **path**: string or ExcelWriter object
  File path or existing ExcelWriter
- **na_rep**: string, default ''
  Missing data representation
- **engine**: string, default None
  Write engine to use - you can also set this via the options

Other Parameters:
- **float_format**: string, default None
  Format string for floating point numbers
- **cols**: sequence, optional
  Columns to write
- **header**: boolean or list of string, default True
  Write out column names. If a list of string is given it is assumed to be aliases for the column names
- **index**: boolean, default True
  Write row names (index)
- **index_label**: string or sequence, 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 DataFrame uses MultiIndex.
- **startrow**: upper left cell row to dump data frame
- **startcol**: upper left cell column to dump data frame
Notes

Keyword arguments (and na_rep) are passed to the `to_excel` method for each DataFrame written.

**pandas.Panel.to_hdf**

`Panel.to_hdf(path_or_buf, key, **kwargs)`

activate the HDFStore

**Parameters**

- **path_or_buf**: the path (string) or HDFStore object
- **key**: string
  - identifier for the group in the store
- **mode**: optional, {'a', 'w', 'r', 'r+'}, default ‘a’
  - ‘r’  Read-only; no data can be modified.
  - ‘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+’  It is similar to ‘a’, but the file must already exist.
- **format**: ‘fixed(f)|table(t)’, default is ‘fixed’
  - fixed(f)  [Fixed format] Fast writing/reading. Not-appendable, nor searchable
  - table(t)  [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**: boolean, default False
  - For Table formats, append the input data to the existing
- **complevel**: int, 1-9, default 0
  - If a complib is specified compression will be applied where possible
- **complib**: {'zlib', 'bzip2', 'lzo', 'blosc', None}, default None
  - If complevel is > 0 apply compression to objects written in the store wherever possible
- **fletcher32**: bool, default False
  - If applying compression use the fletcher32 checksum
- **dropna**: boolean, default False.
  - If true, ALL nan rows will not be written to store.

**pandas.Panel.to_json**

`Panel.to_json(path_or_buf=None, orient=None, date_format='epoch', double_precision=10, force_ascii=True, date_unit='ms', default_handler=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*: the path or buffer to write the result string  
  if this is None, return a StringIO of the converted string  

*orient*: string  
  - Series  
    - default is ‘index’  
    - allowed values are: ‘split’, ‘records’, ‘index’  
  - DataFrame  
    - default is ‘columns’  
    - allowed values are: ‘split’, ‘records’, ‘index’, ‘columns’, ‘values’  

- 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 -> {index -> value}}  
  - values: just the values array  

*date_format*: {'epoch', 'iso'}  
  Type of date conversion. *epoch* = epoch milliseconds, *iso* = ISO8601, default is epoch.  

*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*: string, 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.  

**Returns**  
same type as input object with filtered info axis

---

**pandas.Panel.to_sparse**  

`Panel.to_sparse(fill_value=None, kind='block')`  
Convert to SparsePanel  

**Parameters**  
*fill_value*: float, default NaN  
  *kind*: {'block', 'integer'}  

**Returns**  
y: SparseDataFrame
pandas.Panel.to_frame

Panel.to_frame(filter_observations=True)
Transform wide format into long (stacked) format as DataFrame whose columns are the Panel’s items and whose index is a MultiIndex formed of the Panel’s major and minor axes.

Parameters
- filter_observations: boolean, default True
  Drop (major, minor) pairs without a complete set of observations across all the items

Returns y: DataFrame

pandas.Panel.to_clipboard

Panel.to_clipboard(excel=None, sep=None, **kwargs)
Attempt to write text representation of object to the system clipboard. This can be pasted into Excel, for example.

Parameters
- excel: boolean, defaults to True
  If True, use the provided separator, writing in a csv format for allowing easy pasting into excel. If False, write a string representation of the object to the clipboard
- sep: optional, defaults to tab

Notes

Requirements for your platform
- Linux: xclip, or xsel (with gtk or PyQt4 modules)
- Windows: none
- OS X: none

34.6 Panel4D

34.6.1 Constructor

Panel4D((data, labels, items, major_axis, ...)) Panel4D is a 4-Dimensional named container very much like a Panel, but having 4 named dimensions.

pandas.Panel4D

class pandas.Panel4D(data=None, labels=None, items=None, major_axis=None, minor_axis=None, copy=False, dtype=None)
Panel4D is a 4-Dimensional named container very much like a Panel, but having 4 named dimensions. It is intended as a test bed for more N-Dimensional named containers.

Parameters
- data: ndarray (labels x items x major x minor), or dict of Panels
- labels: Index or array-like
- items: Index or array-like
- major_axis: Index or array-like: axis=2
minor_axis : Index or array-like: axis=3

dtype : dtype, default None

Data type to force, otherwise infer

copy : boolean, default False

Copy data from inputs. Only affects DataFrame / 2d ndarray input

Attributes

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>at</td>
<td>Fast label-based scalar accessor</td>
</tr>
<tr>
<td>axes</td>
<td>Return index label(s) of the internal NDFrame</td>
</tr>
<tr>
<td>blocks</td>
<td>Internal property, property synonym for as_blocks()</td>
</tr>
<tr>
<td>dtypes</td>
<td>Return the dtypes in this object</td>
</tr>
<tr>
<td>empty</td>
<td>True if NDFrame is entirely empty [no items]</td>
</tr>
<tr>
<td>ftypes</td>
<td>Return the ftypes (indication of sparse/dense and dtype) in this object.</td>
</tr>
<tr>
<td>iat</td>
<td>Fast integer location scalar accessor.</td>
</tr>
<tr>
<td>iloc</td>
<td>Purely integer-location based indexing for selection by position.</td>
</tr>
<tr>
<td>is_copy</td>
<td></td>
</tr>
<tr>
<td>ix</td>
<td>A primarily label-location based indexer, with integer position fallback.</td>
</tr>
<tr>
<td>loc</td>
<td>Purely label-location based indexer for selection by label.</td>
</tr>
<tr>
<td>ndim</td>
<td>Number of axes / array dimensions</td>
</tr>
<tr>
<td>shape</td>
<td>Return a tuple of axis dimensions</td>
</tr>
<tr>
<td>size</td>
<td>number of elements in the NDFrame</td>
</tr>
<tr>
<td>values</td>
<td>Numpy representation of NDFrame</td>
</tr>
</tbody>
</table>

pandas.Panel4D.at

Panel4D.at
Fast label-based scalar accessor

Similarly to loc, at provides label based scalar lookups. You can also set using these indexers.

pandas.Panel4D.axes

Panel4D.axes
Return index label(s) of the internal NDFrame

pandas.Panel4D.blocks

Panel4D.blocks
Internal property, property synonym for as_blocks()  

pandas.Panel4D.dtypes

Panel4D.dtypes
Return the dtypes in this object
pandas.Panel4D.empty

Panel4D.empty
True if NDFrame is entirely empty [no items]

pandas.Panel4D.ftypes

Panel4D.ftypes
Return the ftypes (indication of sparse/dense and dtype) in this object.

pandas.Panel4D.iat

Panel4D.iat
Fast integer location scalar accessor.
Similarly to .iloc, .iat provides integer based lookups. You can also set using these indexers.

pandas.Panel4D.iloc

Panel4D.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.
.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

pandas.Panel4D.is_copy

Panel4D.is_copy = None

pandas.Panel4D.ix

Panel4D.ix
A primarily label-location based indexer, with integer position fallback.
.ix[] supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type.
.ix is the most general indexer and will support any of the inputs in .loc and .iloc. .ix also supports floating point label schemes. .ix is exceptionally useful when dealing with mixed positional and label based hierarchical indexes.
However, when an axis is integer based, ONLY label based access and not positional access is supported. Thus, in such cases, it’s usually better to be explicit and use .iloc or .loc.

See more at Advanced Indexing.

**pandas.Panel4D.loc**

Panel4D.loc

Purely label-location based indexer for selection by label.

.iloc[] 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’ (note that contrary to usual python slices, both the start and the stop are included!).
- A boolean array.

.loc will raise a KeyError when the items are not found.

See more at Selection by Label

**pandas.Panel4D.ndim**

Panel4D.ndim

Number of axes / array dimensions

**pandas.Panel4D.shape**

Panel4D.shape

Return a tuple of axis dimensions

**pandas.Panel4D.size**

Panel4D.size

number of elements in the NDFrame

**pandas.Panel4D.values**

Panel4D.values

Numpy representation of NDFrame

**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 upcase to int32.

**Methods**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>abs()</td>
<td>Return an object with absolute value taken.</td>
</tr>
<tr>
<td>add(other[, axis])</td>
<td>Addition of series and other, element-wise (binary operator add).</td>
</tr>
<tr>
<td>add_prefix(prefix)</td>
<td>Concatenate prefix string with panel items names.</td>
</tr>
<tr>
<td>add_suffix(suffix)</td>
<td>Concatenate suffix string with panel items names</td>
</tr>
<tr>
<td>align(other, **kwargs)</td>
<td>Return whether all elements are True over requested axis</td>
</tr>
<tr>
<td>all([axis, bool_only, skipna, level])</td>
<td>Return whether any element is True over requested axis</td>
</tr>
<tr>
<td>any([axis, bool_only, skipna, level])</td>
<td>Applies function along input axis of the Panel</td>
</tr>
<tr>
<td>apply(func[, axis])</td>
<td>Convert the frame to a dict of dtype -&gt; Constructor Types that each has a homogenous dtype.</td>
</tr>
<tr>
<td>as_blocks([copy])</td>
<td>Convert all TimeSeries inside to specified frequency using DateOffset objects.</td>
</tr>
<tr>
<td>asfreq(freq[, method, how, normalize])</td>
<td>Cast object to input numpy.dtype</td>
</tr>
<tr>
<td>astype(dtype[, copy, raise_on_error])</td>
<td>Select values at particular time of day (e.g.</td>
</tr>
<tr>
<td>at_time(time[, asof])</td>
<td>Select values between particular times of the day (e.g., 9:00-9:30 AM)</td>
</tr>
<tr>
<td>between_time(start_time, end_time[, ...])</td>
<td>Synonym for NDFrame.fillna(method='bfill')</td>
</tr>
<tr>
<td>bfill([axis, inplace, limit, downcast])</td>
<td>Return the bool of a single element PandasObject</td>
</tr>
<tr>
<td>clip([lower, upper, out, axis])</td>
<td>Trim values at input threshold(s)</td>
</tr>
<tr>
<td>clip_lower(threshold[, axis])</td>
<td>Return copy of the input with values below given value(s) truncated</td>
</tr>
<tr>
<td>clip_upper(threshold[, axis])</td>
<td>Return copy of input with values above given value(s) truncated</td>
</tr>
<tr>
<td>compound([axis, skipna, level])</td>
<td>Return the compound percentage of the values for the requested axis</td>
</tr>
<tr>
<td>conform(frame[, axis])</td>
<td>Conform input DataFrame to align with chosen axis pair.</td>
</tr>
<tr>
<td>consolidate([implace])</td>
<td>Compute NDFrame with “consolidated” internals (data of each dtype grouped together)</td>
</tr>
<tr>
<td>convert_objects([convert_dates, ...])</td>
<td>Attempt to infer better dtype for object columns</td>
</tr>
<tr>
<td>copy([deep])</td>
<td>Make a copy of this object</td>
</tr>
<tr>
<td>count([axis])</td>
<td>Return number of observations over requested axis.</td>
</tr>
<tr>
<td>cummax([axis, dtype, out, skipna])</td>
<td>Return cumulative max over requested axis</td>
</tr>
<tr>
<td>cummin([axis, dtype, out, skipna])</td>
<td>Return cumulative min over requested axis</td>
</tr>
<tr>
<td>cumprod([axis, dtype, out, skipna])</td>
<td>Return cumulative prod over requested axis</td>
</tr>
<tr>
<td>cumsun([axis, dtype, out, skipna])</td>
<td>Return cumulative sum over requested axis</td>
</tr>
<tr>
<td>describe([percentiles, include, exclude])</td>
<td>Generate various summary statistics, excluding NaN values.</td>
</tr>
<tr>
<td>div(other[, axis])</td>
<td>Floating division of series and other, element-wise (binary operator truediv).</td>
</tr>
<tr>
<td>divide(other[, axis])</td>
<td>Floating division of series and other, element-wise (binary operator truediv).</td>
</tr>
<tr>
<td>drop(labels[, axis, level, inplace, errors])</td>
<td>Return new object with labels in requested axis removed</td>
</tr>
<tr>
<td>dropna(*args, **kwargs)</td>
<td>Wrapper for comparison method eq</td>
</tr>
<tr>
<td>eq(other)</td>
<td>Determines if two NDFrame objects contain the same elements.</td>
</tr>
<tr>
<td>equals(other)</td>
<td>Synonym for NDFrame.fillna(method='bfill')</td>
</tr>
<tr>
<td>fillna([value, method, axis, inplace, ...])</td>
<td>Fill NA/NaN values using the specified method</td>
</tr>
<tr>
<td>filter(*args, **kwargs)</td>
<td>Convenience method for subsetting initial periods of time series data</td>
</tr>
<tr>
<td>first(offset)</td>
<td>Integer division of series and other, element-wise (binary operator floordiv).</td>
</tr>
<tr>
<td>floordiv(other[, axis])</td>
<td>Construct Panel from dict of DataFrame objects</td>
</tr>
<tr>
<td>fromDict(data[, intersect, orient, dtype])</td>
<td>Construct Panel from dict of DataFrame objects</td>
</tr>
<tr>
<td>from_dict(data[, intersect, orient, dtype])</td>
<td>Wrapper for comparison method ge</td>
</tr>
<tr>
<td>ge(other)</td>
<td>Get item from object for given key (DataFrame column, Panel slice, etc.).</td>
</tr>
<tr>
<td>get(key[, default])</td>
<td>Return the counts of dtypes in this object</td>
</tr>
<tr>
<td>get_dtype_counts()</td>
<td>Return the counts of ftypes in this object</td>
</tr>
<tr>
<td>get_ftype_counts()</td>
<td></td>
</tr>
</tbody>
</table>
### Table 34.87 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>get_value(*args, **kwargs)</code></td>
<td>Quickly retrieve single value at (item, major, minor) location</td>
</tr>
<tr>
<td><code>get_values()</code></td>
<td>same as values (but handles sparseness conversions)</td>
</tr>
<tr>
<td><code>groupby(*args, **kwargs)</code></td>
<td>Wrapper for comparison method gt</td>
</tr>
<tr>
<td><code>gt(other)</code></td>
<td>Interpolate values according to different methods.</td>
</tr>
<tr>
<td><code>head([n])</code></td>
<td>Return a boolean same-sized object indicating if the values are null</td>
</tr>
<tr>
<td><code>interpolate([method, axis, limit, inplace, ...])</code></td>
<td>Iterate over (label, values) on info axis</td>
</tr>
<tr>
<td><code>isnull()</code></td>
<td>Interpolate values according to different methods.</td>
</tr>
<tr>
<td><code>iteritems()</code></td>
<td>Get the <code>‘info axis’</code> (see Indexing for more)</td>
</tr>
<tr>
<td><code>iterkv(*args, **kwargs)</code></td>
<td>Return unbiased kurtosis over requested axis using Fishers definition of kurtosis</td>
</tr>
<tr>
<td><code>join(*args, **kwargs)</code></td>
<td>Convenience method for subsetting final periods of time series data</td>
</tr>
<tr>
<td><code>keys()</code></td>
<td>Wrapper for comparison method le</td>
</tr>
<tr>
<td><code>kurt([axis, skipna, level, numeric_only])</code></td>
<td>Wrapper for comparison method lt</td>
</tr>
<tr>
<td><code>kurtosis([axis, skipna, level, numeric_only])</code></td>
<td>Return the mean absolute deviation of the values for the requested axis</td>
</tr>
<tr>
<td><code>last(offset)</code></td>
<td>Return slice of panel along major axis</td>
</tr>
<tr>
<td><code>le(other)</code></td>
<td>Return an object of same shape as self and whose corresponding entries are from this method returns the maximum of the values in the object.</td>
</tr>
<tr>
<td><code>lt(other)</code></td>
<td>Return the mean of the values for the requested axis</td>
</tr>
<tr>
<td><code>mad([axis, skipna, level])</code></td>
<td>This method returns the minimum of the values in the object.</td>
</tr>
<tr>
<td><code>major_xs(key[, copy])</code></td>
<td>Return the median of the values for the requested axis</td>
</tr>
<tr>
<td><code>mask(cond[, other, inplace, axis, level, ...])</code></td>
<td>This method returns the minimum of the values in the object.</td>
</tr>
<tr>
<td><code>max([axis, skipna, level, numeric_only])</code></td>
<td>Return the median of the values for the requested axis</td>
</tr>
<tr>
<td><code>mean([axis, skipna, level, numeric_only])</code></td>
<td>Return the minimum of the values in the object.</td>
</tr>
<tr>
<td><code>median([axis, skipna, level, numeric_only])</code></td>
<td>Return the minimum of the values in the object.</td>
</tr>
<tr>
<td><code>min([axis, skipna, level, numeric_only])</code></td>
<td>Return the minimum of the values in the object.</td>
</tr>
<tr>
<td><code>minor_xs(key[, copy])</code></td>
<td>Return the median of the values for the requested axis</td>
</tr>
<tr>
<td><code>mod(other[, axis])</code></td>
<td>Return the minimum of the values in the object.</td>
</tr>
<tr>
<td><code>mul(other[, axis])</code></td>
<td>Exponential power of series and other, element-wise (binary operator mod).</td>
</tr>
<tr>
<td><code>multiply(other[, axis])</code></td>
<td>Multiplication of series and other, element-wise (binary operator mul).</td>
</tr>
<tr>
<td><code>ne(other)</code></td>
<td>Wraper for comparison method ne</td>
</tr>
<tr>
<td><code>notnull()</code></td>
<td>Return a boolean same-sized object indicating if the values are</td>
</tr>
<tr>
<td><code>pct_change([periods, fill_method, limit, freq])</code></td>
<td>Percent change over given number of periods.</td>
</tr>
<tr>
<td><code>pipe(func, *args, **kwargs)</code></td>
<td>Apply func(self, *args, **kwargs)</td>
</tr>
<tr>
<td><code>pop(item)</code></td>
<td>Return item and drop from frame.</td>
</tr>
<tr>
<td><code>pow(other[, axis])</code></td>
<td>Exponential power of series and other, element-wise (binary operator pow).</td>
</tr>
<tr>
<td><code>prod([axis, skipna, level, numeric_only])</code></td>
<td>Return the product of the values for the requested axis</td>
</tr>
<tr>
<td><code>product([axis, skipna, level, numeric_only])</code></td>
<td>Return the product of the values for the requested axis</td>
</tr>
<tr>
<td><code>radd(other[, axis])</code></td>
<td>Addition of series and other, element-wise (binary operator radd).</td>
</tr>
<tr>
<td><code>rdiv(other[, axis])</code></td>
<td>Floating division of series and other, element-wise (binary operator rtruediv).</td>
</tr>
<tr>
<td><code>reindex([items, major_axis, minor_axis])</code></td>
<td>Conform Panel to new index with optional filling logic, placing NA/NaN in locations where NA/NaN was missing in the Panel.</td>
</tr>
<tr>
<td><code>reindex_axis(items[, axis, method, level, ...])</code></td>
<td>Conform input object to new index with optional filling logic, placing NA/NaN in locations where NA/NaN was missing in the object.</td>
</tr>
<tr>
<td><code>rename_like(other[, method, copy, limit, ...])</code></td>
<td>Alter axis input function or functions.</td>
</tr>
<tr>
<td><code>rename_axis(mapper[, axis, copy, inplace])</code></td>
<td>Alter index and / or columns using input function or functions.</td>
</tr>
<tr>
<td><code>replace(to_replace, value, inplace, limit, ...)</code></td>
<td>Convenience method for frequency conversion and resampling of regular time-series data.</td>
</tr>
<tr>
<td><code>resample(rule[, how, axis, fill_method, ...])</code></td>
<td>Integer division of series and other, element-wise (binary operator rtruediv).</td>
</tr>
<tr>
<td><code>rfloordiv(other[, axis])</code></td>
<td>Modulo of series and other, element-wise (binary operator rmod).</td>
</tr>
<tr>
<td><code>rmod(other[, axis])</code></td>
<td>Multiplication of series and other, element-wise (binary operator rmul).</td>
</tr>
<tr>
<td><code>rpow(other[, axis])</code></td>
<td>Exponential power of series and other, element-wise (binary operator rpow).</td>
</tr>
<tr>
<td><code>rsub(other[, axis])</code></td>
<td>Subtraction of series and other, element-wise (binary operator rsub).</td>
</tr>
<tr>
<td><code>rtruediv(other[, axis])</code></td>
<td>Floating division of series and other, element-wise (binary operator rtruediv).</td>
</tr>
<tr>
<td><code>sample([n, frac, replace, weights, ...])</code></td>
<td>Returns a random sample of items from an axis of object.</td>
</tr>
<tr>
<td><code>select(crit[, axis])</code></td>
<td>Return data corresponding to axis labels matching criteria</td>
</tr>
</tbody>
</table>
### pandas.Panel4D

**abs()**

Return an object with absolute value taken. Only applicable to objects that are all numeric.

**Returns**

- **abs**: type of caller

**add(other, axis=0)**

Addition of series and other, element-wise (binary operator `add`). Equivalent to `panel + other`.

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<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(axis, labels)</td>
<td>public version of axis assignment</td>
</tr>
<tr>
<td>set_value(*args, **kwargs)</td>
<td>Quickly set single value at (item, major, minor) location</td>
</tr>
<tr>
<td>shift(*args, **kwargs)</td>
<td>Return unbiased skew over requested axis</td>
</tr>
<tr>
<td>skew(axis, skipna, level, numeric_only)</td>
<td>Equivalent to <code>shift</code> without copying data.</td>
</tr>
<tr>
<td>slice_shift([periods, axis])</td>
<td>Sort object by labels (along an axis)</td>
</tr>
<tr>
<td>sort_index([axis, level, ascending, ...])</td>
<td>squeeze length 1 dimensions</td>
</tr>
<tr>
<td>sort_values(by[, axis, ascending, inplace, ...])</td>
<td>Return unbiased standard deviation over requested axis.</td>
</tr>
<tr>
<td>std(axis, skipna, level, ddof, numeric_only)</td>
<td>Subtraction of series and other, element-wise (binary operator <code>sub</code>).</td>
</tr>
<tr>
<td>subtract(other[, axis])</td>
<td>Subtraction of series and other, element-wise (binary operator <code>sub</code>).</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>Analogous to ndarray.take</td>
</tr>
<tr>
<td>take(indices[, axis, convert, is_copy])</td>
<td>Attempt to write text representation of object to the system clipboard This can be done by accessing Panel4D.to_clipboard().</td>
</tr>
<tr>
<td>toLong(*args, **kwargs)</td>
<td>Return dense representation of NDFrame (as opposed to sparse)</td>
</tr>
<tr>
<td>to_clipboard([excel, sep])</td>
<td>activate the HDFStore</td>
</tr>
<tr>
<td>to_dense()</td>
<td>Convert the object to a JSON string.</td>
</tr>
<tr>
<td>to_excel(*args, **kwargs)</td>
<td>msgpack (serialize) object to input file path</td>
</tr>
<tr>
<td>to_frame(*args, **kwargs)</td>
<td>Pickle (serialize) object to input file path</td>
</tr>
<tr>
<td>to_hdf(path_or_buf, key, **kwargs)</td>
<td>Write records stored in a DataFrame to a SQL database.</td>
</tr>
<tr>
<td>to_json([path_or_buf, orient, date_format, ...])</td>
<td>Permute the dimensions of the Panel</td>
</tr>
<tr>
<td>to_long(*args, **kwargs)</td>
<td>Floating division of series and other, element-wise (binary operator <code>truediv</code>).</td>
</tr>
<tr>
<td>to_msgpack([path_or_buf])</td>
<td>Truncates a sorted NDFrame before and/or after some particular dates.</td>
</tr>
<tr>
<td>to_pickle(path)</td>
<td>Convert tz-aware axis to target time zone.</td>
</tr>
<tr>
<td>to_sparse(*args, **kwargs)</td>
<td>Localize tz-naive TimeSeries to target time zone</td>
</tr>
<tr>
<td>to_sql(name, con[, flavor, schema, ...])</td>
<td>Modify Panel in place using non-NA values from passed Panel, or object coercible to Panel.</td>
</tr>
<tr>
<td>transpose(*args, **kwargs)</td>
<td>Return unbiased variance over requested axis.</td>
</tr>
<tr>
<td>truediv(other[, axis])</td>
<td>Return an object of same shape as self and whose corresponding entries are from <code>other</code>.</td>
</tr>
<tr>
<td>truncate([before, after, axis, copy])</td>
<td>Return slice of panel along selected axis</td>
</tr>
<tr>
<td>tshift([periods, freq, axis])</td>
<td></td>
</tr>
<tr>
<td>tz_convert(tz[, axis, level, copy])</td>
<td></td>
</tr>
<tr>
<td>tz_localize(*args, **kwargs)</td>
<td></td>
</tr>
<tr>
<td>update(other[, join, overwrite, ...])</td>
<td></td>
</tr>
<tr>
<td>var(axis, skipna, level, ddof, numeric_only)</td>
<td></td>
</tr>
<tr>
<td>where(cond, other, inplace, axis, level, ...)</td>
<td></td>
</tr>
<tr>
<td>xs(key[, axis, copy])</td>
<td></td>
</tr>
</tbody>
</table>
Parameters other : Panel or Panel4D

    axis : [labels, items, major_axis, minor_axis]

        Axis to broadcast over

Returns Panel4D

See also:
Panel4D.radd

pandas.Panel4D.add_prefix

Panel4D.add_prefix(prefix)

    Concatenate prefix string with panel items names.

    Parameters  prefix : string

    Returns   with_prefix : type of caller

pandas.Panel4D.add_suffix

Panel4D.add_suffix(suffix)

    Concatenate suffix string with panel items names

    Parameters  suffix : string

    Returns   with_suffix : type of caller

pandas.Panel4D.align

Panel4D.align(other, **kwargs)

pandas.Panel4D.all

Panel4D.all(axis=None, bool_only=None, skipna=None, level=None, **kwargs)

    Return whether all elements are True over requested axis

    Parameters  axis : [labels (0), items (1), major_axis (2), minor_axis (3)]

        skipna : boolean, 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 Panel

        bool_only : boolean, default None

        Include only boolean data. If None, will attempt to use everything, then use only
        boolean data

    Returns   all : Panel or Panel4D (if level specified)
pandas.Panel4D.any

Panel4D.any (axis=None, bool_only=None, skipna=None, level=None, **kwargs)
Return whether any element is True over requested axis

Parameters
axis: {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna: boolean, 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 Panel

bool_only: boolean, default None
Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns
any: Panel or Panel4D (if level specified)

pandas.Panel4D.apply

Panel4D.apply (func, axis='major', **kwargs)
Applies function along input axis of the Panel

Parameters
func: function
Function to apply to each combination of ‘other’ axes e.g. if axis = ‘items’, then the combination of major_axis/minor_axis will be passed a Series

axis: {'major', 'minor', 'items'}
Additional keyword arguments will be passed as keywords to the function

Returns
result: Pandas Object

Examples

>>> p.apply(numpy.sqrt) # returns a Panel
>>> p.apply(lambda x: x.sum(), axis=0) # equiv to p.sum(0)
>>> p.apply(lambda x: x.sum(), axis=1) # equiv to p.sum(1)
>>> p.apply(lambda x: x.sum(), axis=2) # equiv to p.sum(2)

pandas.Panel4D.as_blocks

Panel4D.as_blocks (copy=True)
Convert the frame to a dict of dtype -> Constructor Types that each has a homogeneous dtype.

NOTE: the dtypes of the blocks WILL BE PRESERVED HERE (unlike in as_matrix)

Parameters
copy: boolean, default True

Returns
values: a dict of dtype -> Constructor Types
pandas.Panel4D.as_matrix

Panel4D.as_matrix()

pandas.Panel4D.asfreq

Panel4D.asfreq(freq=None, method=None, how=None, normalize=False)
Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

Parameters:
- freq : DateOffset object, or string
- method : {'backfill', 'bfill', 'pad', 'ffill', 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 method
- how : {'start', 'end'}, default end
  For PeriodIndex only, see PeriodIndex.asfreq
- normalize : bool, default False
  Whether to reset output index to midnight

Returns:
- converted : type of caller

pandas.Panel4D.astype

Panel4D.astype(dtype=None, copy=True, raise_on_error=True, **kwargs)
Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

Parameters:
- dtype : numpy.dtype or Python type
- raise_on_error : raise on invalid input
- kwargs : keyword arguments to pass on to the constructor

Returns:
- casted : type of caller

pandas.Panel4D.at_time

Panel4D.at_time(time, asof=False)
Select values at particular time of day (e.g. 9:30AM)

Parameters:
- time : datetime.time or string

Returns:
- values_at_time : type of caller

pandas.Panel4D.between_time

Panel4D.between_time(start_time, end_time, include_start=True, include_end=True)
Select values between particular times of the day (e.g., 9:00-9:30 AM)
Parameters `start_time`: datetime.time or string

`end_time`: datetime.time or string

`include_start`: boolean, default True

`include_end`: boolean, default True

Returns `values_between_time`: type of caller

**pandas.Panel4D.bfill**

`Panel4D.bfill` (*axis=None*, *inplace=False*, *limit=None*, *downcast=None*)

Synonym for `NDFrame.fillna(method='bfill')`

**pandas.Panel4D.bool**

`Panel4D.bool()`

Return the bool of a single element PandasObject This must be a boolean scalar value, either True or False

Raise a ValueError if the PandasObject does not have exactly 1 element, or that element is not boolean

**pandas.Panel4D.clip**

`Panel4D.clip` (*lower=None*, *upper=None*, *out=None*, *axis=None*)

Trim values at input threshold(s)

Parameters `lower`: float or array_like, default None

`upper`: float or array_like, default None

`axis`: int or string axis name, optional

Align object with lower and upper along the given axis.

Returns `clipped`: Series

**Examples**

```python
>>> df
   1
0  1.256177
1 -1.367855
2 -1.76076
3  0.679613
4  0.570967
>>> df.clip(-1.0, 0.5)
   1
0 -1.000000
1  0.500000
2 -1.000000
3 -0.679613
4  0.500000
>>> t
   1
0 -0.3
1 -0.2
```
pandas: powerful Python data analysis toolkit, Release 0.17.0

```python
df = pandas.DataFrame(np.array([[1, 2, 3], [4, 5, 6], [7, 8, 9]]), columns=list('ABC'), index=['a', 'b', 'c'])
df
```

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>1.0</td>
<td>2.0</td>
<td>3.0</td>
</tr>
<tr>
<td>b</td>
<td>4.0</td>
<td>5.0</td>
<td>6.0</td>
</tr>
<tr>
<td>c</td>
<td>7.0</td>
<td>8.0</td>
<td>9.0</td>
</tr>
</tbody>
</table>

dtype: float64

```python
>>> df.clip(t, t + 1, axis=0)
```

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.335232</td>
<td>-0.300000</td>
</tr>
<tr>
<td>1</td>
<td>-0.200000</td>
<td>0.746646</td>
</tr>
<tr>
<td>2</td>
<td>0.027753</td>
<td>-0.100000</td>
</tr>
<tr>
<td>3</td>
<td>0.230930</td>
<td>0.000000</td>
</tr>
<tr>
<td>4</td>
<td>1.100000</td>
<td>0.570967</td>
</tr>
</tbody>
</table>

dtype: float64

**pandas.Panel4D.clip_lower**

Panel4D.clip_lower(threshold, axis=None)

Return copy of the input with values below given value(s) truncated

**Parameters**

- **threshold**: float or array_like
  - axis : int or string axis name, optional

Align object with threshold along the given axis.

**Returns**

- **clipped**: same type as input

See also:

clip

**pandas.Panel4D.clip_upper**

Panel4D.clip_upper(threshold, axis=None)

Return copy of input with values above given value(s) truncated

**Parameters**

- **threshold**: float or array_like
  - axis : int or string axis name, optional

Align object with threshold along the given axis.

**Returns**

- **clipped**: same type as input

See also:

clip

**pandas.Panel4D.compound**

Panel4D.compound(axis=None, skipna=None, level=None)

Return the compound percentage of the values for the requested axis

**Parameters**

- **axis**: {labels (0), items (1), major_axis (2), minor_axis (3)}
  - **skipna**: boolean, 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 Panel

**numeric_only**: boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns compounded**: Panel or Panel4D (if level specified)

**pandas.Panel4D.conform**

```
Panel4D.conform(frame, axis='items')
```

Conform input DataFrame to align with chosen axis pair.

**Parameters**

- **frame**: DataFrame
- **axis**: {'items', 'major', 'minor'}

Axis the input corresponds to. E.g., if axis='major', then the frame’s columns would be items, and the index would be values of the minor axis

**Returns** DataFrame

**pandas.Panel4D.consolidate**

```
Panel4D.consolidate(inplace=False)
```

Compute NDFrame with “consolidated” internals (data of each dtype grouped together in a single ndarray). Mainly an internal API function, but available here to the savvy user

**Parameters**

- **inplace**: boolean, default False

If False return new object, otherwise modify existing object

**Returns** consolidated: type of caller

**pandas.Panel4D.convert_objects**

```
Panel4D.convert_objects(convert_dates=True, convert_numeric=False, convert_timedeltas=True, copy=True)
```

Attempt to infer better dtype for object columns

**Parameters**

- **convert_dates**: boolean, default True
  
  If True, convert to date where possible. If ‘coerce’, force conversion, with unconvertible values becoming NaT.

- **convert_numeric**: boolean, default False
  
  If True, attempt to coerce to numbers (including strings), with unconvertible values becoming NaN.

- **convert_timedeltas**: boolean, default True
  
  If True, convert to timedelta where possible. If ‘coerce’, force conversion, with unconvertible values becoming NaT.

- **copy**: boolean, default True
If True, return a copy even if no copy is necessary (e.g. no conversion was done).
Note: This is meant for internal use, and should not be confused with inplace.

Returns converted : same as input object

```
pandas.Panel4D.copy

Panel4D.copy (deep=True)
Make a copy of this object

Parameters deep : boolean or string, default True
Make a deep copy, i.e. also copy data

Returns copy : type of caller

pandas.Panel4D.count

Panel4D.count (axis='major')
Return number of observations over requested axis.

Parameters axis : {'items', 'major', 'minor'} or {0, 1, 2}

Returns count : DataFrame

pandas.Panel4D.cummax

Panel4D.cummax (axis=None, dtype=None, out=None, skipna=True, **kwargs)
Return cumulative max over requested axis.

Parameters axis : {labels (0), items (1), major_axis (2), minor_axis (3)}
skipna : boolean, default True
Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns max : Panel

pandas.Panel4D.cummin

Panel4D.cummin (axis=None, dtype=None, out=None, skipna=True, **kwargs)
Return cumulative min over requested axis.

Parameters axis : {labels (0), items (1), major_axis (2), minor_axis (3)}
skipna : boolean, default True
Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns min : Panel

pandas.Panel4D.cumprod

Panel4D.cumprod (axis=None, dtype=None, out=None, skipna=True, **kwargs)
Return cumulative prod over requested axis.
**Parameters**

- **axis**: {labels (0), items (1), major_axis (2), minor_axis (3)}
- **skipna**: boolean, default True
  
  Exclude NA/null values. If an entire row/column is NA, the result will be NA

**Returns**

- **prod**: Panel

**pandas.Panel4D.cumsum**

```python
Panel4D.cumsum(axis=None, dtype=None, out=None, skipna=True, **kwargs)
```

Return cumulative sum over requested axis.

**Parameters**

- **axis**: {labels (0), items (1), major_axis (2), minor_axis (3)}
- **skipna**: boolean, default True
  
  Exclude NA/null values. If an entire row/column is NA, the result will be NA

**Returns**

- **sum**: Panel

**pandas.Panel4D.describe**

```python
Panel4D.describe(percentiles=None, include=None, exclude=None)
```

Generate various summary statistics, excluding NaN values.

**Parameters**

- **percentiles**: array-like, optional
  
  The percentiles to include in the output. Should all be in the interval [0, 1]. By default `percentiles` is [.25, .5, .75], returning the 25th, 50th, and 75th percentiles.

- **include, exclude**: list-like, 'all', or None (default)
  
  Specify the form of the returned result. Either:

  - None to both (default). The result will include only numeric-typed columns or, if none are, only categorical columns.
  - A list of dtypes or strings to be included/excluded. To select all numeric types use numpy number. To select categorical objects use type object. See also the select_dtypes documentation. eg. df.describe(include=['O'])
  - If include is the string ‘all’, the output column-set will match the input one.

**Returns**

- **summary**: NDFrame of summary statistics

**See also:**

- `DataFrame.select_dtypes`

**Notes**

The output DataFrame index depends on the requested dtypes:

For numeric dtypes, it will include: count, mean, std, min, max, and lower, 50, and upper percentiles.

For object dtypes (e.g. timestamps or strings), the index will include the count, unique, most common, and frequency of the most common. Timestamps also include the first and last items.
For mixed dtypes, the index will be the union of the corresponding output types. Non-applicable entries will be filled with NaN. Note that mixed-dtype outputs can only be returned from mixed-dtype inputs and appropriate use of the include/exclude arguments.

If multiple values have the highest count, then the count and most common pair will be arbitrarily chosen from among those with the highest count.

The include, exclude arguments are ignored for Series.

**pandas.Panel4D.div**

Panel4D.div (other, axis=0)
Floating division of series and other, element-wise (binary operator truediv). Equivalent to panel / other.

Parameters other: Panel or Panel4D
axis: [labels, items, major_axis, minor_axis]  
Axis to broadcast over

Returns Panel4D

See also:
Panel4D.rtruediv

**pandas.Panel4D.divide**

Panel4D.divide (other, axis=0)  
Floating division of series and other, element-wise (binary operator truediv). Equivalent to panel / other.

Parameters other: Panel or Panel4D
axis: [labels, items, major_axis, minor_axis]  
Axis to broadcast over

Returns Panel4D

See also:
Panel4D.rtruediv

**pandas.Panel4D.drop**

Panel4D.drop (labels, axis=0, level=None, inplace=False, errors='raise')
Return new object with labels in requested axis removed

Parameters labels: single label or list-like
axis: int or axis name
level: int or level name, default None
For MultiIndex
inplace: bool, default False
If True, do operation inplace and return None.
errors : {'ignore', 'raise'}, default 'raise'
    If 'ignore', suppress error and existing labels are dropped.
    New in version 0.16.1.

Returns dropped : type of caller

pandas.Panel4D.dropna

Panel4D.dropna(*args, **kwargs)

pandas.Panel4D.eq

Panel4D.eq(other)
    Wrapper for comparison method eq

pandas.Panel4D.equals

Panel4D.equals(other)
    Determines if two NDFrame objects contain the same elements. NaNs in the same location are considered equal.

pandas.Panel4D.ffill

Panel4D.ffill(axis=None, inplace=False, limit=None, downcast=None)
    Synonym for NDFrame.fillna(method='ffill')

pandas.Panel4D.fillna

Panel4D.fillna(value=None, method=None, axis=None, inplace=False, limit=None, downcast=None, **kwargs)
    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, 1, 2, 'items', 'major_axis', 'minor_axis'}

inplace : boolean, 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.

**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 filled**: Panel

**See also:**
reindex, asfreq

**pandas.Panel4D.filter**

Panel4D.filter(*args, **kwargs)

**pandas.Panel4D.first**

Panel4D.first(offset)

Convenience method for subsetting initial periods of time series data based on a date offset

**Parameters offset**: string, DateOffset, dateutil.relativedelta

**Returns subset**: type of caller

**Examples**

ts.last('10D') -> First 10 days

**pandas.Panel4D.floordiv**

Panel4D.floordiv(other, axis=0)

Integer division of series and other, element-wise (binary operator floordiv). Equivalent to panel // other.

**Parameters other**: Panel or Panel4D

**axis**: [labels, items, major_axis, minor_axis]

Axis to broadcast over

**Returns** Panel4D

**See also:**
Panel4D.rfloordiv
**pandas.Panel4D.fromDict**

**classmethod Panel4D. fromDict** *(data, intersect=False, orient='items', dtype=None)*

Construct Panel from dict of DataFrame objects

**Parameters**
- **data** : dict
  - {field : DataFrame}
- **intersect** : boolean
  - Intersect indexes of input DataFrames
- **orient** : {‘items’, ‘minor’}, default ‘items’
  - The “orientation” of the data. If the keys of the passed dict should be the items of the result panel, pass ‘items’ (default). Otherwise if the columns of the values of the passed DataFrame objects should be the items (which in the case of mixed-dtype data you should do), instead pass ‘minor’
- **dtype** : dtype, default None
  - Data type to force, otherwise infer

**Returns** Panel

**pandas.Panel4D.from_dict**

**classmethod Panel4D. from_dict** *(data, intersect=False, orient='items', dtype=None)*

Construct Panel from dict of DataFrame objects

**Parameters**
- **data** : dict
  - {field : DataFrame}
- **intersect** : boolean
  - Intersect indexes of input DataFrames
- **orient** : {‘items’, ‘minor’}, default ‘items’
  - The “orientation” of the data. If the keys of the passed dict should be the items of the result panel, pass ‘items’ (default). Otherwise if the columns of the values of the passed DataFrame objects should be the items (which in the case of mixed-dtype data you should do), instead pass ‘minor’
- **dtype** : dtype, default None
  - Data type to force, otherwise infer

**Returns** Panel

**pandas.Panel4D.ge**

Panel4D.ge(*other*)

Wrapper for comparison method ge
pandas.Panel4D.get

Panel4D.get(key, default=None)
Get item from object for given key (DataFrame column, Panel slice, etc.). Returns default value if not found

Parameters  key : object

Returns  value : type of items contained in object

pandas.Panel4D.get_dtype_counts

Panel4D.get_dtype_counts()
Return the counts of dtypes in this object

pandas.Panel4D.get_ftype_counts

Panel4D.get_ftype_counts()
Return the counts of ftypes in this object

pandas.Panel4D.get_value

Panel4D.get_value(*args, **kwargs)
Quickly retrieve single value at (item, major, minor) location

Parameters  item : item label (panel item)
        major : major axis label (panel item row)
        minor : minor axis label (panel item column)
       takeable : interpret the passed labels as indexers, default False

Returns  value : scalar value

pandas.Panel4D.get_values

Panel4D.get_values()
same as values (but handles sparseness conversions)

pandas.Panel4D.groupby

Panel4D.groupby(*args, **kwargs)

pandas.Panel4D.gt

Panel4D.gt(other)
Wrapper for comparison method gt
pandas.Panel4D.head

Panel4D.head(n=5)

pandas.Panel4D.interpolate

Panel4D.interpolate(method='linear', axis=0, limit=None, inplace=False, limit_direction='forward', downcast=None, **kwargs)

Interpolate values according to different methods.

Please note that only method='linear' is supported for DataFrames/Series with a MultiIndex.

Parameters

- method : {'linear', 'time', 'index', 'values', 'nearest', 'zero',
  'slinear', 'quadratic', 'cubic', 'barycentric', 'krogh', 'polynomial', 'spline'
  'piecewise_polynomial', 'pchip'}

  - 'linear': ignore the index and treat the values as equally spaced. This is the
    only method supported on MultiIndexes. default
  - 'time': interpolation works on daily and higher resolution data to interpolate
    given length of interval
  - 'index', 'values': use the actual numerical values of the index
  - 'nearest', 'zero', 'slinear', 'quadratic', 'cubic', 'barycentric', 'polynomial'
    is passed to scipy.interpolate.interp1d. Both 'polynomial' and 'spline' require
    that you also specify an order (int), e.g. df.interpolate(method='polynomial', order=4).
    These use the actual numerical values of the index.
  - 'krogh', 'piecewise_polynomial', 'spline', and 'pchip' are all wrappers around
    the scipy interpolation methods of similar names. These use the actual numerical
    values of the index. See the scipy documentation for more on their behavior
    here and here

- axis : {0, 1}, default 0

  - 0: fill column-by-column
  - 1: fill row-by-row

- limit : int, default None.

  Maximum number of consecutive NaNs to fill.

- limit_direction : {'forward', 'backward', 'both'}, defaults to ‘forward’

  If limit is specified, consecutive NaNs will be filled in this direction.
  New in version 0.17.0.

- inplace : bool, default False

  Update the NDFrame in place if possible.

- 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 of same shape interpolated at the NaNs
See also:

reindex, replace, fillna

Examples

Filling in NaNs

```python
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s.interpolate()
0    0
1    1
2    2
3    3
dtype: float64
```

pandas.Panel4D.isnull

Panel4D.isnull()

Return a boolean same-sized object indicating if the values are null

See also:

notnull boolean inverse of isnull

pandas.Panel4D.iteritems

Panel4D.iteritems()

Iterate over (label, values) on info axis

This is index for Series, columns for DataFrame, major_axis for Panel, and so on.

pandas.Panel4D.iterkv

Panel4D.iterkv(*args, **kwargs)

iteritems alias used to get around 2to3. Deprecated

pandas.Panel4D.join

Panel4D.join(*args, **kwargs)

pandas.Panel4D.keys

Panel4D.keys()

Get the ‘info axis’ (see Indexing for more)

This is index for Series, columns for DataFrame and major_axis for Panel.
pandas.Panel4D.kurt

Panel4D.kurt (axis=None, skipna=None, level=None, numeric_only=None, **kwargs)
Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters

axis : {labels (0), items (1), major_axis (2), minor_axis (3)}
skipna : boolean, 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 Panel
numeric_only : boolean, default None
   Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns kurt : Panel or Panel4D (if level specified)

pandas.Panel4D.kurtosis

Panel4D.kurtosis (axis=None, skipna=None, level=None, numeric_only=None, **kwargs)
Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters

axis : {labels (0), items (1), major_axis (2), minor_axis (3)}
skipna : boolean, 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 Panel
numeric_only : boolean, default None
   Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns kurt : Panel or Panel4D (if level specified)

pandas.Panel4D.last

Panel4D.last (offset)
Convenience method for subsetting final periods of time series data based on a date offset

Parameters offset : string, DateOffset, dateutil.relativedelta

Returns subset : type of caller

Examples

ts.last('5M') -> Last 5 months
pandas.Panel4D.le

Panel4D.le(other)
Wrapper for comparison method le

pandas.Panel4D.lt

Panel4D.lt(other)
Wrapper for comparison method lt

pandas.Panel4D.mad

Panel4D.mad(axis=None, skipna=None, level=None)
Return the mean absolute deviation of the values for the requested axis

Parameters:
- **axis**: {labels (0), items (1), major_axis (2), minor_axis (3)}
- **skipna**: boolean, 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 Panel
- **numeric_only**: boolean, default None
  Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns:
- **mad**: Panel or Panel4D (if level specified)

pandas.Panel4D.major_xs

Panel4D.major_xs(key, copy=None)
Return slice of panel along major axis

Parameters:
- **key**: object
  Major axis label
- **copy**: boolean [deprecated]
  Whether to make a copy of the data

Returns:
- **y**: DataFrame
  index -> minor axis, columns -> items

Notes

major_xs is only for getting, not setting values.
MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of major_xs functionality, see MultiIndex Slicers
pandas.Panel4D.mask

Panel4D.mask (cond, other=nan, inplace=False, axis=None, level=None, try_cast=False, raise_on_error=True)

Return an object of same shape as self and whose corresponding entries are from self where cond is False and otherwise are from other.

Parameters cond : boolean NDFrame or array
    other : scalar or NDFrame
    inplace : boolean, default False
      Whether to perform the operation in place on the data
    axis : alignment axis if needed, default None
    level : alignment level if needed, default None
    try_cast : boolean, default False
      try to cast the result back to the input type (if possible),
    raise_on_error : boolean, default True
      Whether to raise on invalid data types (e.g. trying to where on strings)

Returns wh : same type as caller

pandas.Panel4D.max

Panel4D.max (axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

This method returns the maximum of the values in the object. If you want the index of the maximum, use idxmax. This is the equivalent of the numpy.ndarray method argmax.

Parameters axis : {labels (0), items (1), major_axis (2), minor_axis (3)}
    skipna : boolean, 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 Panel
    numeric_only : boolean, default None
      Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns max : Panel or Panel4D (if level specified)

pandas.Panel4D.mean

Panel4D.mean (axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

Return the mean of the values for the requested axis

Parameters axis : {labels (0), items (1), major_axis (2), minor_axis (3)}
    skipna : boolean, default True
      Exclude NA/null values. If an entire row/column is NA, the result will be NA
**pandas: powerful Python data analysis toolkit, Release 0.17.0**

**Returns**

- **level**: int or level name, default None
  - If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel
- **numeric_only**: boolean, default None
  - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**

- **mean**: Panel or Panel4D (if level specified)

---

**pandas.Panel4D.median**

Panel4D.median(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

Return the median of the values for the requested axis

**Parameters**

- **axis**: {labels (0), items (1), major_axis (2), minor_axis (3)}
- **skipna**: boolean, 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 Panel
- **numeric_only**: boolean, default None
  - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**

- **median**: Panel or Panel4D (if level specified)

---

**pandas.Panel4D.min**

Panel4D.min(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

This method returns the minimum of the values in the object. If you want the index of the minimum, use idxmin. This is the equivalent of the numpy.ndarray method argmin.

**Parameters**

- **axis**: {labels (0), items (1), major_axis (2), minor_axis (3)}
- **skipna**: boolean, 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 Panel
- **numeric_only**: boolean, default None
  - Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns**

- **min**: Panel or Panel4D (if level specified)
pandas.Panel4D.minor_xs

Panel4D.minor_xs(key, copy=None)
Return slice of panel along minor axis

Parameters key: object
Minor axis label

Parameters copy: boolean [deprecated]
Whether to make a copy of the data

Returns y: DataFrame
index -> major axis, columns -> items

Notes

minor_xs is only for getting, not setting values.
MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of minor_xs functionality, see `MultiIndex Slicers`

pandas.Panel4D.mod

Panel4D.mod(other, axis=0)
Modulo of series and other, element-wise (binary operator mod). Equivalent to panel % other.

Parameters other : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}
Axis to broadcast over

Returns Panel4D

See also:
Panel4D.rmod

pandas.Panel4D.mul

Panel4D.mul(other, axis=0)
Multiplication of series and other, element-wise (binary operator mul). Equivalent to panel * other.

Parameters other : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}
Axis to broadcast over

Returns Panel4D

See also:
Panel4D.rmul
pandas.Panel4D.multiply

Panel4D.multiply(other, axis=0)

Multiplication of series and other, element-wise (binary operator `mul`). Equivalent to `panel * other`.

Parameters

- **other**: Panel or Panel4D
- **axis**: {labels, items, major_axis, minor_axis}
  
  Axis to broadcast over

Returns

Panel4D

See also:

Panel4D.rmul

pandas.Panel4D.ne

Panel4D.ne(other)

Wrapper for comparison method `ne`

pandas.Panel4D.notnull

Panel4D.notnull()

Return a boolean same-sized object indicating if the values are not null

See also:

isnull boolean inverse of `notnull`

pandas.Panel4D.pct_change

Panel4D.pct_change(periods=1, fill_method='pad', limit=None, freq=None, **kwargs)

Percent change over given number of periods.

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 offset alias string, optional
  
  Increment to use from time series API (e.g. ‘M’ or BDay())

Returns

chg : NDFrame

Notes

By default, the percentage change is calculated along the stat axis: 0, or Index, for DataFrame and 1, or minor for Panel. You can change this with the axis keyword argument.
pandas.Panel4D.pipe

Panel4D.pipe(func, *args, **kwargs)
Apply func(self, *args, **kwargs)
New in version 0.16.2.

Parameters func : function

function to apply to the NDFrame. 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 NDFrame.

args : positional arguments passed into func.

kwargs : a dictionary of keyword arguments passed into func.

Returns object : the return type of func.

See also:
pandas.DataFrame.apply, pandas.DataFrame.applymap, pandas.Series.map

Notes

Use .pipe when chaining together functions that expect on Series or DataFrames. Instead of writing

```python
>>> f(g(h(df), arg1=a), arg2=b, arg3=c)
```

You can write

```python
>>> (df.pipe(h)
...   .pipe(g, arg1=a)
...   .pipe(f, 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((f, 'arg2'), arg1=a, arg3=c)
...)
```

pandas.Panel4D.pop

Panel4D.pop(item)
Return item and drop from frame. Raise KeyError if not found.

pandas.Panel4D.pow

Panel4D.pow(other, axis=0)
Exponential power of series and other, element-wise (binary operator pow). Equivalent to panel ** other.
Parameters  other : Panel or Panel4D

 axis : {labels, items, major_axis, minor_axis}

 Axis to broadcast over

 Returns  Panel4D

 See also:

 Panel4D.rpow

 pandas.Panel4D.prod

 Panel4D .prod (axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

 Return the product of the values for the requested axis

 Parameters  axis : {labels (0), items (1), major_axis (2), minor_axis (3)}

 skipna : boolean, 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 Panel

 numeric_only : boolean, default None

 Include only float, int, boolean data. If None, will attempt to use everything, then
 use only numeric data

 Returns  prod : Panel or Panel4D (if level specified)

 pandas.Panel4D.product

 Panel4D .product (axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

 Return the product of the values for the requested axis

 Parameters  axis : {labels (0), items (1), major_axis (2), minor_axis (3)}

 skipna : boolean, 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 Panel

 numeric_only : boolean, default None

 Include only float, int, boolean data. If None, will attempt to use everything, then
 use only numeric data

 Returns  prod : Panel or Panel4D (if level specified)
pandas.Panel4D.radd

Panel4D.radd(other, axis=0)
Addition of series and other, element-wise (binary operator radd). Equivalent to other + panel.

Parameters other : Panel or Panel4D
axis : {labels, items, major_axis, minor_axis}
Axis to broadcast over

Returns Panel4D

See also:
Panel4D.add

pandas.Panel4D.rdiv

Panel4D.rdiv(other, axis=0)
Floating division of series and other, element-wise (binary operator rtruediv). Equivalent to other / panel.

Parameters other : Panel or Panel4D
axis : {labels, items, major_axis, minor_axis}
Axis to broadcast over

Returns Panel4D

See also:
Panel4D.truediv

pandas.Panel4D.reindex

Panel4D.reindex(items=None, major_axis=None, minor_axis=None, **kwargs)
Conform Panel to new index with optional filling logic, placing 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 items, major_axis, minor_axis : array-like, optional (can be specified in order, or as keywords) New labels / index to conform to. Preferably an Index object to avoid duplicating data
Method to use for filling holes in reindexed DataFrame:
  • 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 : boolean, 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.

New in version 0.17.0.

Returns reindexed : Panel

Examples

>>> df.reindex(index=[date1, date2, date3], columns=['A', 'B', 'C'])

pandas.Panel4D.reindex_axis

Panel4D.reindex_axis(labels, axis=0, method=None, level=None, copy=True, limit=None, fill_value=nan)
Conform input object to new index with optional filling logic, placing 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 labels : array-like
New labels / index to conform to. Preferably an Index object to avoid duplicating data

axis : {0, 1, 2, ‘items’, ‘major_axis’, ‘minor_axis’}


Method to use for filling holes in reindexed DataFrame:
• 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 : boolean, 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

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 $|index[indexer] - target| \leq tolerance$.

New in version 0.17.0.

Returns reindexed : Panel

See also:
reindex, reindex_like

Examples

```python
>>> df.reindex_axis(['A', 'B', 'C'], axis=1)
```

pandas.Panel4D.reindex_like

Panel4D.reindex_like (other, method=None, copy=True, limit=None, tolerance=None)
return an object with matching indices to myself

Parameters other : Object
method : string or None

Returns reindexed : same as input

Notes

Like calling s.reindex(index=other.index, columns=other.columns, method=...)

pandas.Panel4D.rename

Panel4D.rename (items=None, major_axis=None, minor_axis=None, **kwargs)
Alter axes input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters items, major_axis, minor_axis : dict-like or function, optional

Transformation to apply to that axis values

Returns reindexed : Panel4D

See also:
reindex, reindex_like

Examples

```python
>>> df.reindex_axis(['A', 'B', 'C'], axis=1)
```
Also copy underlying data

**inplace** : boolean, default False

Whether to return a new Panel. If True then value of copy is ignored.

Returns **renamed** : Panel (new object)

### pandas.Panel4D.rename_axis

Panel4D.rename_axis *(mapper, axis=0, copy=True, inplace=False)*

Alter index and / or columns using input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

**Parameters**

- **mapper** : dict-like or function, optional
- **axis** : int or string, default 0
- **copy** : boolean, default True
- **inplace** : boolean, default False

Returns **renamed** : type of caller

### pandas.Panel4D.replace

Panel4D.replace *(to_replace=None, value=None, inplace=False, limit=None, regex=False, method='pad', axis=None)*

Replace values given in `to_replace` with `value`.

**Parameters**

- **to_replace** : str, regex, list, dict, Series, numeric, or None
  - str or regex:
    - 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 and regex rules apply as above.
  - dict:
    - Nested dictionaries, e.g., {'a': {'b': nan}}, are read as follows: look in column ‘a’ for the value ‘b’ and replace it with nan. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) **cannot** be regular expressions.
    - Keys map to column names and values map to substitution values. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
  - 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 use to fill holes (e.g. 0), alternately a dict of values specifying 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** : boolean, default False

If True, in place. Note: this will modify any other views on this object (e.g. a column form 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. Otherwise, `to_replace` must be `None` because this parameter will be interpreted as a regular expression or a list, dict, or array of regular expressions.

**method** : string, optional, {'pad', 'ffill', 'bfill'}

The method to use when for replacement, when `to_replace` is a list.

**Returns**

filled : NDFrame

**Raises**

AssertionError

- If `regex` is not a `bool` and `to_replace` is not `None`.

TypeError

- 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.

 ValueError

- If `to_replace` and `value` are lists or ndarrays, but they are not the same length.

**See also:**

NDFrame.reindex, NDFrame.asfreq, NDFrame.fillna

**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.

**pandas.Panel4D.resample**

Panel4D.resample(rule, how=None, axis=0, fill_method=None, closed=None, label=None, convention='start', kind=None, loffset=None, limit=None, base=0)

Convenience method for frequency conversion and resampling of regular time-series data.

**Parameters**

- **rule**: string
  
  the offset string or object representing target conversion

- **how**: string
  
  method for down- or re-sampling, default to ‘mean’ for downsampling

- **axis**: int, optional, default 0

- **fill_method**: string, default None
  
  fill_method for upsampling

- **closed**: {'right', 'left'}
  
  Which side of bin interval is closed

- **label**: {'right', 'left'}
  
  Which bin edge label to label bucket with

- **convention**: {'start', 'end', 's', 'e'}

- **kind**: “period”/“timestamp”

- **loffset**: timedelta
  
  Adjust the resampled time labels

- **limit**: int, default None
  
  Maximum size gap to when reindexing with fill_method

- **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

**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', how='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', how='sum', label='right')
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', how='sum', label='right', closed='right')
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')[0:5] #select first 5 rows
2000-01-01 00:00:00 0
2000-01-01 00:00:30 NaN
2000-01-01 00:01:00 1
2000-01-01 00:01:30 NaN
2000-01-01 00:02:00 2
Freq: 30S, dtype: float64
```

Upsample the series into 30 second bins and fill the NaN values using the `pad` method.

```python
>>> series.resample('30S', fill_method='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', fill_method='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 to `how`.

```python
>>> def custom_resampler(array_like):
...    return np.sum(array_like)+5

>>> series.resample('3T', how=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
```

**pandas.Panel4D.rfloordiv**

Panel4D.rfloordiv(oother, axis=0)

Integer division of series and other, element-wise (binary operator `rfloordiv`). Equivalent to `other // panel`.

Parameters

- **other**: Panel or Panel4D
- **axis**: {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns

Panel4D

See also:

Panel4D.floordiv

**pandas.Panel4D.rmod**

Panel4D.rmod(oother, axis=0)

Modulo of series and other, element-wise (binary operator `rmod`). Equivalent to `other % panel`.

Parameters

- **other**: Panel or Panel4D
- **axis**: {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns

Panel4D

See also:

Panel4D.mod

**pandas.Panel4D.rmul**

Panel4D.rmul(oother, axis=0)

Multiplication of series and other, element-wise (binary operator `rmul`). Equivalent to `other * panel`.

Parameters

- **other**: Panel or Panel4D

- **axis**: {labels, items, major_axis, minor_axis}
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Axis to broadcast over

**Returns** Panel4D

See also:

Panel4D.mul

pandas.Panel4D.rpow

Panel4D.rpow(other, axis=0)

Exponential power of series and other, element-wise (binary operator *rpow*). Equivalent to other ** panel.

**Parameters**

other : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

**Returns** Panel4D

See also:

Panel4D.pow

pandas.Panel4D.rsub

Panel4D.rsub(other, axis=0)

Subtraction of series and other, element-wise (binary operator *rsub*). Equivalent to other - panel.

**Parameters**

other : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

**Returns** Panel4D

See also:

Panel4D.sub

pandas.Panel4D.rtruediv

Panel4D.rtruediv(other, axis=0)

Floating division of series and other, element-wise (binary operator *rtruediv*). Equivalent to other / panel.

**Parameters**

other : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

**Returns** Panel4D

See also:

Panel4D.truediv
**pandas.Panel4D.sample**

Panel4D.sample(n=None, frac=None, replace=False, weights=None, random_state=None, axis=None)

Returns a random sample of items from an axis of object.

New in version 0.16.1.

**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**: boolean, optional
  - Sample with or without replacement. Default = False.
- **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. inf and -inf values not allowed.
- **random_state**: int or numpy.random.RandomState, optional
  - Seed for the random number generator (if int), or numpy RandomState object.
- **axis**: int or string, optional
  - Axis to sample. Accepts axis number or name. Default is stat axis for given data type (0 for Series and DataFrames, 1 for Panels).

**Returns**

A new object of same type as caller.

**pandas.Panel4D.select**

Panel4D.select(crit, axis=0)

Return data corresponding to axis labels matching criteria

**Parameters**

- **crit**: function
  - To be called on each index (label). Should return True or False
- **axis**: int

**Returns**

selection : type of caller

**pandas.Panel4D.sem**

Panel4D.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 : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, 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 Panel

numeric_only : boolean, default None
   Include only float, int, boolean data. If None, will attempt to use everything, then
   use only numeric data

Returns sem : Panel or Panel4D (if level specified)

pandas.Panel4D.set_axis

Panel4D.set_axis (axis, labels)
   public version of axis assignment

pandas.Panel4D.set_value

Panel4D.set_value (*args, **kwargs)
   Quickly set single value at (item, major, minor) location

   Parameters item : item label (panel item)
      major : major axis label (panel item row)
      minor : minor axis label (panel item column)
      value : scalar
      takeable : interpret the passed labels as indexers, default False

   Returns panel : Panel
      If label combo is contained, will be reference to calling Panel, otherwise a new
      object

pandas.Panel4D.shift

Panel4D.shift (*args, **kwargs)

pandas.Panel4D.skew

Panel4D.skew (axis=None, skipna=None, level=None, numeric_only=None, **kwargs)
   Return unbiased skew over requested axis Normalized by N-1

   Parameters axis : {labels (0), items (1), major_axis (2), minor_axis (3)}
      skipna : boolean, 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
pandas: powerful Python data analysis toolkit, Release 0.17.0

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

**numeric_only** : boolean, default None
Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns skew : Panel or Panel4D (if level specified)

**pandas.Panel4D.slice_shift**

Panel4D.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.Panel4D.sort_index**

Panel4D.sort_index (axis=0, level=None, ascending=True, inplace=False, kind='quicksort', na_position='last', sort_remaining=True)
Sort object by labels (along an axis)

Parameters axis : axes to direct sorting

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 : boolean, default True
Sort ascending vs. descending

inplace : bool
if True, perform operation in-place

kind : {quicksort, mergesort, heapsort}
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'}
first puts NaNs at the beginning, last puts NaNs at the end

sort_remaining : bool
if true and sorting by level and index is multilevel, sort by other levels too (in order) after sorting by specified level
returns sorted_obj: NDFrame

pandas.Panel4D.sort_values

Panel4D.sort_values(by, axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last')

pandas.Panel4D.squeeze

Panel4D.squeeze()
squeeze length 1 dimensions

pandas.Panel4D.std

Panel4D.std(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)
Return unbiased standard deviation over requested axis.
Normalized by N-1 by default. This can be changed using the ddof argument

Parameters axis : {labels (0), items (1), major_axis (2), minor_axis (3)}
skipna : boolean, 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 Panel
numeric_only : boolean, default None
Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns std : Panel or Panel4D (if level specified)

pandas.Panel4D.sub

Panel4D.sub(other, axis=0)
Subtraction of series and other, element-wise (binary operator sub). Equivalent to panel - other.

Parameters other : Panel or Panel4D
axis : {labels, items, major_axis, minor_axis}
Axis to broadcast over

Returns Panel4D

See also:
Panel4D.rsub
pandas.Panel4D.subtract

Panel4D.subtract(other, axis=0)
Subtraction of series and other, element-wise (binary operator sub). Equivalent to panel - other.

Parameters
other : Panel or Panel4D
axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns
Panel4D

See also:
Panel4D.rsub

pandas.Panel4D.sum

Panel4D.sum(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)
Return the sum of the values for the requested axis

Parameters
axis : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, 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 Panel

numeric_only : boolean, default None
Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns
sum : Panel or Panel4D (if level specified)

pandas.Panel4D.swapaxes

Panel4D.swapaxes(axis1, axis2, copy=True)
Interchange axes and swap values axes appropriately

Returns
y : same as input

pandas.Panel4D.swaplevel

Panel4D.swaplevel(i, j, axis=0)
Swap levels i and j in a MultiIndex on a particular axis

Parameters
i, j : int, string (can be mixed)
Level of index to be swapped. Can pass level name as string.

Returns
swapped : type of caller (new object)
`pandas.Panel4D.tail`

`Panel4D.tail(n=5)`

`pandas.Panel4D.take`

`Panel4D.take(indices, axis=0, convert=True, is_copy=True)`
Analogous to ndarray.take

**Parameters**
- `indices`: list / array of ints
- `axis`: int, default 0
- `convert`: translate neg to pos indices (default)
- `is_copy`: mark the returned frame as a copy

**Returns**
- `taken`: type of caller

`pandas.Panel4D.toLong`

`Panel4D.toLong(*args, **kwargs)`

`pandas.Panel4D.to_clipboard`

`Panel4D.to_clipboard(excel=None, sep=None, **kwargs)`
Attempt to write text representation of object to the system clipboard. This can be pasted into Excel, for example.

**Parameters**
- `excel`: boolean, defaults to True
  - if True, use the provided separator, writing in a csv format for allowing easy pasting into excel. If False, write a string representation of the object to the clipboard
- `sep`: optional, defaults to tab
- `other keywords are passed to to_csv`

**Notes**

**Requirements for your platform**
- Linux: xclip, or xsel (with gtk or PyQt4 modules)
- Windows: none
- OS X: none

`pandas.Panel4D.to_dense`

`Panel4D.to_dense()`
Return dense representation of NDFrame (as opposed to sparse)
pandas.Panel4D.to_excel

Panel4D.to_excel(*args, **kwargs)

pandas.Panel4D.to_frame

Panel4D.to_frame(*args, **kwargs)

pandas.Panel4D.to_hdf

Panel4D.to_hdf(path_or_buf, key, **kwargs)

activate the HDFStore

Parameters

path_or_buf : the path (string) or HDFStore object

key : string

identifier for the group in the store

mode : optional, {'a', 'w', 'r', 'r+'}, default 'a'

'r'  Read-only; no data can be modified.

'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.

'rw'  It is similar to 'a', but the file must already exist.

format : 'fixed(f)|table(t)', default is 'fixed'

fixed(f) [Fixed format] Fast writing/reading. Not-appendable, nor searchable

table(t) [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 : boolean, default False

For Table formats, append the input data to the existing

complevel : int, 1-9, default 0

If a complib is specified compression will be applied where possible

complib : {'zlib', 'bzip2', 'lzo', 'blosc', None}, default None

If complevel is > 0 apply compression to objects written in the store wherever possible

fletcher32 : bool, default False

If applying compression use the fletcher32 checksum

dropna : boolean, default False.

If true, ALL nan rows will not be written to store.
**pandas.Panel4D.to_json**

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** : the path or buffer to write the result string
  - if this is None, return a StringIO of the converted string
- **orient** : string
  - Series
    - default is ‘index’
    - allowed values are: {‘split’,‘records’,‘index’}
  - DataFrame
    - default is ‘columns’
    - allowed values are: {‘split’,‘records’,‘index’,‘columns’,‘values’}
  - 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 -> {index -> value}}
    - values : just the values array
- **date_format** : {‘epoch’, ‘iso’}
  - Type of date conversion. *epoch* = epoch milliseconds, *iso* = ISO8601, default is epoch.
- **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** : string, 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.

**Returns**

same type as input object with filtered info axis
pandas.Panel4D.to_long

Panel4D.to_long(*args, **kwargs)

pandas.Panel4D.to_msgpack

Panel4D.to_msgpack(path_or_buf=None, **kwargs)
msgpack (serialize) object to input file path

THIS IS AN EXPERIMENTAL LIBRARY and the storage format may not be stable until a future release.

Parameters path : string File path, buffer-like, or None
  if None, return generated string
append : boolean whether to append to an existing msgpack
  (default is False)
compress : type of compressor (zlib or blosc), default to None (no
  compression)

pandas.Panel4D.to_pickle

Panel4D.to_pickle(path)
Pickle (serialize) object to input file path

Parameters path : string
  File path

pandas.Panel4D.to_sparse

Panel4D.to_sparse(*args, **kwargs)

pandas.Panel4D.to_sql

Panel4D.to_sql(name, con, flavor='sqlite', schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None)
Write records stored in a DataFrame to a SQL database.

Parameters name : string
  Name of SQL table
con : SQLAlchemy engine or DBAPI2 connection (legacy mode)
  Using SQLAlchemy makes it possible to use any DB supported by that library. If
  a DBAPI2 object, only sqlite3 is supported.
flavor : {'sqlite', 'mysql'}, default 'sqlite'
  The flavor of SQL to use. Ignored when using SQLAlchemy engine. ‘mysql’ is
  deprecated and will be removed in future versions, but it will be further supported
  through SQLAlchemy engines.
schema : string, default None
Specify the schema (if database flavor supports this). If None, use default schema.

**if_exists** : {'fail', 'replace', 'append'}, default ‘fail’
- fail: If table exists, do nothing.
- replace: If table exists, drop it, recreate it, and insert data.
- append: If table exists, insert data. Create if does not exist.

**index** : boolean, default True
Write DataFrame index as a column.

**index_label** : string 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, default None
If not None, then rows will be written in batches of this size at a time. If None, all rows will be written at once.

**dtype** : dict of column name to SQL type, default None
Optional specifying the datatype for columns. The SQL type should be a SQLAlchemy type, or a string for sqlite3 fallback connection.

**pandas.Panel4D.transpose**

Panel4D.transpose(*args, **kwargs)
Permute the dimensions of the Panel

**Parameters**
- **args** : three positional arguments: each one of
  - 0, 1, 2, ‘items’, ‘major_axis’, ‘minor_axis’
- **copy** : boolean, default False
  Make a copy of the underlying data. Mixed-dtype data will always result in a copy

**Returns**
- **y** : same as input

**Examples**

```python
>>> p.transpose(2, 0, 1)
>>> p.transpose(2, 0, 1, copy=True)
```

**pandas.Panel4D.truediv**

Panel4D.truediv(other, axis=0)
Floating division of series and other, element-wise (binary operator truediv). Equivalent to panel / other.

**Parameters**
- **other** : Panel or Panel4D
- **axis** : {labels, items, major_axis, minor_axis}
Axis to broadcast over

Returns Panel4D

See also:
Panel4D.rtruediv

**pandas.Panel4D.truncate**

Panel4D.truncate(before=None, after=None, axis=None, copy=True)
Truncates a sorted NDFrame before and/or after some particular dates.

Parameters

- **before** : date
  - Truncate before date
- **after** : date
  - Truncate after date
- **axis** : the truncation axis, defaults to the stat axis
- **copy** : boolean, default is True,
  - return a copy of the truncated section

Returns truncated : type of caller

**pandas.Panel4D.tshift**

Panel4D.tshift(periods=1, freq=None, axis='major')

**pandas.Panel4D.tz_convert**

Panel4D.tz_convert(tz, axis=0, level=None, copy=True)
Convert tz-aware axis to target time zone.

Parameters

- **tz** : string or pytz.timezone 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** : boolean, default True
  - Also make a copy of the underlying data

Raises TypeError
If the axis is tz-naive.

**pandas.Panel4D.tz_localize**

Panel4D.tz_localize(*args, **kwargs)
Localize tz-naive TimeSeries to target time zone
**Parameters**

- **tz**: string or pytz.timezone object
  - `axis`: the axis to localize
  - `level`: int, str, default None
    - If axis is a MultiIndex, localize a specific level. Otherwise must be None
  - `copy`: boolean, default True
    - Also make a copy of the underlying data
  - `ambiguous`: ‘infer’, bool-ndarray, ‘NaT’, default ‘raise’
    - ‘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
  - `infer_dst`: boolean, default False (DEPRECATED)
    - Attempt to infer fall dst-transition hours based on order

**Raises**

- **TypeError**
  - If the TimeSeries is tz-aware and tz is not None.

---

**pandas.Panel4D.update**

`Panel4D.update(other, join='left', overwrite=True, filter_func=None, raise_conflict=False)`

Modify Panel in place using non-NA values from passed Panel, or object coercible to Panel. Aligns on items

- **Parameters**
  - `other`: Panel, or object coercible to Panel
  - `join`: How to join individual DataFrames
    - {‘left’, ‘right’, ‘outer’, ‘inner’}, default ‘left’
  - `overwrite`: boolean, default True
    - If True then overwrite values for common keys in the calling panel
  - `filter_func`: callable(1d-array) -> 1d-array<boolean>, default None
    - Can choose to replace values other than NA. Return True for values that should be updated
  - `raise_conflict`: bool
    - If True, will raise an error if a DataFrame and other both contain data in the same place.

---

**pandas.Panel4D.var**

`Panel4D.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 : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, 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 Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns  

var : Panel or Panel4D (if level specified)

pandas.Panel4D.where

Panel4D.where (cond, other=nan, inplace=False, axis=None, level=None, try_cast=False, raise_on_error=True)

Return an object of same shape as self and whose corresponding entries are from self where cond is True and otherwise are from other.

Parameters  

cond : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns  

wh : same type as caller

pandas.Panel4D.xs

Panel4D.xs (key, axis=1, copy=None)

Return slice of panel along selected axis

Parameters  

key : object

Label

axis : {‘items’, ‘major’, ‘minor’}, default 1/major

copy : boolean [deprecated]

Whether to make a copy of the data

Returns  

y : ndim(self)-1
Notes

xs is only for getting, not setting 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

34.6.2 Attributes and underlying data

Axes

- **labels**: axis 1; each label corresponds to a Panel contained inside
- **items**: axis 2; each item corresponds to a DataFrame contained inside
- **major_axis**: axis 3; the index (rows) of each of the DataFrames
- **minor_axis**: axis 4; the columns of each of the DataFrames

<table>
<thead>
<tr>
<th>Panel4D method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel4D.values</td>
<td>Numpy representation of NDFrame</td>
</tr>
<tr>
<td>Panel4D.axes</td>
<td>Return index label(s) of the internal NDFrame</td>
</tr>
<tr>
<td>Panel4D.ndim</td>
<td>Number of axes / array dimensions</td>
</tr>
<tr>
<td>Panel4D.size</td>
<td>number of elements in the NDFrame</td>
</tr>
<tr>
<td>Panel4D.shape</td>
<td>Return a tuple of axis dimensions</td>
</tr>
<tr>
<td>Panel4D.dtypes</td>
<td>Return the dtypes in this object</td>
</tr>
<tr>
<td>Panel4D.ftypes</td>
<td>Return the ftypes (indication of sparse/dense and dtype) in this object.</td>
</tr>
<tr>
<td>Panel4D.get_dtype_counts()</td>
<td>Return the counts of dtypes in this object</td>
</tr>
<tr>
<td>Panel4D.get_ftype_counts()</td>
<td>Return the counts of ftypes in this object</td>
</tr>
</tbody>
</table>

**pandas.Panel4D.values**

Panel4D.values

Numpy representation of NDFrame

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 upcase to int32.

**pandas.Panel4D.axes**

Panel4D.axes

Return index label(s) of the internal NDFrame

**pandas.Panel4D.ndim**

Panel4D.ndim

Number of axes / array dimensions
pandas.Panel4D.size

Panel4D.size

number of elements in the NDFrame

pandas.Panel4D.shape

Panel4D.shape

Return a tuple of axis dimensions

pandas.Panel4D.dtypes

Panel4D.dtypes

Return the dtypes in this object

pandas.Panel4D.ftypes

Panel4D.ftypes

Return the ftypes (indication of sparse/dense and dtype) in this object.

pandas.Panel4D.get_dtype_counts

Panel4D.get_dtypes_counts()

Return the counts of dtypes in this object

pandas.Panel4D.get_ftype_counts

Panel4D.get_ftype_counts()

Return the counts of ftypes in this object

34.6.3 Conversion

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel4D.astype(dtype[, copy, raise_on_error])</td>
<td>Cast object to input numpy.dtype</td>
</tr>
<tr>
<td>Panel4D.copy([deep])</td>
<td>Make a copy of this object</td>
</tr>
<tr>
<td>Panel4D.isnull()</td>
<td>Return a boolean same-sized object indicating if the values are null</td>
</tr>
<tr>
<td>Panel4D.notnull()</td>
<td>Return a boolean same-sized object indicating if the values are not null</td>
</tr>
</tbody>
</table>

pandas.Panel4D.astype

Panel4D.astype(dtype, copy=True, raise_on_error=True, **kwargs)

Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

Parameters
dtype : numpy.dtype or Python type
raise_on_error : raise on invalid input
kwargs : keyword arguments to pass on to the constructor

Returns
casted : type of caller
pandas.Panel4D.copy

Panel4D.copy (deep=True)
Make a copy of this object

Parameters  
- **deep**: boolean or string, default True
  Make a deep copy, i.e. also copy data

Returns  
- **copy**: type of caller

pandas.Panel4D.isnull

Panel4D.isnull()
Return a boolean same-sized object indicating if the values are null

See also:
- **notnull** boolean inverse of isnull

pandas.Panel4D.notnull

Panel4D.notnull()
Return a boolean same-sized object indicating if the values are not null

See also:
- **isNull** boolean inverse of notnull

### 34.7 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 | Immutable ndarray implementing an ordered, sliceable set. |

#### 34.7.1 pandas.Index

**class pandas.Index**
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)
- **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

**Notes**

An Index instance can **only** contain hashable objects

**Attributes**

- `T` return the transpose, which is by definition self
- `asi8` return the base object if the memory of the underlying data is shared
- `base` return the data pointer of the underlying data
- `data`
- `dtype`
- `dtype_str`
- `flags`
- `has_duplicates`
- `hasnans`
- `inferred_type`
- `is_all_dates`
- `is_monotonic`
- `is_monotonic_decreasing`
- `is_monotonic_increasing`
- `is_unique`
- `itemsize`
- `name`
- `names`
- `nbytes`
- `ndim`
- `nlevels`
- `shape`
- `size`
- `strides`
- `values`

**pandas.Index.T**

Index.T

  return the transpose, which is by definition self

**pandas.Index.asi8**

Index.asi8 = None

**pandas.Index.base**

Index.base

  return the base object if the memory of the underlying data is shared
pandas.Index.data

Index.data
return the data pointer of the underlying data

pandas.Index.dtype

Index.dtype = None

pandas.Index.dtype_str

Index.dtype_str = None

pandas.Index.flags

Index.flags

pandas.Index.has_duplicates

Index.has_duplicates

pandas.Index.hasnans

Index.hasnans = None

pandas.Index.inferred_type

Index.inferred_type = None

pandas.Index.is_all_dates

Index.is_all_dates = None

pandas.Index.is_monotonic

Index.is_monotonic
alias for is_monotonic_increasing (deprecated)

pandas.Index.is_monotonic_decreasing

Index.is_monotonic_decreasing
return if the index is monotonic decreasing (only equal or decreasing) values.

pandas.Index.is_monotonic_increasing

Index.is_monotonic_increasing
return if the index is monotonic increasing (only equal or increasing) values.
pandas: powerful Python data analysis toolkit, Release 0.17.0

pandas.Index.is_unique

Index.is_unique = None

pandas.Index.itemsize

Index.itemsize

return the size of the dtype of the item of the underlying data

pandas.Index.name

Index.name = None

pandas.Index.names

Index.names

pandas.Index.nbytes

Index.nbytes

return the number of bytes in the underlying data

pandas.Index.ndim

Index.ndim

return the number of dimensions of the underlying data, by definition 1

pandas.Index.nlevels

Index.nlevels

pandas.Index.shape

Index.shape

return a tuple of the shape of the underlying data

pandas.Index.size

Index.size

return the number of elements in the underlying data

pandas.Index.strides

Index.strides

return the strides of the underlying data
**pandas.Index.values**

Index.values
return the underlying data as an ndarray

**Methods**

- `all(*args, **kwargs)`
  - Return whether all elements are True
- `any(*args, **kwargs)`
  - Return whether any element is True
- `append(other)`
  - Append a collection of Index options together
- `argmax([axis])`
  - Return a collection of Index options together
- `argmin([axis])`
  - Return a collection of the minimum argument indexer
- `argsort(*args, **kwargs)`
  - For a sorted index, return the most recent label up to and including the passed label
- `asof(index)`
  - Where : array of timestamps
  - Make a copy of this object.
- `astype(dtype)`
  - Make new Index with passed location(-s) deleted
- `copy(names, name, dtype, deep)`
  - Compute sorted set difference of two Index objects
- `delete(loc)`
  - Make new Index with passed location(-s) deleted
- `diff(*args, **kwargs)`
  - Make new Index with passed list of labels deleted
- `difference(other)`
  - Return Index with duplicate values removed
- `drop(labels[, errors])`
  - Determines if two Index objects contain the same elements.
- `drop_duplicates(*args, **kwargs)`
  - Encode the object as an enumerated type or categorical variable
- `equals(other)`
  - Render a string representation of the Index
- `factorize([sort, na_sentinel])`
  - Compute indexer and mask for new index given the current index.
- `format([name, formatter])`
  - guaranteed return of an indexer even when non-unique
- `get_duplicates()`
  - return an indexer suitable for taking from a non unique index
- `get_indexer(target[, method, limit, tolerance])`
  - return vector of label values for requested level, equal to the length
- `get_indexer_for(target, **kwargs)`
  - Get integer location for requested label
- `get_indexer_non_unique(target)`
  - Calculate slice bound that corresponds to given label.
- `get_slice_bound(label, side, kind)`
  - return the underlying data as an ndarray
- `get_value(series, key)`
  - Group the index labels by a given array of values.
- `get_values()`
  - Similar to equals, but check that other comparable attributes are
- `groupby(to_groupby)`
  - Make new Index inserting new item at location.
- `holds_integer()`
  - Form the intersection of two Index objects.
- `identical(other)`
  - More flexible, faster check like is but that works through views
- `insert(loc, item)`
  - Compute boolean array of whether each index value is found in the passed set of
- `intersection(other)`
  - return the first element of the underlying data as a python scalar
- `is_(other)`
- `is_boolean()`
- `is_categorical()`
- `is_floating()`
- `is_integer()`
- `is_lexsorted_for_tuple(tup)`
- `is_mixed()`
- `is_numeric()`
- `is_object()`
- `is_type_compatible(kind)`
- `isin(values[, level])`
- `item()`

Continued on next page
Table 34.92 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>join()</code></td>
<td>this is an internal non-public method</td>
</tr>
<tr>
<td><code>map()</code></td>
<td>The maximum value of the object</td>
</tr>
<tr>
<td><code>max()</code></td>
<td>The minimum value of the object</td>
</tr>
<tr>
<td><code>min()</code></td>
<td>Return number of unique elements in the object.</td>
</tr>
<tr>
<td><code>nunique()</code></td>
<td>Return sorted copy of Index</td>
</tr>
<tr>
<td><code>order()</code></td>
<td>return a new Index of the values set with the mask</td>
</tr>
<tr>
<td><code>putmask()</code></td>
<td>return an ndarray of the flattened values of the underlying data</td>
</tr>
<tr>
<td><code>ravel()</code></td>
<td>Create index with target’s values (move/add/delete values as necessary)</td>
</tr>
<tr>
<td><code>reindex()</code></td>
<td>Set new names on index.</td>
</tr>
<tr>
<td><code>rename()</code></td>
<td>return a new Index of the values repeated n times</td>
</tr>
<tr>
<td><code>repeat()</code></td>
<td>np.ndarray searchsorted compat</td>
</tr>
<tr>
<td><code>searchsorted()</code></td>
<td>Set new names on index.</td>
</tr>
<tr>
<td><code>set_names()</code></td>
<td>Fast lookup of value from 1-dimensional ndarray.</td>
</tr>
<tr>
<td><code>set_value()</code></td>
<td>Shift Index containing datetime objects by input number of periods and For an ordered Index, compute the slice indexer for input labels and Compute slice locations for input labels.</td>
</tr>
<tr>
<td><code>sort()</code></td>
<td>Return sorted copy of Index</td>
</tr>
<tr>
<td><code>sort_values()</code></td>
<td>For internal compatibility with with the Index API</td>
</tr>
<tr>
<td><code>str()</code></td>
<td>alias of StringMethods</td>
</tr>
<tr>
<td><code>summary()</code></td>
<td>Compute the sorted symmetric difference of two Index objects.</td>
</tr>
<tr>
<td><code>sym_diff()</code></td>
<td>return a new Index of the values selected by the indexer</td>
</tr>
<tr>
<td><code>take()</code></td>
<td>For an Index containing strings or datetime.datetime objects, attempt slice and dice then format</td>
</tr>
<tr>
<td><code>to_datetime()</code></td>
<td>Create a Series with both index and values equal to the index keys</td>
</tr>
<tr>
<td><code>to_native_types()</code></td>
<td>return a list of the Index values</td>
</tr>
<tr>
<td><code>to_series()</code></td>
<td>return the transpose, which is by definition self</td>
</tr>
<tr>
<td><code>tolist()</code></td>
<td>Form the union of two Index objects and sorts if possible</td>
</tr>
<tr>
<td><code>transpose()</code></td>
<td>Returns object containing counts of unique values.</td>
</tr>
<tr>
<td><code>union()</code></td>
<td>A single element array_like may be converted to bool.</td>
</tr>
<tr>
<td><code>unique()</code></td>
<td>A single element array_like may be converted to bool.</td>
</tr>
</tbody>
</table>

---

**pandas.Index.all**

Index\.all (*args, **kwargs*)

Return whether all elements are True

**Parameters** All arguments to numpy.all are accepted.

**Returns** all : bool or array_like (if axis is specified)

A single element array_like may be converted to bool.

**pandas.Index.any**

Index\.any (*args, **kwargs*)

Return whether any element is True

**Parameters** All arguments to numpy.any are accepted.

**Returns** any : bool or array_like (if axis is specified)

A single element array_like may be converted to bool.
**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)*

return a ndarray of the maximum argument indexer

**See also:**

- numpy.ndarray.argmax

**pandas.Index.argmin**

*Index.argmin(axis=None)*

return a ndarray of the minimum argument indexer

**See also:**

- numpy.ndarray.argmin

**pandas.Index.argsort**

*Index.argsort(*args, **kwargs)*

return an ndarray indexer of the underlying data

**See also:**

- numpy.ndarray.argsort

**pandas.Index.asof**

*Index.asof(label)*

For a sorted index, return the most recent label up to and including the passed label. Return NaN if not found.

**See also:**

- get_loc

  asof is a thin wrapper around get_loc with method='pad'

**pandas.Index.asof_locs**

*Index.asof_locs(where, mask)*

where : array of timestamps

mask : array of booleans where data is not NA

**pandas.Index.astype**

*Index.astype(dtype)*
pandas.Index.copy

Index.copy (names=None, name=None, dtype=None, deep=False)
Make a copy of this object. Name and dtype sets those attributes on the new object.

Parameters  name : string, optional
dtype : numpy dtype or pandas type

Returns  copy : Index

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

Returns  new_index : Index

pandas.Index.diff

Index.diff (*args, **kwargs)

pandas.Index.difference

Index.difference (other)
Compute sorted set difference of two Index objects

Parameters  other : Index or array-like

Returns  diff : Index

Notes
One can do either of these and achieve the same result

>>> index.difference(index2)

pandas.Index.drop

Index.drop (labels, errors='raise')
Make new Index with passed list of labels deleted

Parameters  labels : array-like
effects : {‘ignore’, ‘raise’}, default ‘raise’
If ‘ignore’, suppress error and existing labels are dropped.

Returns  dropped : Index
pandas.Index.drop_duplicates

Index.drop_duplicates(*args, **kwargs)
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.

take_last : deprecated

Returns deduplicated : Index

pandas.Index.duplicated

Index.duplicated(*args, **kwargs)
Return boolean np.array denoting duplicate values

Parameters keep : {'first', 'last', False}, default ‘first’
  • 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.

take_last : deprecated

Returns duplicated : np.array

pandas.Index.equals

Index.equals(other)
Determines if two Index objects contain the same elements.

pandas.Index.factorize

Index.factorize(sort=False, na_sentinel=-1)
Encode the object as an enumerated type or categorical variable

Parameters sort : boolean, default False
  Sort by values

na_sentinel : int, default -1
  Value to mark “not found”

Returns labels : the indexer to the original array
  uniques : the unique Index

pandas.Index.format

Index.format(name=False, formatter=None, **kwargs)
Render a string representation of the Index
pandas.Index.get_duplicates

Index.get_duplicates()

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 abs(index[indexer] - target) <= tolerance.

New in version 0.17.0.

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

>>> indexer = index.get_indexer(new_index)
>>> new_values = cur_values.take(indexer)

pandas.Index.get_indexer_for

Index.get_indexer_for(target, **kwargs)

guaranteed return of an indexer even when non-unique

pandas.Index.get_indexer_non_unique

Index.get_indexer_non_unique(target)

return an indexer suitable for taking from a non unique index return the labels in the same order as the target, and return a missing indexer into the target (missing are marked as -1 in the indexer); target must be an iterable
pandas.Index.get_level_values

Index.get_level_values(level)
Return vector of label values for requested level, equal to the length of the index

Parameters level : int
Returns values : ndarray

pandas.Index.get_loc

Index.get_loc(key, method=None, tolerance=None)
Get integer location 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 : 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.

New in version 0.17.0.

Returns loc : int if unique index, possibly slice or mask if not

pandas.Index.get_slice_bound

Index.get_slice_bound(label, side, kind)
Calculate slice bound that corresponds to given label.

Returns leftmost (one-past-the-rightmost if side==’right’) position of given label.

Parameters label : object
    side : {‘left’, ‘right’}
    kind : string / None, the type of indexer

pandas.Index.get_value

Index.get_value(series, key)
Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you’re doing

pandas.Index.get_values

Index.get_values()
return the underlying data as an ndarray
pandas.Index.groupby

Index.groupby(to_groupby)
Group the index labels by a given array of values.

Parameters to_groupby : array
Values used to determine the groups.

Returns groups : dict
{group name -> group labels}

pandas.Index.holds_integer

Index.holds_integer()

pandas.Index.identical

Index.identical(other)
Similar to equals, but check that other comparable attributes are also equal

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)
Form the intersection of two Index objects. Sortedness of the result is not guaranteed

Parameters other : Index or array-like

Returns intersection : Index

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 True if both have same underlying data, False otherwise : bool
pandas.Index.is_boolean
Index.is_boolean()

pandas.Index.is_categorical
Index.is_categorical()

pandas.Index.is_floating
Index.is_floating()

pandas.Index.is_integer
Index.is_integer()

pandas.Index.is_lexsorted_for_tuple
Index.is_lexsorted_for_tuple(tup)

pandas.Index.is_mixed
Index.is_mixed()

pandas.Index.is_numeric
Index.is_numeric()

pandas.Index.is_object
Index.is_object()

pandas.Index.is_type_compatible
Index.is_type_compatible(kind)

pandas.Index.isin
Index.isin(values, level=None)
    Compute boolean array of whether each index value is found in the passed set of values.

Parameters  values : set or sequence of values
    Sought values.

    level : str or int, optional
        Name or position of the index level to use (if the index is a MultiIndex).

Returns  is_contained : ndarray (boolean dtype)
Notes

If level 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.

**pandas.Index.item**

`Index.item()` return the first element of the underlying data as a python scalar

**pandas.Index.join**

`Index.join(other, how='left', level=None, return_indexers=False)` this is an internal non-public method

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**: boolean, default False

**Returns**

join_index, (left_indexer, right_indexer)

**pandas.Index.map**

`Index.map(mapper)`

**pandas.Index.max**

`Index.max()` The maximum value of the object

**pandas.Index.min**

`Index.min()` The minimum value of the object

**pandas.Index.nunique**

`Index.nunique(dropna=True)` Return number of unique elements in the object.

Excludes NA values by default.

**Parameters**

- **dropna**: boolean, default True

  Don’t include NaN in the count.

**Returns**

nunique : int
pandas.Index.order

Index.order(return_indexer=False, ascending=True)
Return sorted copy of Index
DEPRECATED: use Index.sort_values()

pandas.Index.putmask

Index.putmask(mask, value)
return a new Index of the values set with the mask
See also:
numpy.ndarray.putmask

pandas.Index.ravel

Index.ravel(order='C')
return an ndarray of the flattened values of the underlying data
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 (move/add/delete values as necessary)
Parameters target : an iterable
Returns new_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)
Set new names on index. Defaults to returning new index.
Parameters name : str or list
    name to set
inplace : bool
    if True, mutates in place
Returns new index (of same type and class...etc) [if inplace, returns None]
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**pandas.Index.repeat**

Index.repeat(n)

return a new Index of the values repeated n times

See also:

numpy.ndarray.repeat

**pandas.Index.searchsorted**

Index.searchsorted(key, side='left')

np.ndarray.searchsorted compat

**pandas.Index.set_names**

Index.set_names(names, level=None, inplace=False)

Set new names on index. Defaults to returning new index.

Parameters

names : str or sequence

name(s) to set

level : int or level name, or sequence of int / level names (default None)

If the index is a MultiIndex (hierarchical), level(s) to set (None for all levels)
Otherwise level must be None

inplace : bool

if True, mutates in place

Returns

new index (of same type and class...etc) [if inplace, returns None]

Examples

```python
>>> Index([1, 2, 3, 4]).set_names('foo')
Int64Index([1, 2, 3, 4], dtype='int64')
>>> Index([1, 2, 3, 4]).set_names(['foo'])
Int64Index([1, 2, 3, 4], dtype='int64')
>>> idx = MultiIndex.from_tuples([(1, 'one'), (1, 'two'),
                                (2, 'one'), (2, 'two')],
                               names=['foo', 'bar'])
>>> idx.set_names(['baz', 'quz'])
MultiIndex(levels=[[1, 2], [u'one', u'two']],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
           names=[u'baz', u'quz'])
>>> idx.set_names('baz', level=0)
MultiIndex(levels=[[1, 2], [u'one', u'two']],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
           names=[u'baz', u'bar'])
```

**pandas.Index.set_value**

Index.set_value(arr, key, value)

Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you're doing
**pandas.Index.shift**

`Index.shift(periods=1, freq=None)`  
Shift Index containing datetime objects by input number of periods and DateOffset  

**Returns**  
shifted : Index

**pandas.Index.slice_indexer**

`Index.slice_indexer(start=None, end=None, step=None, kind=None)`  
For an ordered Index, compute the slice indexer for input labels and step  

**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 : string, default None

**Returns**  
indexer : ndarray or slice

**Notes**

This function assumes that the data is sorted, so use at your own peril

**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, default None  
kind : string, default None

**Returns**  
start, end : int

**pandas.Index.sort**

`Index.sort(*args, **kwargs)`
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pandas.Index.sort_values

Index.sort_values(return_indexer=False, ascending=True)
Return sorted copy of Index

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 : boolean, default True
    False to sort in descending order
level, sort_remaining are compat paramaters
Returns sorted_index : 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

    >>> s.str.split('_')
    >>> s.str.replace('_', '')

pandas.Index.summary

Index.summary(name=None)

pandas.Index.sym_diff

Index.sym_diff(other, result_name=None)
Compute the sorted symmetric difference of two Index objects.
Parameters other : Index or array-like
    result_name : str
Returns sym_diff : Index

Notes

sym_diff contains elements that appear in either idx1 or idx2 but not both. Equivalent to the Index created by (idx1 - idx2) + (idx2 - idx1) with duplicates dropped.
The sorting of a result containing NaN values is not guaranteed across Python versions. See GitHub issue #6444.
Examples

```python
>>> idx1 = Index([1, 2, 3, 4])
>>> idx2 = Index([2, 3, 4, 5])
```  
```python
>>> idx1.sym_diff(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)

return a new Index of the values selected by the indexer

For internal compatibility with numpy arrays.

# filling must always be None/nan here # but is passed thru internally

**See also:**

numpy.ndarray.take

**pandas.Index.to_datetime**

Index.to_datetime(dayfirst=False)

For an Index containing strings or datetime.datetime objects, attempt conversion to DatetimeIndex

**pandas.Index.to_native_types**

Index.to_native_types(slicer=None, **kwargs)

slice and dice then format

**pandas.Index.to_series**

Index.to_series(**kwargs)

Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index

**Returns** Series : dtype will be based on the type of the Index values.

**pandas.Index.tolist**

Index.tolist()

return a list of the Index values

**pandas.Index.transpose**

Index.transpose()

return the transpose, which is by definition self
pandas: powerful Python data analysis toolkit, Release 0.17.0

**pandas.Index.union**

`Index.union(other)`
Form the union of two Index objects and sorts if possible

**Parameters**
- `other`: Index or array-like

**Returns**
- `union`: Index

**pandas.Index.unique**

`Index.unique()`
Return array of unique values in the object. Significantly faster than numpy.unique. Includes NA values.

**Returns**
- `uniques`: ndarray

**pandas.Index.value_counts**

`Index.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)`
Returns object 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`: boolean, default False
  If True then the object returned will contain the relative frequencies of the unique values.

- `sort`: boolean, default True
  Sort by values

- `ascending`: boolean, default False
  Sort in ascending order

- `bins`: integer, optional
  Rather than count values, group them into half-open bins, a convenience for pd.cut, only works with numeric data

- `dropna`: boolean, default True
  Don’t include counts of NaN.

**Returns**
- `counts`: Series

**pandas.Index.view**

`Index.view(cls=None)`

**34.7.2 Attributes**

- `Index.values`: return the underlying data as an ndarray
- `Index.is_monotonic`: alias for `is_monotonic_increasing` (deprecated)
- `Index.is_monotonic_increasing`: return if the index is monotonic increasing (only equal or
### Table 34.93 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Index.is_monotonic_decreasing</code></td>
<td>return if the index is monotonic decreasing (only equal or decreasing) values.</td>
</tr>
<tr>
<td><code>Index.is_unique</code></td>
<td>return a tuple of the shape of the underlying data</td>
</tr>
<tr>
<td><code>Index.has_duplicates</code></td>
<td>return the number of bytes in the underlying data</td>
</tr>
<tr>
<td><code>Index.dtype</code></td>
<td>return the number of dimensions of the underlying data, by definition 1</td>
</tr>
<tr>
<td><code>Index.inferred_type</code></td>
<td>return the number of elements in the underlying data</td>
</tr>
<tr>
<td><code>Index.is_all_dates</code></td>
<td>return the strides of the underlying data</td>
</tr>
<tr>
<td><code>Index.shape</code></td>
<td>return the size of the dtype of the item of the underlying data</td>
</tr>
<tr>
<td><code>Index.nbytes</code></td>
<td>return the base object if the memory of the underlying data is shared</td>
</tr>
<tr>
<td><code>Index.ndim</code></td>
<td>return the transpose, which is by definition self</td>
</tr>
<tr>
<td><code>Index.size</code></td>
<td><code>pandas.Index.values</code></td>
</tr>
<tr>
<td><code>Index.values</code></td>
<td>return the underlying data as an ndarray</td>
</tr>
<tr>
<td><code>pandas.Index.is_monotonic</code></td>
<td><code>Index.is_monotonic</code></td>
</tr>
<tr>
<td></td>
<td>alias for is_monotonic_increasing (deprecated)</td>
</tr>
<tr>
<td><code>pandas.Index.is_monotonic_increasing</code></td>
<td>return if the index is monotonic increasing (only equal or increasing) values.</td>
</tr>
<tr>
<td><code>pandas.Index.is_monotonic_decreasing</code></td>
<td>return if the index is monotonic decreasing (only equal or decreasing) values.</td>
</tr>
<tr>
<td><code>pandas.Index.is_unique</code></td>
<td><code>Index.is_unique = None</code></td>
</tr>
<tr>
<td><code>pandas.Index.has_duplicates</code></td>
<td><code>Index.has_duplicates</code></td>
</tr>
<tr>
<td><code>pandas.Index.dtype</code></td>
<td><code>Index.dtype = None</code></td>
</tr>
</tbody>
</table>

34.7. Index
pandas.Index.inferred_type
Index.inferred_type = None

pandas.Index.is_all_dates
Index.is_all_dates = None

pandas.Index.shape
Index.shape
return a tuple of the shape of the underlying data

pandas.Index.nbytes
Index.nbytes
return the number of bytes in the underlying data

pandas.Index.ndim
Index.ndim
return the number of dimensions of the underlying data, by definition 1

pandas.Index.size
Index.size
return the number of elements in the underlying data

pandas.Index.strides
Index.strides
return the strides of the underlying data

pandas.Index.itemsize
Index.itemsize
return the size of the dtype of the item of the underlying data

pandas.Index.base
Index.base
return the base object if the memory of the underlying data is shared

pandas.Index.T
Index.T
return the transpose, which is by definition self
34.7.3 Modifying and Computations

| pandas/Index.all(|*args, **kwargs|) | Return whether all elements are True |
| pandas/Index.any(|*args, **kwargs|) | Return whether any element is True |
| pandas/Index.argmin(|[axis]|) | return a ndarray of the minimum argument indexer |
| pandas/Index.argmax(|[axis]|) | return a ndarray of the maximum argument indexer |
| pandas/Index.copy(|[names, name, dtype, deep]|) | Make a copy of this object. |
| pandas/Index.delete(|loc|) | Make new Index with passed location(-s) deleted |
| pandas/Index.drop(|labels[, errors]|) | Make new Index with passed list of labels deleted |
| pandas/Index.drop_duplicates(|*args, **kwargs|) | Return Index with duplicate values removed |
| pandas/Index.equals(|other|) | Determines if two Index objects contain the same elements. |
| pandas/Index.factorize(|[sort, na_sentinel]|) | Encode the object as an enumerated type or categorical variable |
| pandas/Index.identical(|other|) | Similar to equals, but check that other comparable attributes are |
| pandas/Index.insert(|loc, item|) | Make new Index inserting new item at location. |
| pandas/Index.min() | The minimum value of the object |
| pandas/Index.max() | The maximum value of the object |
| pandas/Index.reindex(|target[, method, level, ...]|) | Create index with target’s values (move/add/delete values as necessary) |
| pandas/Index.repeat(|n|) | return a new Index of the values repeated n times |
| pandas/Index.take(|indices[, axis, allow_fill, ...]|) | return a new Index of the values selected by the indexer |
| pandas/Index.putmask(|mask, value|) | return a new Index of the values set with the mask |
| pandas/Index.set_names(|names[, level, inplace]|) | Set new names on index. |
| pandas/Index.unique() | Return array of unique values in the object. |
| pandas/Index.nunique(|[dropna]|) | Return number of unique elements in the object. |
| pandas/Index.value_counts(|[normalize, sort, ...]|) | Returns object containing counts of unique values. |

pandas.Index.all

Index.all(*args, **kwargs)

Return whether all elements are True

Parameters All arguments to numpy.all are accepted.

Returns all : bool or array_like (if axis is specified)

A single element array_like may be converted to bool.

pandas.Index.any

Index.any(*args, **kwargs)

Return whether any element is True

Parameters All arguments to numpy.any are accepted.

Returns any : bool or array_like (if axis is specified)

A single element array_like may be converted to bool.

pandas.Index.argmin

Index.argmin(axis=None)

return a ndarray of the minimum argument indexer

See also:
pandas: powerful Python data analysis toolkit, Release 0.17.0

numpy.ndarray.argmin

pandas.Index.argmax

Index.argmax (axis=None)
return a ndarray of the maximum argument indexer

See also:
numpy.ndarray.argmax

pandas.Index.copy

Index.copy (names=None, name=None, dtype=None, deep=False)
Make a copy of this object. Name and dtype sets those attributes on the new object.

Parameters name : string, optional
dtype : numpy dtype or pandas type

Returns copy : Index

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

Returns new_index : Index

pandas.Index.drop

Index.drop (labels, errors='raise')
Make new Index with passed list of labels deleted

Parameters labels : array-like
ersrors : {‘ignore’, ‘raise’}, default ‘raise’
If ‘ignore’, suppress error and existing labels are dropped.

Returns dropped : Index

pandas.Index.drop_duplicates

Index.drop_duplicates (*args, **kwargs)
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.

take_last : deprecated

Returns deduplicated : Index

pandas.Index.duplicated

Index.duplicated(*args, **kwargs)

Return boolean np.array denoting duplicate values

Parameters keep : {'first', 'last', False}, default ‘first’
• 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.

take_last : deprecated

Returns duplicated : np.array

pandas.Index.equals

Index.equals(other)

Determines if two Index objects contain the same elements.

pandas.Index.factorize

Index.factorize(sort=False, na_sentinel=-1)

Encode the object as an enumerated type or categorical variable

Parameters sort : boolean, default False
    Sort by values

na_sentinel: int, default -1
    Value to mark “not found”

Returns labels : the indexer to the original array

uniques : the unique Index

pandas.Index.identical

Index.identical(other)

Similar to equals, but check that other comparable attributes are also equal

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.min`

`Index.min()`
The minimum value of the object

`pandas.Index.max`

`Index.max()`
The maximum value of the object

`pandas.Index.reindex`

`Index.reindex(target, method=None, level=None, limit=None, tolerance=None)`
Create index with target’s values (move/add/delete values as necessary)

Parameters `target` : an iterable
Returns `new_index` : pd.Index
    Resulting index
    `indexer` : np.ndarray or None
        Indices of output values in original index

`pandas.Index.repeat`

`Index.repeat(n)`
return a new Index of the values repeated n times

See also:
    `numpy.ndarray.repeat`

`pandas.Index.take`

`Index.take(indices, axis=0, allow_fill=True, fill_value=None)`
return a new Index of the values selected by the indexer

For internal compatibility with numpy arrays.
# filling must always be None/nan here # but is passed thru internally

See also:
    `numpy.ndarray.take`
pandas.Index.putmask

Index.putmask(mask, value)
return a new Index of the values set with the mask

See also:
numpy.ndarray.putmask

pandas.Index.set_names

Index.set_names(names, level=None, inplace=False)
Set new names on index. Defaults to returning new index.

Parameters names : str or sequence
    name(s) to set

level : int or level name, or sequence of int / level names (default None)
    If the index is a MultiIndex (hierarchical), level(s) to set (None for all levels) Otherwise level must be None

inplace : bool
    if True, mutates in place

Returns new index (of same type and class...etc) [if inplace, returns None]

Examples

>>> Index([1, 2, 3, 4]).set_names('foo')
Int64Index([1, 2, 3, 4], dtype='int64')

>>> Index([1, 2, 3, 4]).set_names(['foo'])
Int64Index([1, 2, 3, 4], dtype='int64')

>>> idx = MultiIndex.from_tuples([(1, u'one'), (1, u'two'), (2, u'one'), (2, u'two')], names=['foo', 'bar'])

>>> idx.set_names(['baz', 'quz'])
MultiIndex(levels=[[1, 2], [u'one', u'two']], labels=[[0, 0, 1, 1], [0, 1, 0, 1]], names=['baz', 'quz'])

>>> idx.set_names('baz', level=0)
MultiIndex(levels=[[1, 2], [u'one', u'two']], labels=[[0, 0, 1, 1], [0, 1, 0, 1]], names=['baz', 'bar'])

pandas.Index.unique

Index.unique()
Return array of unique values in the object. Significantly faster than numpy.unique. Includes NA values.

Returns uniques : ndarray
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pandas.Index.nunique

Index.nunique(dropna=True)
Return number of unique elements in the object.
Excludes NA values by default.

Parameters dropna : boolean, default True
Don’t include NaN in the count.

Returns nunique : int

pandas.Index.value_counts

Index.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)
Returns object 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 : boolean, default False
If True then the object returned will contain the relative frequencies of the unique values.

sort : boolean, default True
Sort by values

ascending : boolean, default False
Sort in ascending order

bins : integer, optional
Rather than count values, group them into half-open bins, a convenience for pd.cut, only works with numeric data

dropna : boolean, default True
Don’t include counts of NaN.

Returns counts : Series

34.7.4 Conversion

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Index.astype(dtype)</td>
<td>return a list of the Index values</td>
</tr>
<tr>
<td>Index.tolist()</td>
<td>For an Index containing strings or datetime.datetime objects, attempt</td>
</tr>
<tr>
<td>Index.to_datetime(dayfirst)</td>
<td>Create a Series with both index and values equal to the index keys</td>
</tr>
</tbody>
</table>

pandas.Index.astype

Index.astype(dtype)
pandas.Index.tolist

Index.tolist()  
return a list of the Index values

pandas.Index.to_datetime

Index.to_datetime(dayfirst=False)  
For an Index containing strings or datetime.datetime objects, attempt conversion to DatetimeIndex

pandas.Index.to_series

Index.to_series(**kwargs)  
Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index  
Returns Series: dtype will be based on the type of the Index values.

34.7.5 Sorting

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Index.argsort(*args, **kwargs)</td>
<td>return an ndarray indexer of the underlying data</td>
</tr>
<tr>
<td>Index.sort_values([return_indexer, ascending])</td>
<td>Return sorted copy of Index</td>
</tr>
</tbody>
</table>

pandas.Index.argsort

Index.argsort(*args, **kwargs)  
return an ndarray indexer of the underlying data  
See also:  
numpy.ndarray.argsort

pandas.Index.sort_values

Index.sort_values(return_indexer=False, ascending=True)  
Return sorted copy of Index

34.7.6 Time-specific operations

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Index.shift([periods, freq])</td>
<td>Shift Index containing datetime objects by input number of periods and DateOffset</td>
</tr>
</tbody>
</table>

pandas.Index.shift

Index.shift(periods=1, freq=None)  
Shift Index containing datetime objects by input number of periods and DateOffset  
Returns shifted: Index
34.7.7 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, return_indexers])</code></td>
<td>this is an internal non-public method</td>
</tr>
<tr>
<td><code>Index.intersection(other)</code></td>
<td>Form the intersection of two Index objects.</td>
</tr>
<tr>
<td><code>Index.union(other)</code></td>
<td>Form the union of two Index objects and sorts if possible</td>
</tr>
<tr>
<td><code>Index.difference(other)</code></td>
<td>Compute sorted set difference of two Index objects</td>
</tr>
<tr>
<td><code>Index.sym_diff(other[, result_name])</code></td>
<td>Compute the sorted symmetric difference of two Index objects.</td>
</tr>
</tbody>
</table>

**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.join**

**Index.join(other, how='left', level=None, return_indexers=False)**

this is an internal non-public method

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`: boolean, default False

**Returns**
- `join_index`, (left_indexer, right_indexer)

**pandas.Index.intersection**

**Index.intersection(other)**

Form the intersection of two Index objects. Sortedness of the result is not guaranteed

**Parameters**
- `other`: Index or array-like

**Returns**
- `intersection`: Index

**pandas.Index.union**

**Index.union(other)**

Form the union of two Index objects and sorts if possible

**Parameters**
- `other`: Index or array-like

**Returns**
- `union`: Index
**pandas.Index.difference**

Index.difference(other)  
Compute sorted set difference of two Index objects  

Parameters  
other : Index or array-like  

Returns  
diff : Index  

Notes  
One can do either of these and achieve the same result  
>>> index.difference(index2)

**pandas.Index.sym_diff**

Index.sym_diff(other, result_name=None)  
Compute the sorted symmetric difference of two Index objects.  

Parameters  
other : Index or array-like  
result_name : str  

Returns  
sym_diff : Index  

Notes  
sym_diff contains elements that appear in either idx1 or idx2 but not both. Equivalent to the Index created by (idx1 - idx2) + (idx2 - idx1) with duplicates dropped.  
The sorting of a result containing NaN values is not guaranteed across Python versions. See GitHub issue #6444.

Examples  
>>> idx1 = Index([1, 2, 3, 4])  
>>> idx2 = Index([2, 3, 4, 5])  
>>> idx1.sym_diff(idx2)  
Int64Index([1, 5], dtype='int64')

You can also use the ^ operator:  
>>> idx1 ^ idx2  
Int64Index([1, 5], dtype='int64')

### 34.7.8 Selecting

Index.get_indexer(target[, method, limit, ...])  
Compute indexer and mask for new index given the current index.  
return an indexer suitable for taking from a non unique index  
return vector of label values for requested level, equal to the length  
Get integer location for requested label  
Fast lookup of value from 1-dimensional ndarray.
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Table 34.99 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Index.isin(values[, level])</code></td>
<td>Compute boolean array of whether each index value is found in the passed set of values.</td>
</tr>
<tr>
<td><code>Index.slice_indexer([start, end, step, kind])</code></td>
<td>For an ordered Index, compute the slice indexer for input labels and positions.</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>

**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 `abs(index[indexer] - target) <= tolerance`.

**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
>>> indexer = index.get_indexer(new_index)
>>> new_values = cur_values.take(indexer)
```

**pandas.Index.get_indexer_non_unique**

`Index.get_indexer_non_unique(target)`

return an indexer suitable for taking from a non unique index return the labels in the same order as the target, and return a missing indexer into the target (missing are marked as -1 in the indexer); target must be an iterable

**pandas.Index.get_level_values**

`Index.get_level_values(level)`

Return vector of label values for requested level, equal to the length of the index

**Parameters**

- **level**: int
Returns values: ndarray

### pandas.Index.get_loc

Index.get_loc(key, method=None, tolerance=None)

Get integer location for requested label

- **Parameters**
  - key : label
    - 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 : optional
    - Maximum distance from index value for inexact matches. The value of the index at the matching location most satisfy the equation \( \text{abs(index[loc] - key)} <= \text{tolerance} \).

New in version 0.17.0.

- **Returns**
  - loc : int if unique index, possibly slice or mask if not

### pandas.Index.get_value

Index.get_value(series, key)

Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you’re doing

### pandas.Index.isin

Index.isin(values, level=None)

Compute boolean array of whether each index value is found in the passed set of values.

- **Parameters**
  - values : set or sequence of values
    - Sought values.
  - level : str or int, optional
    - Name or position of the index level to use (if the index is a MultiIndex).

- **Returns**
  - is_contained : ndarray (boolean dtype)

### Notes

If level 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.
pandas.Index.slice_indexer

Index.slice_indexer (start=None, end=None, step=None, kind=None)
For an ordered Index, compute the slice indexer for input labels and step

   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 : string, default None

   Returns indexer : ndarray or slice

   Notes

   This function assumes that the data is sorted, so use at your own peril

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, default None
                      kind : string, default None

   Returns start, end : int

34.8 CategoricalIndex

CategoricalIndex  Immutable Index implementing an ordered, sliceable set.

34.8.1 pandas.CategoricalIndex

class pandas.CategoricalIndex
   Immutable Index implementing an ordered, sliceable set. CategoricalIndex represents a sparsely populated
   Index with an underlying Categorical.

   New in version 0.16.1.

   Parameters data : array-like or Categorical, (1-dimensional)
categories : optional, array-like
categories for the CategoricalIndex

ordered : boolean,
designating if the categories are ordered

copy : bool
Make a copy of input ndarray

name : object
Name to be stored in the index

Attributes

T
asi8
base
categories
codes
data
dtype
dtype_str
flags
has_duplicates
hasnans
inferred_type
is_all_dates
is_monotonic
is_monotonic_decreasing
is_monotonic_increasing
is_unique
itemsize
name
names
nbytes
ndim
nlevels
ordered
shape
size
strides
values

pandas.CategoricalIndex.T

CategoricalIndex.T
return the transpose, which is by definition self

pandas.CategoricalIndex.asi8

CategoricalIndex.asi8 = None
pandas.CategoricalIndex.base

CategoricalIndex.base
return the base object if the memory of the underlying data is shared

pandas.CategoricalIndex.categories

CategoricalIndex.categories

pandas.CategoricalIndex.codes

CategoricalIndex.codes

pandas.CategoricalIndex.data

CategoricalIndex.data
return the data pointer of the underlying data

pandas.CategoricalIndex.dtype

CategoricalIndex.dtype = None

pandas.CategoricalIndex.dtype_str

CategoricalIndex.dtype_str = None

pandas.CategoricalIndex.flags

CategoricalIndex.flags

pandas.CategoricalIndex.has_duplicates

CategoricalIndex.has_duplicates

pandas.CategoricalIndex.hasnans

CategoricalIndex.hasnans = None

pandas.CategoricalIndex.inferred_type

CategoricalIndex.inferred_type

pandas.CategoricalIndex.is_all_dates

CategoricalIndex.is_all_dates = None
pandas.CategoricalIndex.is_monotonic

CategoricalIndex.is_monotonic

   alias for is_monotonic_increasing (deprecated)

pandas.CategoricalIndex.is_monotonic_decreasing

CategoricalIndex.is_monotonic_decreasing

    return if the index is monotonic decreasing (only equal or decreasing) values.

pandas.CategoricalIndex.is_monotonic_increasing

CategoricalIndex.is_monotonic_increasing

    return if the index is monotonic increasing (only equal or increasing) values.

pandas.CategoricalIndex.is_unique

CategoricalIndex.is_unique = None

pandas.CategoricalIndex.itemsize

CategoricalIndex.itemsize

    return the size of the dtype of the item of the underlying data

pandas.CategoricalIndex.name

CategoricalIndex.name = None

pandas.CategoricalIndex.names

CategoricalIndex.names

pandas.CategoricalIndex.nbytes

CategoricalIndex.nbytes

    return the number of bytes in the underlying data

pandas.CategoricalIndex.ndim

CategoricalIndex.ndim

    return the number of dimensions of the underlying data, by definition 1

pandas.CategoricalIndex.nlevels

CategoricalIndex.nlevels
pandas.CategoricalIndex.ordered

CategoricalIndex.ordered

pandas.CategoricalIndex.shape

CategoricalIndex.shape
return a tuple of the shape of the underlying data

pandas.CategoricalIndex.size

CategoricalIndex.size
return the number of elements in the underlying data

pandas.CategoricalIndex.strides

CategoricalIndex.strides
return the strides of the underlying data

pandas.CategoricalIndex.values

CategoricalIndex.values
return the underlying data, which is a Categorical

Methods

add_categories(*args, **kwargs) Add new categories.
all([other])
any([other])
append(other) Append a collection of CategoricalIndex options together
argmax([axis])
argmin([axis])
argsort(*args, **kwargs)
as_ordered(*args, **kwargs) Sets the Categorical to be ordered
as_unordered(*args, **kwargs) Sets the Categorical to be unordered
asof(label) For a sorted index, return the most recent label up to and including the passed
asof_locs(where, mask) where : array of timestamps
astype(dtype) Make a copy of this object.
copy([names, name, dtype, deep]) Make new Index with passed location(-s) deleted
delete(loc) Compute sorted set difference of two Index objects
diff(*args, **kwargs) Make new Index with passed list of labels deleted
difference(other) Return Index with duplicate values removed
drop(labels[, errors]) Return boolean np.array denoting duplicate values
drop_duplicates(*args, **kwargs) Determines if two CategoricalIndex objects contain the same elements.
duplicated(*args, **kwargs) Encode the object as an enumerated type or categorical variable
drop_duplicates() Render a string representation of the Index
**get_indexer**(target[, method, limit, tolerance])
Compute indexer and mask for new index given the current index. guaranteed return of an indexer even when non-unique
this is the same for a CategoricalIndex for get_indexer: the API returns the mask
Return vector of label values for requested level, equal to the length
Get integer location for requested label
Calculate slice bound that corresponds to given label.
Fast lookup of value from 1-dimensional ndarray.
return the underlying data as an ndarray.
Group the index labels by a given array of values.

**get_indexer_for**(target, **kwargs)
**get_indexer_non_unique**(target)
**get_level_values**(level)
**get_loc**(key[, method])
**get_slice_bound**(label, side, kind)
**get_value**(series, key)
**get_values**()
**groupby**(to_groupby)
**holds_integer**()
**identical**(other)
**insert**(loc, item)
**intersection**(other)
**is_(other)**
**is_boolean**()
**is_categorical**()
**is_float**()
**is_integer**()
**is_lexsorted_for_tuple**(tup)
**is_mixed**()
**is_numeric**()
**is_object**()
**is_type_compatible**(kind)
**isin**(values[, level])
**item**()
**join**(other[, how, level, return_indexers])
**map**(mapper)
**max**(args, **kwargs)
**min**(args, **kwargs)
**nunique**(dropna)
**order**(return_indexer, ascending)
**putmask**(mask, value)
**ravel**(order)
**reindex**(target[, method, limit, limit, ...])
**remove_categories**(args, **kwargs)
**remove_unused_categories**(args, **kwargs)
**rename**(name[, inplace])
**rename_categories**(args, **kwargs)
**reorder_categories**(args, **kwargs)
**repeat**(n)
**searchsorted**(key[, side])
**set_categories**(args, **kwargs)
**set_names**(names[, level, inplace])
**set_value**(arr, key, value)
**shift**(periods, freq)
**slice_indexer**([start, end, step, kind])
**slice_locs**([start, end, step, kind])
**sort**(args, **kwargs)
**sort_values**([return_indexer, ascending])
**sortlevel**([level, ascending, sort_remaining])
**str**
**summary**(name)

**get_indexer_get_indexer_for_get_indexer_non_unique_get_level_values_get_loc_get_slice_bound_get_value_get_get_values_groupby_holds_integer_identical_insert_intersection_is_is_boolean_is_categorical_is_float_is_integer_is_lexsorted_for_tuple_is_mixed_is_numeric_is_object_is_type_compatible_isin_item_join_map_max_min_nunique_order_putmask_ravel_reindex_remove_categories_remove_unused_categories_rename_rename_categories_reorder_categories_repeat_searchsorted_set_categories_set_names_set_value_shift_slice_indexer_slice_locs_sort_sort_values_sortlevel_str_summary_get_indexer_get_indexer_for_get_indexer_non_unique_get_level_values_get_loc_get_slice_bound_get_value_get_get_values_groupby_holds_integer_identical_insert_intersection_is_is_boolean_is_categorical_is_float_is_integer_is_lexsorted_for_tuple_is_mixed_is_numeric_is_object_is_type_compatible_isin_item_join_map_max_min_nunique_order_putmask_ravel_reindex_remove_categories_remove_unused_categories_rename_rename_categories_reorder_categories_repeat_searchsorted_set_categories_set_names_set_value_shift_slice_indexer_slice_locs_sort_sort_values_sortlevel_str_summary_
### Table 34.102 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>sym_diff</code></td>
<td>Compute the sorted symmetric difference of two Index objects. For internal compatibility with numpy arrays.</td>
</tr>
<tr>
<td><code>take</code></td>
<td>For an Index containing strings or datetime.datetime objects, attempt slice and dice then format. Create a Series with both index and values equal to the index keys.</td>
</tr>
<tr>
<td><code>to_datetime</code></td>
<td>return a list of the Index values.</td>
</tr>
<tr>
<td><code>to_native_types</code></td>
<td>return the transpose, which is by definition self.</td>
</tr>
<tr>
<td><code>to_series</code></td>
<td>Form the union of two Index objects and sorts if possible.</td>
</tr>
<tr>
<td><code>tolist</code></td>
<td>Returns array of unique values in the object.</td>
</tr>
<tr>
<td><code>transpose</code></td>
<td>Returns object containing counts of unique values.</td>
</tr>
<tr>
<td><code>union</code></td>
<td>pandas.CategoricalIndex.add_categories</td>
</tr>
</tbody>
</table>
| `unique` | CategoricalIndex.**add_categories** (*args, **kwargs*)

Add new categories.

- **new_categories**: category or list-like of category
- **inplace**: boolean (default: False)

- Parameters **new_categories**: category or list-like of category
- **inplace**: boolean (default: False)

- 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`, `reorder_categories`, `remove_categories`, `remove_unused_categories`, `set_categories`

pandas.CategoricalIndex.all

- CategoricalIndex.**all** (*other=None*)

pandas.CategoricalIndex.any

- CategoricalIndex.**any** (*other=None*)

pandas.CategoricalIndex.append

- CategoricalIndex.**append** (*other*)

  Append a collection of CategoricalIndex options together

  - Parameters **other**: Index or list/tuple of indices
  - Returns **appended**: Index
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Raises  ValueError if other is not in the categories

pandas.CategoricalIndex.argmax

CategoricalIndex.argmax(axis=None)
return a ndarray of the maximum argument indexer

See also:
numpy.ndarray.argmax

pandas.CategoricalIndex.argmin

CategoricalIndex.argmin(axis=None)
return a ndarray of the minimum argument indexer

See also:
numpy.ndarray.argmin

pandas.CategoricalIndex.argsort

CategoricalIndex.argsort(*args, **kwargs)

pandas.CategoricalIndex.as_ordered

CategoricalIndex.as_ordered(*args, **kwargs)
Sets the Categorical to be ordered

Parameters inplace : boolean (default: False)
Whether or not to set the ordered attribute inplace or return a copy of this categorical with ordered set to True

pandas.CategoricalIndex.as_unordered

CategoricalIndex.as_unordered(*args, **kwargs)
Sets the Categorical to be unordered

Parameters inplace : boolean (default: False)
Whether or not to set the ordered attribute inplace or return a copy of this categorical with ordered set to False

pandas.CategoricalIndex.asof

CategoricalIndex.asof(label)
For a sorted index, return the most recent label up to and including the passed label. Return NaN if not found.

See also:

get_loc  asof is a thin wrapper around get_loc with method='pad'
pandas.CategoricalIndex.asof_locs

CategoricalIndex.asof_locs(\texttt{where, mask})

\texttt{where} : array of timestamps \texttt{mask} : array of booleans where data is not NA

pandas.CategoricalIndex.astype

CategoricalIndex.astype(\texttt{dtype})

pandas.CategoricalIndex.copy

CategoricalIndex.copy(\texttt{\texttt{\texttt{names}=None, \texttt{name}=None, \texttt{dtype}=None, \texttt{deep}=False}})

Make a copy of this object. Name and dtype sets those attributes on the new object.

\textbf{Parameters}

\texttt{name} : string, optional

\texttt{dtype} : numpy dtype or pandas type

\textbf{Returns}

\texttt{copy} : Index

\textbf{Notes}

In most cases, there should be no functional difference from using \texttt{deep}, but if \texttt{deep} is passed it will attempt to deepcopy.

pandas.CategoricalIndex.delete

CategoricalIndex.delete(\texttt{loc})

Make new Index with passed location(-s) deleted

\textbf{Returns}

\texttt{new\_index} : Index

pandas.CategoricalIndex.diff

CategoricalIndex.diff(\texttt{\texttt{\texttt{\texttt{*args, **kwargs}}}})

pandas.CategoricalIndex.difference

CategoricalIndex.difference(\texttt{other})

Compute sorted set difference of two Index objects

\textbf{Parameters}

\texttt{other} : Index or array-like

\textbf{Returns}

\texttt{diff} : Index

\textbf{Notes}

One can do either of these and achieve the same result

\texttt{>>> index.difference(index2)}
pandas.CategoricalIndex.drop

CategoricalIndex.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

pandas.CategoricalIndex.drop_duplicates

CategoricalIndex.drop_duplicates(*args, **kwargs)
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.
take_last : deprecated

Returns deduplicated : Index

pandas.CategoricalIndex.duplicated

CategoricalIndex.duplicated(*args, **kwargs)
Return boolean np.array denoting duplicate values

Parameters keep : {'first', 'last', False}, default 'first'
  • 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.
take_last : deprecated

Returns duplicated : np.array

pandas.CategoricalIndex.equals

CategoricalIndex.equals(other)
Determines if two CategoricalIndex objects contain the same elements.

pandas.CategoricalIndex.factorize

CategoricalIndex.factorize(sort=False, na_sentinel=-1)
Encode the object as an enumerated type or categorical variable

Parameters sort : boolean, default False
  Sort by values
na_sentinel: int, default -1

Value to mark “not found”

Returns
labels : the indexer to the original array
uniques : the unique Index

pandas.CategoricalIndex.format

CategoricalIndex.format(name=False, formatter=None, **kwargs)

Render a string representation of the Index

pandas.CategoricalIndex.get_duplicates

CategoricalIndex.get_duplicates()

pandas.CategoricalIndex.get_indexer

CategoricalIndex.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. The mask determines whether labels are found or not in the current index

Parameters

- target : MultiIndex or Index (of tuples)
- method : {'pad', 'ffill', 'backfill', 'bfill'}
  
  pad / ffill: propagate LAST valid observation forward to next valid backfill / bfill:
  use NEXT valid observation to fill gap

Returns

- (indexer, mask) : (ndarray, ndarray)

Notes

This is a low-level method and probably should be used at your own risk

Examples

>>> indexer, mask = index.get_indexer(new_index)
>>> new_values = cur_values.take(indexer)
>>> new_values[-mask] = np.nan

pandas.CategoricalIndex.get_indexer_for

CategoricalIndex.get_indexer_for(target, **kwargs)

guaranteed return of an indexer even when non-unique

pandas.CategoricalIndex.get_indexer_non_unique

CategoricalIndex.get_indexer_non_unique(target)

this is the same for a CategoricalIndex for get_indexer; the API returns the missing values as well
**pandas.CategoricalIndex.get_level_values**

*CategoricalIndex.get_level_values*(level)  
Return vector of label values for requested level, equal to the length of the index

- **Parameters**  
  - level : int  
  - **Returns**  
  - values : ndarray

**pandas.CategoricalIndex.get_loc**

*CategoricalIndex.get_loc*(key, method=None)  
Get integer location for requested label

- **Parameters**  
  - key : label  
  - method : {None}  
  - • default: exact matches only.  
  - **Returns**  
  - loc : int if unique index, possibly slice or mask if not

**pandas.CategoricalIndex.get_slice_bound**

*CategoricalIndex.get_slice_bound*(label, side, kind)  
Calculate slice bound that corresponds to given label.

- Returns leftmost (one-past-the-rightmost if side==’right’) position of given label.

- **Parameters**  
  - label : object  
  - side : {'left', 'right'}  
  - kind : string / None, the type of indexer

**pandas.CategoricalIndex.get_value**

*CategoricalIndex.get_value*(series, key)  
Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you’re doing

**pandas.CategoricalIndex.get_values**

*CategoricalIndex.get_values*()  
return the underlying data as an ndarray

**pandas.CategoricalIndex.groupby**

*CategoricalIndex.groupby*(to_groupby)  
Group the index labels by a given array of values.

- **Parameters**  
  - to_groupby : array  
  - Values used to determine the groups.  
  - **Returns**  
  - groups : dict  
  - {group name -> group labels}
pandas.CategoricalIndex.holds_integer

CategoricalIndex.holds_integer()

pandas.CategoricalIndex.identical

CategoricalIndex.identical(other)
Similar to equals, but check that other comparable attributes are also equal

pandas.CategoricalIndex.insert

CategoricalIndex.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

Raises  
ValueError if the item is not in the categories

pandas.CategoricalIndex.intersection

CategoricalIndex.intersection(other)
Form the intersection of two Index objects. Sortedness of the result is not guaranteed

Parameters  
other : Index or array-like

Returns  
intersection : Index

pandas.CategoricalIndex.is

CategoricalIndex.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  
True if both have same underlying data, False otherwise : bool

pandas.CategoricalIndex.is_boolean

CategoricalIndex.is_boolean()

pandas.CategoricalIndex.is_categorical

CategoricalIndex.is_categorical()
pandas.CategoricalIndex.is_floating
CategoricalIndex.is_floating()

pandas.CategoricalIndex.is_integer
CategoricalIndex.is_integer()

pandas.CategoricalIndex.is_lexsorted_for_tuple
CategoricalIndex.is_lexsorted_for_tuple(tup)

pandas.CategoricalIndex.is_mixed
CategoricalIndex.is_mixed()

pandas.CategoricalIndex.is_numeric
CategoricalIndex.is_numeric()

pandas.CategoricalIndex.is_object
CategoricalIndex.is_object()

pandas.CategoricalIndex.is_type_compatible
CategoricalIndex.is_type_compatible(kind)

pandas.CategoricalIndex.isin
CategoricalIndex.isin(values, level=None)
Compute boolean array of whether each index value is found in the passed set of values.

Parameters
values : set or sequence of values
Sought values.
level : str or int, optional
Name or position of the index level to use (if the index is a MultiIndex).

Returns
is_contained : ndarray (boolean dtype)

Notes
If level 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.
pandas.CategoricalIndex.item

CategoricalIndex.item()  
return the first element of the underlying data as a python scalar

pandas.CategoricalIndex.join

CategoricalIndex.join(other, how='left', level=None, return_indexers=False)  
this is an internal non-public method  
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 : boolean, default False

Returns join_index, (left_indexer, right_indexer)

pandas.CategoricalIndex.map

CategoricalIndex.map(mapper)

pandas.CategoricalIndex.max

CategoricalIndex.max(*args, **kwargs)  
The maximum value of the object.  
Only ordered Categoricals have a maximum!

Returns max : the maximum of this Categorical

Raises TypeError  
If the Categorical is not ordered.

pandas.CategoricalIndex.min

CategoricalIndex.min(*args, **kwargs)  
The minimum value of the object.  
Only ordered Categoricals have a minimum!

Returns min : the minimum of this Categorical

Raises TypeError  
If the Categorical is not ordered.
pandas.CategoricalIndex.nunique

CategoricalIndex.nunique (dropna=True)
Return number of unique elements in the object.
Excludes NA values by default.

Parameters dropna : boolean, default True
Don’t include NaN in the count.

Returns nunique : int

pandas.CategoricalIndex.order

CategoricalIndex.order (return_indexer=False, ascending=True)
Return sorted copy of Index
DEPRECATED: use Index.sort_values()

pandas.CategoricalIndex.putmask

CategoricalIndex.putmask (mask, value)
return a new Index of the values set with the mask

See also:
numpy.ndarray.putmask

pandas.CategoricalIndex.ravel

CategoricalIndex.ravel (order='C')
return an ndarray of the flattened values of the underlying data

See also:
numpy.ndarray.ravel

pandas.CategoricalIndex.reindex

CategoricalIndex.reindex (target, method=None, level=None, limit=None, tolerance=None)
Create index with target’s values (move/add/delete values as necessary)

Returns new_index : pd.Index
Resulting index

indexer : np.ndarray or None
Indices of output values in original index

pandas.CategoricalIndex.remove_categories

CategoricalIndex.remove_categories (*args, **kwargs)
Removes 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 : boolean (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, reorder_categories, add_categories, remove_unused_categories, set_categories

---

**pandas.CategoricalIndex.remove_unused_categories**

CategoricalIndex.remove_unused_categories(*args, **kwargs)

Removes categories which are not used.

**Parameters** inplace : boolean (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, reorder_categories, add_categories, remove_categories, set_categories

---

**pandas.CategoricalIndex.rename**

CategoricalIndex.rename(name, inplace=False)

Set new names on index. Defaults to returning new index.

**Parameters** name : str or list

name to set

inplace : bool

if True, mutates in place

**Returns** new index (of same type and class...etc) [if inplace, returns None]

---

**pandas.CategoricalIndex.rename_categories**

CategoricalIndex.rename_categories(*args, **kwargs)

Renames categories.

The new categories 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.

**Parameters** new_categories : Index-like
The renamed categories.

**inplace** : boolean (default: False)

Whether or not to rename the categories inplace or return a copy of this categorical with renamed categories.

**Returns** **cat** : Categorical with renamed categories added or None if inplace.

**Raises** **ValueError**

If the new categories do not have the same number of items than the current categories or do not validate as categories

**See also:**

rename_categories, add_categories, remove_categories, remove_unused_categories, set_categories

---

**pandas.CategoricalIndex.reorder_categories**

CategoricalIndex.reorder_categories(*args, **kwargs)

Reorders 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** : boolean, optional

Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

**inplace** : boolean (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, add_categories, remove_categories, remove_unused_categories, set_categories

---

**pandas.CategoricalIndex.repeat**

CategoricalIndex.repeat(n)

return a new Index of the values repeated n times

**See also:**

numpy.ndarray.repeat
pandas.CategoricalIndex.searchsorted

CategoricalIndex.searchsorted(key, side='left')
   np.ndarray searchsorted compat

pandas.CategoricalIndex.set_categories

CategoricalIndex.set_categories(*args, **kwargs)
   Sets the categories to the specified new_categories.
   new_categories can include new categories (which will result in unused categories) or 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 on python3, 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 : boolean, (default: False)
      Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.
   rename : boolean (default: False)
      Whether or not the new_categories should be considered as a rename of the old categories or as reordered categories.
   inplace : boolean (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 new_categories does not validate as categories

See also:
   rename_categories, reorder_categories, add_categories, remove_categories, remove_unused_categories

pandas.CategoricalIndex.set_names

CategoricalIndex.set_names(names, level=None, inplace=False)
   Set new names on index. Defaults to returning new index.

Parameters names : str or sequence
   name(s) to set

   level : int or level name, or sequence of int / level names (default None)
If the index is a MultiIndex (hierarchical), level(s) to set (None for all levels)
Otherwise level must be None

**inplace** : bool
if True, mutates in place

**Returns** new index (of same type and class...etc) [if inplace, returns None]

**Examples**

```python
>>> Index([1, 2, 3, 4]).set_names('foo')
Int64Index([1, 2, 3, 4], dtype='int64')
>>> Index([1, 2, 3, 4]).set_names(['foo'])
Int64Index([1, 2, 3, 4], dtype='int64')
>>> idx = MultiIndex.from_tuples(((1, u'one'), (1, u'two'),
                                (2, u'one'), (2, u'two')),
                               names=['foo', 'bar'])
>>> idx.set_names(['baz', 'quz'])
MultiIndex(levels=[[1, 2], [u'one', u'two']],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
           names=[u'baz', u'quz'])
>>> idx.set_names('baz', level=0)
MultiIndex(levels=[[1, 2], [u'one', u'two']],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
           names=[u'baz', u'bar'])
```

**pandas.CategoricalIndex.set_value**

*CategoricalIndex.*set_value*(arr, key, value)*
Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you’re doing

**pandas.CategoricalIndex.shift**

*CategoricalIndex.*shift*(periods=1, freq=None)*
Shift Index containing datetime objects by input number of periods and DateOffset

**Returns** shifted : Index

**pandas.CategoricalIndex.slice_indexer**

*CategoricalIndex.*slice_indexer*(start=None, end=None, step=None, kind=None)*
For an ordered Index, compute the slice indexer for input labels and step

**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 : string, default None

**Returns** indexer : ndarray or slice
Notes

This function assumes that the data is sorted, so use at your own peril

pandas.CategoricalIndex.slice_locs

CategoricalIndex.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**: string, defaults None

Returns

- **start, end**: int

pandas.CategoricalIndex.sort

CategoricalIndex.sort(*args, **kwargs)

pandas.CategoricalIndex.sort_values

CategoricalIndex.sort_values(return_indexer=False, ascending=True)
Return sorted copy of Index

pandas.CategoricalIndex.sortlevel

CategoricalIndex.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**: boolean, default True
  - False to sort in descending order
- **level, sort_remaining are compat paramaters**

Returns

- **sorted_index**: Index

pandas.CategoricalIndex.str

CategoricalIndex.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.str.split('_')
>>> s.str.replace('_', '')
```

**pandas.CategoricalIndex.summary**

```
CategoricalIndex.summary(name=None)
```

**pandas.CategoricalIndex.sym_diff**

```
CategoricalIndex.sym_diff(other, result_name=None)
```

Parameters

- `other` : Index or array-like
- `result_name` : str

Returns

- `sym_diff` : Index

Notes

- `sym_diff` contains elements that appear in either `idx1` or `idx2` but not both. Equivalent to the Index created by `(idx1 - idx2) + (idx2 - idx1)` with duplicates dropped.

The sorting of a result containing NaN values is not guaranteed across Python versions. See GitHub issue #6444.

Examples

```python
>>> idx1 = Index([1, 2, 3, 4])
>>> idx2 = Index([2, 3, 4, 5])
>>> idx1.sym_diff(idx2)
Int64Index([1, 5], dtype='int64')
```

You can also use the `^` operator:

```python
>>> idx1 ^ idx2
Int64Index([1, 5], dtype='int64')
```

**pandas.CategoricalIndex.take**

```
CategoricalIndex.take(indexer, axis=0, allow_fill=True, fill_value=None)
```

For internal compatibility with numpy arrays.

# filling must always be None/nan here # but is passed thru internally assert isnull(fill_value)

See also:

- `numpy.ndarray.take`

34.8. CategoricalIndex 1573
**pandas.CategoricalIndex.to_datetime**

CategoricalIndex\[to\_datetime](dayfirst=False)

For an Index containing strings or datetime.datetime objects, attempt conversion to DatetimeIndex.

**pandas.CategoricalIndex.to_native_types**

CategoricalIndex\[to\_native\_types](slicer=None, **kwargs)

Slice and dice then format.

**pandas.CategoricalIndex.to_series**

CategoricalIndex\[to\_series](**kwargs)

Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index.

**Returns** Series: dtype will be based on the type of the Index values.

**pandas.CategoricalIndex.tolist**

CategoricalIndex\[tolist\]()

Return a list of the Index values.

**pandas.CategoricalIndex.transpose**

CategoricalIndex\[transpose\]()

Return the transpose, which is by definition self.

**pandas.CategoricalIndex.union**

CategoricalIndex\[union\](other)

Form the union of two Index objects and sorts if possible.

**Parameters** other: Index or array-like

**Returns** union: Index

**pandas.CategoricalIndex.unique**

CategoricalIndex\[unique\]()

Return array of unique values in the object. Significantly faster than numpy.unique. Includes NA values.

**Returns** uniques: ndarray

**pandas.CategoricalIndex.value_counts**

CategoricalIndex\[value\_counts\](normalize=False, sort=True, ascending=False, bins=None, dropna=True)

Returns object 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**: boolean, default False
  If True then the object returned will contain the relative frequencies of the unique values.

- **sort**: boolean, default True
  Sort by values

- **ascending**: boolean, default False
  Sort in ascending order

- **bins**: integer, optional
  Rather than count values, group them into half-open bins, a convenience for \texttt{pd.cut}, only works with numeric data

- **dropna**: boolean, default True
  Don’t include counts of NaN.

Returns

- **counts**: Series

\texttt{pandas.CategoricalIndex.view}

\texttt{CategoricalIndex.view(cls=None)}

### 34.8.2 Categorical Components

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>\texttt{CategoricalIndex.codes}</td>
<td>Returns the codes of the categories.</td>
</tr>
<tr>
<td>\texttt{CategoricalIndex.categories}</td>
<td>Returns the categories of the CategoricalIndex.</td>
</tr>
<tr>
<td>\texttt{CategoricalIndex.ordered}</td>
<td>Returns the ordered CategoricalIndex.</td>
</tr>
<tr>
<td>\texttt{CategoricalIndex.rename_categories(*args,...)}</td>
<td>Renames the categories.</td>
</tr>
<tr>
<td>\texttt{CategoricalIndex.reorder_categories(*args,...)}</td>
<td>Reorders categories as specified in new_categories.</td>
</tr>
<tr>
<td>\texttt{CategoricalIndex.add_categories(*args,**kwargs)}</td>
<td>Add new categories.</td>
</tr>
<tr>
<td>\texttt{CategoricalIndex.remove_categories(*args,...)}</td>
<td>Removes the specified categories.</td>
</tr>
<tr>
<td>\texttt{CategoricalIndex.remove_unused_categories(...)}</td>
<td>Removes categories which are not used.</td>
</tr>
<tr>
<td>\texttt{CategoricalIndex.set_categories(*args,**kwargs)}</td>
<td>Sets the categories to the specified new_categories.</td>
</tr>
<tr>
<td>\texttt{CategoricalIndex.as_ordered(*args,**kwargs)}</td>
<td>Sets the Categorical to be ordered.</td>
</tr>
<tr>
<td>\texttt{CategoricalIndex.as_unordered(*args,**kwargs)}</td>
<td>Sets the Categorical to be unordered.</td>
</tr>
</tbody>
</table>

\texttt{pandas.CategoricalIndex.codes}

\texttt{CategoricalIndex.codes}

\texttt{pandas.CategoricalIndex.categories}

\texttt{CategoricalIndex.categories}

\texttt{pandas.CategoricalIndex.ordered}

\texttt{CategoricalIndex.ordered}
pandas.CategoricalIndex.rename_categories

CategoricalIndex.rename_categories(*args, **kwargs)

Renames categories.

The new categories 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.

Parameters new_categories : Index-like

The renamed categories.

inplace : boolean (default: False)

Whether or not to rename the categories inplace or return a copy of this categorical
with renamed categories.

Returns cat : Categorical with renamed categories added or None if inplace.

Raises ValueError

If the new categories do not have the same number of items than the current cate-
gories or do not validate as categories

See also:

reorder_categories, add_categories, remove_categories,
remove_unused_categories, set_categories

pandas.CategoricalIndex.reorder_categories

CategoricalIndex.reorder_categories(*args, **kwargs)

Reorders 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 : boolean, optional

Whether or not the categorical is treated as a ordered categorical. If not given, do
not change the ordered information.

inplace : boolean (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, add_categories, remove_categories,
remove_unused_categories, set_categories
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 : boolean (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, reorder_categories, remove_categories, remove_unused_categories, set_categories

pandas.CategoricalIndex.remove_categories

CategoricalIndex.remove_categories(*args, **kwargs)

Removes 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 : boolean (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, reorder_categories, add_categories, remove_unused_categories, set_categories

pandas.CategoricalIndex.remove_unused_categories

CategoricalIndex.remove_unused_categories(*args, **kwargs)

Removes categories which are not used.

**Parameters**

inplace : boolean (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, reorder_categories, add_categories, remove_categories, set_categories

**pandas.CategoricalIndex.set_categories**

CategoricalIndex.set_categories(*args, **kwargs)

Sets the categories to the specified new_categories.

new_categories can include new categories (which will result in unused categories) or 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 on python3, 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 : boolean, (default: False)

Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

rename : boolean (default: False)

Whether or not the new_categories should be considered as a rename of the old categories or as reordered categories.

inplace : boolean (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 new_categories does not validate as categories

See also:

rename_categories, reorder_categories, add_categories, remove_categories, remove_unused_categories

**pandas.CategoricalIndex.as_ordered**

CategoricalIndex.as_ordered(*args, **kwargs)

Sets the Categorical to be ordered

**Parameters** inplace : boolean (default: False)
Whether or not to set the ordered attribute inplace or return a copy of this categorical with ordered set to True

**pandas.CategoricalIndex.as_unordered**

CategoricalIndex.as_unordered(*args, **kwargs)

Sets the Categorical to be unordered

**Parameters** inplace : boolean (default: False)

Whether or not to set the ordered attribute inplace or return a copy of this categorical with ordered set to False

### 34.9 DatetimeIndex

**DatetimeIndex** Immutable ndarray of datetime64 data, represented internally as int64, and which can be boxed to Timestamp objects that are subclasses of datetime and carry metadata such as frequency information.

#### 34.9.1 pandas.DatetimeIndex

**class pandas.DatetimeIndex**

Immutable ndarray of datetime64 data, represented internally as int64, and which can be boxed to Timestamp objects that are subclasses of datetime and carry metadata such as frequency information.

**Parameters**

**data** : array-like (1-dimensional), optional

Optional datetime-like data to construct index with

**copy** : bool

Make a copy of input ndarray

**freq** : string or pandas offset object, optional

One of pandas date offset strings or corresponding objects

**start** : starting value, datetime-like, optional

If data is None, start is used as the start point in generating regular timestamp data.

**periods** : int, optional, > 0

Number of periods to generate, if generating index. Takes precedence over end argument

**end** : end time, datetime-like, optional

If periods is none, generated index will extend to first conforming time on or just past end argument

**closed** : string or None, default None

Make the interval closed with respect to the given frequency to the ‘left’, ‘right’, or both sides (None)

**tz** : pytz.timezone or dateutil.tz.tzfile

**ambiguous** : ‘infer’, bool-ndarray, ‘NaT’, default ‘raise’

• ‘infer’ will attempt to infer fall dst-transition hours based on order
pandas: powerful Python data analysis toolkit, Release 0.17.0

- 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

**infer_dst**: boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

**name**: object

Name to be stored in the index

### Attributes

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>T</td>
<td>return the transpose, which is by definition self</td>
</tr>
<tr>
<td>asi8</td>
<td>return the base object if the memory of the underlying data is shared</td>
</tr>
<tr>
<td>asobject</td>
<td>return the data pointer of the underlying data</td>
</tr>
<tr>
<td>base</td>
<td>Returns numpy array of datetime.date.</td>
</tr>
<tr>
<td>data</td>
<td>The days of the datetime</td>
</tr>
<tr>
<td>date</td>
<td>The day of the week with Monday=0, Sunday=6</td>
</tr>
<tr>
<td>day</td>
<td>The ordinal day of the year</td>
</tr>
<tr>
<td>dayofweek</td>
<td>The number of days in the month</td>
</tr>
<tr>
<td>dayofyear</td>
<td>The number of days in the month</td>
</tr>
<tr>
<td>days_in_month</td>
<td>The number of days in the month</td>
</tr>
<tr>
<td>daysinmonth</td>
<td>get/set the frequency of the Index</td>
</tr>
<tr>
<td>dtype</td>
<td>return the frequency object as a string if its set, otherwise None</td>
</tr>
<tr>
<td>dtype_str</td>
<td>The hours of the datetime</td>
</tr>
<tr>
<td>flags</td>
<td>alias for is_monotonic_increasing (deprecated)</td>
</tr>
<tr>
<td>freq</td>
<td>return if the index is monotonic decreasing (only equal or</td>
</tr>
<tr>
<td>freqstr</td>
<td>return if the index is monotonic increasing (only equal or</td>
</tr>
<tr>
<td>has_duplicates</td>
<td>Logical indicating if last day of month (defined by frequency)</td>
</tr>
<tr>
<td>hasnans</td>
<td>Logical indicating if first day of month (defined by frequency)</td>
</tr>
<tr>
<td>hour</td>
<td>Logical indicating if last day of quarter (defined by frequency)</td>
</tr>
<tr>
<td>inferred_freq</td>
<td>Logical indicating if first day of quarter (defined by frequency)</td>
</tr>
<tr>
<td>inferred_type</td>
<td>alias for is_monotonic_increasing (deprecated)</td>
</tr>
<tr>
<td>is_all_dates</td>
<td>Logical indicating if last day of year (defined by frequency)</td>
</tr>
<tr>
<td>is_monotonic</td>
<td>Logical indicating if first day of year (defined by frequency)</td>
</tr>
<tr>
<td>is_monotonic_decreasing</td>
<td>return the size of the dtype of the item of the underlying data</td>
</tr>
<tr>
<td>is_monotonic_increasing</td>
<td>The microseconds of the datetime</td>
</tr>
<tr>
<td>is_month_end</td>
<td>The milliseconds of the datetime</td>
</tr>
<tr>
<td>is_month_start</td>
<td>The minutes of the datetime</td>
</tr>
<tr>
<td>is_normalized</td>
<td>The month as January=1, December=12</td>
</tr>
<tr>
<td>is_quarter_end</td>
<td>Logical indicating if last day of quarter (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_unique</td>
<td>Logical indicating if last day of year (defined by frequency)</td>
</tr>
<tr>
<td>is_year_end</td>
<td>Logical indicating if first day of year (defined by frequency)</td>
</tr>
<tr>
<td>is_year_start</td>
<td>return the size of the dtype of the item of the underlying data</td>
</tr>
<tr>
<td>itemsize</td>
<td>The microseconds of the datetime</td>
</tr>
<tr>
<td>millisecond</td>
<td>The milliseconds of the datetime</td>
</tr>
<tr>
<td>minute</td>
<td>The minutes of the datetime</td>
</tr>
<tr>
<td>month</td>
<td>The month as January=1, December=12</td>
</tr>
</tbody>
</table>

Continued on next page
Table 34.105 – continued from previous page

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>name</td>
<td>names</td>
</tr>
<tr>
<td>nanosecond</td>
<td>The nanoseconds of the datetime</td>
</tr>
<tr>
<td>nbytes</td>
<td>return the number of bytes in the underlying data</td>
</tr>
<tr>
<td>ndim</td>
<td>return the number of dimensions of the underlying data, by definition 1</td>
</tr>
<tr>
<td>nlevels</td>
<td>offset</td>
</tr>
<tr>
<td>quarter</td>
<td>The quarter of the date</td>
</tr>
<tr>
<td>resolution</td>
<td>The seconds of the datetime</td>
</tr>
<tr>
<td>second</td>
<td>return a tuple of the shape of the underlying data</td>
</tr>
<tr>
<td>shape</td>
<td>return the number of elements in the underlying data</td>
</tr>
<tr>
<td>size</td>
<td>return the strides of the underlying data</td>
</tr>
<tr>
<td>strides</td>
<td>time</td>
</tr>
<tr>
<td>time</td>
<td>Returns numpy array of datetime.time.</td>
</tr>
<tr>
<td>tz</td>
<td>tzinfo</td>
</tr>
<tr>
<td>values</td>
<td>Alias for tz attribute</td>
</tr>
<tr>
<td>week</td>
<td>return the underlying data as an ndarray</td>
</tr>
<tr>
<td>weekday</td>
<td>The day of the week with Monday=0, Sunday=6</td>
</tr>
<tr>
<td>weekofyear</td>
<td>The week ordinal of the year</td>
</tr>
<tr>
<td>year</td>
<td>The year of the datetime</td>
</tr>
</tbody>
</table>

**pandas.DatetimeIndex.T**

Datet imeIndex.T
return the transpose, which is by definition self

**pandas.DatetimeIndex.asi8**

Datet imeIndex.asi8

**pandas.DatetimeIndex.asobject**

Datet imeIndex.asobject

**pandas.DatetimeIndex.base**

Datet imeIndex.base
return the base object if the memory of the underlying data is shared

**pandas.DatetimeIndex.data**

Datet imeIndex.data
return the data pointer of the underlying data

**pandas.DatetimeIndex.date**

Datet imeIndex.date
Returns numpy array of datet ime.date. The date part of the Timestamps.
pandas.DatetimeIndex.day

```
DatetimeIndex.day
The days of the datetime
```

pandas.DatetimeIndex.dayofweek

```
DatetimeIndex.dayofweek
The day of the week with Monday=0, Sunday=6
```

pandas.DatetimeIndex.dayofyear

```
DatetimeIndex.dayofyear
The ordinal day of the year
```

pandas.DatetimeIndex.days_in_month

```
DatetimeIndex.days_in_month
The number of days in the month
New in version 0.16.0.
```

pandas.DatetimeIndex.daysinmonth

```
DatetimeIndex.daysinmonth
The number of days in the month
New in version 0.16.0.
```

pandas.DatetimeIndex.dtype

```
DatetimeIndex.dtype = None
```

pandas.DatetimeIndex.dtype_str

```
DatetimeIndex.dtype_str = None
```

pandas.DatetimeIndex.flags

```
DatetimeIndex.flags
```

pandas.DatetimeIndex.freq

```
DatetimeIndex.freq
get/set the frequency of the Index
```
pandas.DatetiimelIndex.freqstr

```
DatetimeIndex.freqstr
return the frequency object as a string if its set, otherwise None
```

pandas.DatetiimelIndex.has_duplicates

```
DatetimeIndex.has_duplicates
```

pandas.DatetiimelIndex.hasnans

```
DatetimeIndex.hasnans = None
```

pandas.DatetiimelIndex.hour

```
DatetimeIndex.hour
The hours of the datetime
```

pandas.DatetiimelIndex.inferred_freq

```
DatetimeIndex.inferred_freq = None
```

pandas.DatetiimelIndex.inferred_type

```
DatetimeIndex.inferred_type
```

pandas.DatetiimelIndex.is_all_dates

```
DatetimeIndex.is_all_dates
```

pandas.DatetiimelIndex.is_monotonic

```
DatetimeIndex.is_monotonic
alias for is_monotonic_increasing (deprecated)
```

pandas.DatetiimelIndex.is_monotonic_decreasing

```
DatetimeIndex.is_monotonic_decreasing
return if the index is monotonic decreasing (only equal or decreasing) values.
```

pandas.DatetiimelIndex.is_monotonic_increasing

```
DatetimeIndex.is_monotonic_increasing
return if the index is monotonic increasing (only equal or increasing) values.
```
pandas.DatetimeIndex.is_month_end

DatetimeIndex.is_month_end
Logical indicating if last day of month (defined by frequency)

pandas.DatetimeIndex.is_month_start

DatetimeIndex.is_month_start
Logical indicating if first day of month (defined by frequency)

pandas.DatetimeIndex.is_normalized

DatetimeIndex.is_normalized = None

pandas.DatetimeIndex.is_quarter_end

DatetimeIndex.is_quarter_end
Logical indicating if last day of quarter (defined by frequency)

pandas.DatetimeIndex.is_quarter_start

DatetimeIndex.is_quarter_start
Logical indicating if first day of quarter (defined by frequency)

pandas.DatetimeIndex.is_unique

DatetimeIndex.is_unique = None

pandas.DatetimeIndex.is_year_end

DatetimeIndex.is_year_end
Logical indicating if last day of year (defined by frequency)

pandas.DatetimeIndex.is_year_start

DatetimeIndex.is_year_start
Logical indicating if first day of year (defined by frequency)

pandas.DatetimeIndex.itemsize

DatetimeIndex.itemsize
return the size of the dtype of the item of the underlying data

pandas.DatetimeIndex.microsecond

DatetimeIndex.microsecond
The microseconds of the datetime
pandas.DatetimeIndex.millisecond

DatetimeIndex.millisecond
The milliseconds of the datetime

pandas.DatetimeIndex.minute

DatetimeIndex.minute
The minutes of the datetime

pandas.DatetimeIndex.month

DatetimeIndex.month
The month as January=1, December=12

pandas.DatetimeIndex.name

DatetimeIndex.name = None

pandas.DatetimeIndex.names

DatetimeIndex.names

pandas.DatetimeIndex.nanosecond

DatetimeIndex.nanosecond
The nanoseconds of the datetime

pandas.DatetimeIndex.nbytes

DatetimeIndex.nbytes
return the number of bytes in the underlying data

pandas.DatetimeIndex.ndim

DatetimeIndex.ndim
return the number of dimensions of the underlying data, by definition 1

pandas.DatetimeIndex.nlevels

DatetimeIndex.nlevels

pandas.DatetimeIndex.offset

DatetimeIndex.offset = None
pandas.DatetimeIndex.quarter

DatetimeIndex.quarter
The quarter of the date

pandas.DatetimeIndex.resolution

DatetimeIndex.resolution = None

pandas.DatetimeIndex.second

DatetimeIndex.second
The seconds of the datetime

pandas.DatetimeIndex.shape

DatetimeIndex.shape
return a tuple of the shape of the underlying data

pandas.DatetimeIndex.size

DatetimeIndex.size
return the number of elements in the underlying data

pandas.DatetimeIndex.strides

DatetimeIndex.strides
return the strides of the underlying data

pandas.DatetimeIndex.time

DatetimeIndex.time
Returns numpy array of datetime.time. The time part of the Timestamps.

pandas.DatetimeIndex.tz

DatetimeIndex.tz = None

pandas.DatetimeIndex.tzinfo

DatetimeIndex.tzinfo
Alias for tz attribute

pandas.DatetimeIndex.values

DatetimeIndex.values
return the underlying data as an ndarray
**pandas.DatetimeIndex.week**

DatetimeIndex.week
The week ordinal of the year

**pandas.DatetimeIndex.weekday**

DatetimeIndex.weekday
The day of the week with Monday=0, Sunday=6

**pandas.DatetimeIndex.weekofyear**

DatetimeIndex.weekofyear
The week ordinal of the year

**pandas.DatetimeIndex.year**

DatetimeIndex.year
The year of the datetime

**Methods**

- `all([other])`
  - Append a collection of Index options together
  - Return a ndarray of the maximum argument indexer

- `any([other])`
  - Return a ndarray of the minimum argument indexer
  - Return an ndarry indexer of the underlying data

- `append(other)`
  - For a sorted index, return the most recent label up to and including the passed label.
  - Where : array of timestamps

- `argmax([axis])`
  - Make a copy of this object.
  - Make a new DatetimeIndex with passed location(s) deleted.

- `argmin([axis])`
  - Compute sorted set difference of two Index objects
  - Make new Index with passed list of labels deleted
  - Return Index with duplicate values removed

- `argsort(*args, **kwargs)`
  - Determines if two Index objects contain the same elements.
  - Encode the object as an enumerated type or categorical variable

- `asof(label)`
  - Render a string representation of the Index
  - Render a string representation of the Index

- `asof_locs(where, mask)`
  - Get integer location for requested label
  - Get integer location for requested label

- `astype(dtype)`
  - Get slice bound that corresponds to given label.
  - Fast lookup of value from 1-dimensional ndarray.

- `copy([names, name, dtype, deep])`
  - Get slice bound that corresponds to given label.
  - Fast lookup of value from 1-dimensional ndarray.

- `delete(loc)`
  - Returns an array of timestamps

- `diff(*args, **kwargs)`
  - Returns an array of timestamps

- `difference(other)`
  - Returns an array of timestamps

- `drop(labels[, errors])`
  - Returns an array of timestamps

- `drop_duplicates(*args, **kwarsgs)`
  - Returns an array of timestamps

- `duplicated(*args, **kwarsgs)`
  - Returns an array of timestamps

- `equals(other)`
  - Returns an array of timestamps

- `factorize([sort, na_sentinel])`
  - Returns an array of timestamps

- `format([name, formatter])`
  - Returns an array of timestamps

- `get_duplicates()`
  - Returns an array of timestamps

- `get_indexer(target[, method, limit, tolerance])`
  - Returns an array of timestamps

- `get_indexer_for(target, **kwargs)`
  - Returns an array of timestamps

- `get_indexer_non_unique(target)`
  - Returns an array of timestamps

- `get_level_values(level)`
  - Returns an array of timestamps

- `get_loc(key[, method, tolerance])`
  - Returns an array of timestamps

- `get_slice_bound(label, side, kind)`
  - Returns an array of timestamps

- `get_value(series, key)`
  - Returns an array of timestamps
Table 34.106 – continued from previous page

<table>
<thead>
<tr>
<th>pandas: powerful Python data analysis toolkit, Release 0.17.0</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Method</strong></td>
</tr>
<tr>
<td>get_value_maybe_box</td>
</tr>
<tr>
<td>get_values</td>
</tr>
<tr>
<td>groupby</td>
</tr>
<tr>
<td>holds_integer</td>
</tr>
<tr>
<td>identical</td>
</tr>
<tr>
<td>indexer_at_time</td>
</tr>
<tr>
<td>indexer_between_time</td>
</tr>
<tr>
<td>insert</td>
</tr>
<tr>
<td>intersection</td>
</tr>
<tr>
<td>is_(other)</td>
</tr>
<tr>
<td>is_boolean</td>
</tr>
<tr>
<td>is_categorical</td>
</tr>
<tr>
<td>is_float</td>
</tr>
<tr>
<td>is_integer</td>
</tr>
<tr>
<td>is_lexsorted for_tuple</td>
</tr>
<tr>
<td>is_mixed</td>
</tr>
<tr>
<td>is_numeric</td>
</tr>
<tr>
<td>is_object</td>
</tr>
<tr>
<td>is_type_compatible</td>
</tr>
<tr>
<td>isin</td>
</tr>
<tr>
<td>item</td>
</tr>
<tr>
<td>join</td>
</tr>
<tr>
<td>map</td>
</tr>
<tr>
<td>max</td>
</tr>
<tr>
<td>min</td>
</tr>
<tr>
<td>normalize</td>
</tr>
<tr>
<td>nunique</td>
</tr>
<tr>
<td>order</td>
</tr>
<tr>
<td>putmask</td>
</tr>
<tr>
<td>ravel</td>
</tr>
<tr>
<td>reindex</td>
</tr>
<tr>
<td>rename</td>
</tr>
<tr>
<td>repeat</td>
</tr>
<tr>
<td>searchsorted</td>
</tr>
<tr>
<td>set_names</td>
</tr>
<tr>
<td>set_value</td>
</tr>
<tr>
<td>shift</td>
</tr>
<tr>
<td>slice_indexer</td>
</tr>
<tr>
<td>slice_locs</td>
</tr>
<tr>
<td>snap</td>
</tr>
<tr>
<td>sort</td>
</tr>
<tr>
<td>sort_values</td>
</tr>
<tr>
<td>sortlevel</td>
</tr>
<tr>
<td>str</td>
</tr>
<tr>
<td>strftime</td>
</tr>
<tr>
<td>summary</td>
</tr>
<tr>
<td>sym_diff</td>
</tr>
<tr>
<td>take</td>
</tr>
<tr>
<td>to_datetime</td>
</tr>
<tr>
<td>to_julian_date</td>
</tr>
<tr>
<td>to_native_types</td>
</tr>
<tr>
<td>to_period</td>
</tr>
</tbody>
</table>

*Return the underlying data as an ndarray*

*Similar to equals, but check that other comparable attributes are*

*Select values at particular time of day (e.g.)*

*Select values between particular times of day (e.g., 9:00-9:30AM)*

*Make new Index inserting new item at location*

*SPECIALIZED INTERSECTION FOR DATETIMEINDEX OBJECTS.*

*More flexible, faster check like is but that works through views*

*Compute boolean array of whether each index value is found in the*

*return the first element of the underlying data as a python scalar*

See Index.join

*Return the maximum value of the Index*

*Return the minimum value of the Index*

*Return DatetimeIndex with times to midnight.*

*Return number of unique elements in the object.*

*Return sorted copy of Index*

*Return a new Index of the values set with the mask*

*Return an ndarry of the flattened values of the underlying data*

*Create index with target’s values (move/add/delete values as necessary)*

*Set new names on index.*

*Analogous to ndarray.repeat*

*Set new names on index.*

*Fast lookup of value from 1-dimensional ndarray.*

*Specialized shift which produces a DatetimeIndex*

*Return indexer for specified label slice.*

*Compute slice locations for input labels.*

*Snap time stamps to nearest occurring frequency*

*Return sorted copy of Index*

*For internal compatibility with with the Index API*

*alias of StringMethods*

*Return an array of formatted strings specified by date_format, which supports*

*return a summarized representation*

*Compute the sorted symmetric difference of two Index objects.*

*Analogous to ndarray.take*

*Convert DatetimeIndex to Float64Index of Julian Dates.*

*slicer and dice then format*

*Cast to PeriodIndex at a particular frequency*
<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>to_perioddelta(freq)</code></td>
<td>Calculates TimedeltaIndex of difference between index values and index converted to PeriodIndex at specified freq.</td>
</tr>
<tr>
<td><code>to_pydatetime()</code></td>
<td>Return DatetimeIndex as object ndarray of datetime.datetime objects.</td>
</tr>
<tr>
<td><code>to_series([keep_tz])</code></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 underlying data.</td>
</tr>
<tr>
<td><code>transpose()</code></td>
<td>Return the transpose, which is by definition self.</td>
</tr>
<tr>
<td><code>tz_convert(tz)</code></td>
<td>Convert tz-aware DatetimeIndex from one time zone to another (using pytz/dateutil).</td>
</tr>
<tr>
<td><code>tz_localize(*args, **kwargs)</code></td>
<td>Localize tz-naive DatetimeIndex to given time zone (using pytz/dateutil).</td>
</tr>
<tr>
<td><code>union(other)</code></td>
<td>Specialized union for DatetimeIndex objects.</td>
</tr>
<tr>
<td><code>union_many(others)</code></td>
<td>A bit of a hack to accelerate unioning a collection of indexes.</td>
</tr>
<tr>
<td><code>unique()</code></td>
<td>Index.unique with handling for DatetimeIndex/PeriodIndex metadata.</td>
</tr>
<tr>
<td><code>value_counts([normalize, sort, ascending, ...])</code></td>
<td>Returns object containing counts of unique values.</td>
</tr>
</tbody>
</table>

---

**pandas.DatetimeIndex.all**

```python
DatetimeIndex.all(other=None)
```

**pandas.DatetimeIndex.any**

```python
DatetimeIndex.any(other=None)
```

**pandas.DatetimeIndex.append**

```python
DatetimeIndex.append(other)
```

Parameters

- `other`: Index or list/tuple of indices

Returns

- `appended`: Index

**pandas.DatetimeIndex.argmax**

```python
DatetimeIndex.argmax(axis=None)
```

Returns a ndarray of the maximum argument indexer.

See also:

- `numpy.ndarray.argmax`

**pandas.DatetimeIndex.argmin**

```python
DatetimeIndex.argmin(axis=None)
```

Returns a ndarray of the minimum argument indexer.

See also:

- `numpy.ndarray.argmin`
pandas.DatetimeIndex.argsort

```
DatetimeIndex.argsort(*args, **kwargs)
```

Return an ndarray indexer of the underlying data

See also:

```
numpy.ndarray.argsort
```

pandas.DatetimeIndex.asof

```
DatetimeIndex.asof(label)
```

For a sorted index, return the most recent label up to and including the passed label. Return NaN if not found.

See also:

```
get_loc asof is a thin wrapper around get_loc with method='pad'
```

pandas.DatetimeIndex.asof_locs

```
DatetimeIndex.asof_locs(where, mask)
```

where : array of timestamps
mask : array of booleans where data is not NA

pandas.DatetimeIndex.astype

```
DatetimeIndex.astype(dtype)
```

pandas.DatetimeIndex.copy

```
DatetimeIndex.copy(names=None, name=None, dtype=None, deep=False)
```

Make a copy of this object. Name and dtype sets those attributes on the new object.

Parameters
```
name : string, optional
dtype : numpy dtype or pandas type
```

Returns
```
copy : Index
```

Notes

In most cases, there should be no functional difference from using deep, but if deep is passed it will attempt to deepcopy.

pandas.DatetimeIndex.delete

```
DatetimeIndex.delete(loc)
```

Make a new DatetimeIndex with passed location(s) deleted.

Parameters
```
loc : int, slice or array of ints
```

Indicate which sub-arrays to remove.

Returns
```
new_index : DatetimeIndex
```

pandas.DatetimeIndex.diff

DatetimeIndex.diff(*args, **kwargs)

pandas.DatetimeIndex.difference

DatetimeIndex.difference(other)
Compute sorted set difference of two Index objects

Parameters other : Index or array-like

Returns diff : Index

Notes

One can do either of these and achieve the same result

>>> index.difference(index2)

pandas.DatetimeIndex.drop

DatetimeIndex.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

pandas.DatetimeIndex.drop_duplicates

DatetimeIndex.drop_duplicates(*args, **kwargs)
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.

taxe_last : deprecated

Returns deduplicated : Index

pandas.DatetimeIndex.duplicated

DatetimeIndex.duplicated(*args, **kwargs)
Return boolean np.array denoting duplicate values

Parameters keep : {'first', 'last', False}, default 'first'

- 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.

```
take_last : deprecated
```

Returns duplicated: np.array

**pandas.DatetimeIndex.equals**

```
DatetimeIndex.equals(other)
```
Determines if two Index objects contain the same elements.

**pandas.DatetimeIndex.factorize**

```
DatetimeIndex.factorize(sort=False, na_sentinel=-1)
```
Encode the object as an enumerated type or categorical variable

Parameters sort: boolean, default False
• Sort by values

na_sentinel: int, default -1
• Value to mark “not found”

Returns labels: the indexer to the original array
uniques: the unique Index

**pandas.DatetimeIndex.format**

```
DatetimeIndex.format(name=False, formatter=None, **kwargs)
```
Render a string representation of the Index

**pandas.DatetimeIndex.get_duplicates**

```
DatetimeIndex.get_duplicates()
```

**pandas.DatetimeIndex.get_indexer**

```
DatetimeIndex.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 $\text{abs}(\text{index}[	ext{indexer}] - \text{target}) \leq \text{tolerance}$.

New in version 0.17.0.

**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
>>> indexer = index.get_indexer(new_index)
>>> new_values = cur_values.take(indexer)
```

**pandas.DatetimeIndex.get_indexer_for**

`DatetimeIndex.get_indexer_for(target, **kwargs)`

guaranteed return of an indexer even when non-unique

**pandas.DatetimeIndex.get_indexer_non_unique**

`DatetimeIndex.get_indexer_non_unique(target)`

return an indexer suitable for taking from a non unique index return the labels in the same order as the target, and return a missing indexer into the target (missing are marked as -1 in the indexer); target must be an iterable

**pandas.DatetimeIndex.get_level_values**

`DatetimeIndex.get_level_values(level)`

Return vector of label values for requested level, equal to the length of the index

**Parameters** `level`: int

**Returns** `values`: ndarray

**pandas.DatetimeIndex.get_loc**

`DatetimeIndex.get_loc(key, method=None, tolerance=None)`

Get integer location for requested label

**Returns** `loc`: int
pandas: powerful Python data analysis toolkit, Release 0.17.0

pandas.DatetimeIndex.get_slice_bound

DatetimeIndex.get_slice_bound(label, side, kind)
Calculate slice bound that corresponds to given label.
Returns leftmost (one-past-the-rightmost if side=='right') position of given label.

Parameters  
label : object
side : {'left', 'right'}
kind : string / None, the type of indexer

pandas.DatetimeIndex.get_value

DatetimeIndex.get_value(series, key)
Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you're doing

pandas.DatetimeIndex.get_value_maybe_box

DatetimeIndex.get_value_maybe_box(series, key)

pandas.DatetimeIndex.get_values

DatetimeIndex.get_values()
return the underlying data as an ndarray

pandas.DatetimeIndex.groupby

DatetimeIndex.groupby(f)

pandas.DatetimeIndex.holds_integer

DatetimeIndex.holds_integer()

pandas.DatetimeIndex.identical

DatetimeIndex.identical(other)
Similar to equals, but check that other comparable attributes are also equal

pandas.DatetimeIndex.indexer_at_time

DatetimeIndex.indexer_at_time(time, asof=False)
Select values at particular time of day (e.g. 9:30AM)

Parameters  
time : datetime.time or string
Returns  
values_at_time : TimeSeries
**pandas.DatetimeIndex.indexer_between_time**

```python
DatetimeIndex.indexer_between_time(start_time, end_time, include_start=True, include_end=True)
```

Select values between particular times of day (e.g., 9:00-9:30AM)

- **Parameters**
  - `start_time`: datetime.time or string
  - `end_time`: datetime.time or string
  - `include_start`: boolean, default True
  - `include_end`: boolean, default True
  - `tz`: string or pytz.timezone or dateutil.tz.tzfile, default None

- **Returns**
  - `values_between_time`: TimeSeries

**pandas.DatetimeIndex.insert**

```python
DatetimeIndex.insert(loc, item)
```

Make new Index inserting new item at location

- **Parameters**
  - `loc`: int
  - `item`: object
    - if not either a Python datetime or a numpy integer-like, returned Index dtype will be object rather than datetime.

- **Returns**
  - `new_index`: Index

**pandas.DatetimeIndex.intersection**

```python
DatetimeIndex.intersection(other)
```

Specialized intersection for DatetimeIndex objects. May be much faster than Index.intersection

- **Parameters**
  - `other`: DatetimeIndex or array-like

- **Returns**
  - `y`: Index or DatetimeIndex

**pandas.DatetimeIndex.is**

```python
DatetimeIndex.is_(other)
```

More flexible, faster check like `is` but that works through views

- **Parameters**
  - `other`: object
    - other object to compare against.

- **Returns**
  - `True` if both have same underlying data, `False` otherwise: bool

**pandas.DatetimeIndex.is_boolean**

```python
DatetimeIndex.is_boolean()
```
pandas.DatetimeIndex.is_categorical

DatetimeIndex.is_categorical()

pandas.DatetimeIndex.is_floating

DatetimeIndex.is_floating()

pandas.DatetimeIndex.is_integer

DatetimeIndex.is_integer()

pandas.DatetimeIndex.is_lexsorted_for_tuple

DatetimeIndex.is_lexsorted_for_tuple(tup)

pandas.DatetimeIndex.is_mixed

DatetimeIndex.is_mixed()

pandas.DatetimeIndex.is_numeric

DatetimeIndex.is_numeric()

pandas.DatetimeIndex.is_object

DatetimeIndex.is_object()

pandas.DatetimeIndex.is_type_compatible

DatetimeIndex.is_type_compatible(typ)

pandas.DatetimeIndex.isin

DatetimeIndex.isin(values)

Compute boolean array of whether each index value is found in the passed set of values

Parameters values: set or sequence of values

Returns is_contained: ndarray (boolean dtype)

pandas.DatetimeIndex.item

DatetimeIndex.item()

return the first element of the underlying data as a python scalar
pandas.DatetimeIndex.join

DatetimeIndex.join(other, how='left', level=None, return_indexers=False)
See Index.join

pandas.DatetimeIndex.map

DatetimeIndex.map(f)

pandas.DatetimeIndex.max

DatetimeIndex.max(axis=None)
return the maximum value of the Index
See also:
numpy.ndarray.max

pandas.DatetimeIndex.min

DatetimeIndex.min(axis=None)
return the minimum value of the Index
See also:
numpy.ndarray.min

pandas.DatetimeIndex.normalize

DatetimeIndex.normalize()
Return DatetimeIndex with times to midnight. Length is unaltered

Returns normalized: DatetimeIndex

pandas.DatetimeIndex.nunique

DatetimeIndex.nunique(dropna=True)
Return number of unique elements in the object.
Excludes NA values by default.
Parameters dropna: boolean, default True
Don’t include NaN in the count.
Returns nunique: int

pandas.DatetimeIndex.order

DatetimeIndex.order(return_indexer=False, ascending=True)
Return sorted copy of Index
DEPRECATED: use Index.sort_values()
pandas.DatetimeIndex.putmask

DatetimeIndex.putmask(mask, value)
return a new Index of the values set with the mask

See also:
numpy.ndarray.putmask

pandas.DatetimeIndex.ravel

DatetimeIndex.ravel(order='C')
return an ndarray of the flattened values of the underlying data

See also:
numpy.ndarray.ravel

pandas.DatetimeIndex.reindex

DatetimeIndex.reindex(target, method=None, level=None, limit=None, tolerance=None)
Create index with target’s values (move/add/delete values as necessary)

Parameters
target: an iterable

Returns
new_index: pd.Index
    Resulting index
indexer: np.ndarray or None
    Indices of output values in original index

pandas.DatetimeIndex.rename

DatetimeIndex.rename(name, inplace=False)
Set new names on index. Defaults to returning new index.

Parameters
name: str or list
    name to set
inplace: bool
    if True, mutates in place

Returns
new index (of same type and class...etc) [if inplace, returns None]

pandas.DatetimeIndex.repeat

DatetimeIndex.repeat(repeats, axis=None)
Analogous to ndarray.repeat

pandas.DatetimeIndex.searchsorted

DatetimeIndex.searchsorted(key, side='left')
pandas.DatetimeIndex.set_names

DatetimeIndex.set_names(names, level=None, inplace=False)
Set new names on index. Defaults to returning new index.

Parameters:
- names : str or sequence
  name(s) to set
- level : int or level name, or sequence of int / level names (default None)
  If the index is a MultiIndex (hierarchical), level(s) to set (None for all levels)
  Otherwise level must be None
- inplace : bool
  if True, mutates in place

Returns:
new index (of same type and class...etc) [if inplace, returns None]

Examples

```python
>>> Index([1, 2, 3, 4]).set_names('foo')
Int64Index([1, 2, 3, 4], dtype='int64')
>>> Index([1, 2, 3, 4]).set_names(['foo'])
Int64Index([1, 2, 3, 4], dtype='int64')
>>> idx = MultiIndex.from_tuples([(1, u'one'), (1, u'two'),
                                (2, u'one'), (2, u'two')],
                               names=['foo', 'bar'])
>>> idx.set_names(['baz', 'quz'])
MultiIndex(levels=[[1, 2], [u'one', u'two']],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
           names=['baz', 'quz'])
>>> idx.set_names('baz', level=0)
MultiIndex(levels=[[1, 2], [u'one', u'two']],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
           names=['baz', 'bar'])
```

pandas.DatetimeIndex.set_value

DatetimeIndex.set_value(arr, key, value)
Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you’re doing

pandas.DatetimeIndex.shift

DatetimeIndex.shift(n, freq=None)
Specialized shift which produces a DatetimeIndex

Parameters:
- n : int
  Periods to shift by
- freq : DateOffset or timedelta-like, optional

Returns:
shifted : DatetimeIndex
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**pandas.DatetimeIndex.slice_indexer**

DatetimeIndex.slice_indexer(start=None, end=None, step=None, kind=None)
Return indexer for specified label slice. Index.slice_indexer, customized to handle time slicing.

In addition to functionality provided by Index.slice_indexer, does the following:

• if both start and end are instances of datetime.time, it invokes indexer_between_time

• if start and end are both either string or None perform value-based selection in non-monotonic cases.

**pandas.DatetimeIndex.slice_locs**

DatetimeIndex.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**: string, defaults None

Returns:

- **start, end**: int

**pandas.DatetimeIndex.snap**

DatetimeIndex.snap(freq='S')
Snap time stamps to nearest occurring frequency

**pandas.DatetimeIndex.sort**

DatetimeIndex.sort(*args, **kwargs)

**pandas.DatetimeIndex.sort_values**

DatetimeIndex.sort_values(return_indexer=False, ascending=True)
Return sorted copy of Index

**pandas.DatetimeIndex.sortlevel**

DatetimeIndex.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**: boolean, default True
  False to sort in descending order

- **level, sort_remaining** are compat paramaters
Returns `sorted_index`: Index

**pandas.DatetimeIndex.str**

`DatetimeIndex.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.str.split('_')
```

```python
>>> s.str.replace('_', '')
```

**pandas.DatetimeIndex.strftime**

`DatetimeIndex.strftime(date_format)`

Return an array 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 the python string format doc. New in version 0.17.0.

**Parameters**

- `date_format`: str
  
  date format string (e.g. “%Y-%m-%d”)

**Returns**

- ndarray of formatted strings

**pandas.DatetimeIndex.summary**

`DatetimeIndex.summary(name=None)`

return a summarized representation

**pandas.DatetimeIndex.sym_diff**

`DatetimeIndex.sym_diff(other, result_name=None)`

Compute the sorted symmetric difference of two Index objects.

**Parameters**

- `other`: Index or array-like
  
  result_name: str

**Returns**

- `sym_diff`: Index

**Notes**

`sym_diff` contains elements that appear in either `idx1` or `idx2` but not both. Equivalent to the Index created by `(idx1 - idx2) + (idx2 - idx1)` with duplicates dropped.

The sorting of a result containing NaN values is not guaranteed across Python versions. See GitHub issue #6444.
Examples

```python
>>> idx1 = Index([1, 2, 3, 4])
>>> idx2 = Index([2, 3, 4, 5])
>>> idx1.sym_diff(idx2)
Int64Index([1, 5], dtype='int64')
```

You can also use the `^` operator:

```python
>>> idx1 ^ idx2
Int64Index([1, 5], dtype='int64')
```

**pandas.DatetimeIndex.take**

```python
DatetimeIndex.take(indices, axis=0, **kwargs)
```

Analogous to ndarray.take

**pandas.DatetimeIndex.to_datetime**

```python
DatetimeIndex.to_datetime(dayfirst=False)
```

**pandas.DatetimeIndex.to_julian_date**

```python
DatetimeIndex.to_julian_date()
```

Convert DatetimeIndex to Float64Index of Julian Dates. 0 Julian date is noon January 1, 4713 BC.
http://en.wikipedia.org/wiki/Julian_day

**pandas.DatetimeIndex.to_native_types**

```python
DatetimeIndex.to_native_types(slicer=None, **kwargs)
```

Slice and dice then format

**pandas.DatetimeIndex.to_period**

```python
DatetimeIndex.to_period(freq=None)
```

Cast to PeriodIndex at a particular frequency

**pandas.DatetimeIndex.to_perioddelta**

```python
DatetimeIndex.to_perioddelta(freq)
```

Calculate TimedeltaIndex of difference between index values and index converted to PeriodIndex at specified freq. Used for vectorized offsets

New in version 0.17.0.

**Parameters**

- `freq` : Period frequency

**Returns**

- `y` : TimedeltaIndex
**pandas.DatetimeIndex.to_pydatetime**

`DatetimeIndex.to_pydatetime()`

Return DatetimeIndex as object ndarray of datetime.datetime objects

**Returns**  
datetimes : ndarray

**pandas.DatetimeIndex.to_series**

`DatetimeIndex.to_series(keep_tz=False)`

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 False.

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.

**Returns** Series

**pandas.DatetimeIndex.tolist**

`DatetimeIndex.tolist()`

return a list of the underlying data

**pandas.DatetimeIndex.transpose**

`DatetimeIndex.transpose()`

return the transpose, which is by definition self

**pandas.DatetimeIndex.tz_convert**

`DatetimeIndex.tz_convert(tz)`

Convert tz-aware DatetimeIndex from one time zone to another (using pytz/dateutil)

**Parameters**  
tz : string, pytz.timezone, dateutil.tz.tzfile or None

Time zone for time. Corresponding timestamps would be converted to time zone of the TimeSeries. None will remove timezone holding UTC time.

**Returns** normalized : DatetimeIndex

**Raises** TypeError

If DatetimeIndex is tz-naive.
pandas.DatetimeIndex.tz_localize

DatetimeIndex.tz_localize(*args, **kwargs)
Localize tz-naive DatetimeIndex to given time zone (using pytz/dateutil), or remove timezone from tz-aware DatetimeIndex

Parameters tz : string, pytz.timezone, dateutil.tz.tzfile or None
   Time zone for time. Corresponding timestamps would be converted to time zone of the TimeSeries. None will remove timezone holding local time.

ambiguous : ‘infer’, bool-ndarray, ‘NaT’, default ‘raise’
   - ‘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

infer_dst : boolean, default False (DEPRECATED)
   Attempt to infer fall dst-transition hours based on order

Returns localized : DatetimeIndex

Raises TypeError
   If the DatetimeIndex is tz-aware and tz is not None.

pandas.DatetimeIndex.union

DatetimeIndex.union(other)
Specialized union for DatetimeIndex objects. If combine overlapping ranges with the same DateOffset, will be much faster than Index.union

Parameters other : DatetimeIndex or array-like

Returns y : Index or DatetimeIndex

pandas.DatetimeIndex.union_many

DatetimeIndex.union_many(others)
A bit of a hack to accelerate unioning a collection of indexes

pandas.DatetimeIndex.unique

DatetimeIndex.unique()
Index.unique with handling for DatetimeIndex/PeriodIndex metadata

Returns result : DatetimeIndex or PeriodIndex
pandas.DatetimeIndex.value_counts

`DatetimeIndex.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)`

Returns object 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` : boolean, default False
  - If True then the object returned will contain the relative frequencies of the unique values.
- `sort` : boolean, default True
  - Sort by values
- `ascending` : boolean, default False
  - Sort in ascending order
- `bins` : integer, optional
  - Rather than count values, group them into half-open bins, a convenience for `pd.cut`, only works with numeric data
- `dropna` : boolean, default True
  - Don’t include counts of NaN.

**Returns**
- `counts` : Series

pandas.DatetimeIndex.view

`DatetimeIndex.view(cls=None)`

34.9.2 Time/Date Components

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DatetimeIndex.year</td>
<td>The year of the datetime</td>
</tr>
<tr>
<td>DatetimeIndex.month</td>
<td>The month as January=1, December=12</td>
</tr>
<tr>
<td>DatetimeIndex.day</td>
<td>The days of the datetime</td>
</tr>
<tr>
<td>DatetimeIndex.hour</td>
<td>The hours of the datetime</td>
</tr>
<tr>
<td>DatetimeIndex.minute</td>
<td>The minutes of the datetime</td>
</tr>
<tr>
<td>DatetimeIndex.second</td>
<td>The seconds of the datetime</td>
</tr>
<tr>
<td>DatetimeIndex.microsecond</td>
<td>The microseconds of the datetime</td>
</tr>
<tr>
<td>DatetimeIndex.nanosecond</td>
<td>The nanoseconds of the datetime</td>
</tr>
<tr>
<td>DatetimeIndex.date</td>
<td>Returns numpy array of datetime.date.</td>
</tr>
<tr>
<td>DatetimeIndex.time</td>
<td>Returns numpy array of datetime.time.</td>
</tr>
<tr>
<td>DatetimeIndex.dayofyear</td>
<td>The ordinal day of the year</td>
</tr>
<tr>
<td>DatetimeIndex.weekofyear</td>
<td>The week ordinal of the year</td>
</tr>
<tr>
<td>DatetimeIndex.week</td>
<td>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></td>
</tr>
<tr>
<td>DatetimeIndex.freq</td>
<td>get/set the frequency of the Index</td>
</tr>
</tbody>
</table>

Continued on next page
### Table 34.107 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>.freqstr</code></td>
<td>return the frequency object as a string if its set, otherwise None</td>
</tr>
<tr>
<td><code>.is_month_start</code></td>
<td>Logical indicating if first day of month (defined by frequency)</td>
</tr>
<tr>
<td><code>.is_month_end</code></td>
<td>Logical indicating if last day of month (defined by frequency)</td>
</tr>
<tr>
<td><code>.is_quarter_start</code></td>
<td>Logical indicating if first day of quarter (defined by frequency)</td>
</tr>
<tr>
<td><code>.is_quarter_end</code></td>
<td>Logical indicating if last day of quarter (defined by frequency)</td>
</tr>
<tr>
<td><code>.is_year_start</code></td>
<td>Logical indicating if first day of year (defined by frequency)</td>
</tr>
<tr>
<td><code>.is_year_end</code></td>
<td>Logical indicating if last day of year (defined by frequency)</td>
</tr>
</tbody>
</table>

### pandas.DatetimeIndex

**`.year`**

The year of the datetime

**`.month`**

The month as January=1, December=12

**`.day`**

The days of the datetime

**`.hour`**

The hours of the datetime

**`.minute`**

The minutes of the datetime

**`.second`**

The seconds of the datetime

**`.microsecond`**

The microseconds of the datetime

**`.nanosecond`**

The nanoseconds of the datetime
pandas.DatetimeIndex.date

DatetimeIndex.date
Returns numpy array of datetime.date. The date part of the Timestamps.

pandas.DatetimeIndex.time

DatetimeIndex.time
Returns numpy array of datetime.time. The time part of the Timestamps.

pandas.DatetimeIndex.dayofyear

DatetimeIndex.dayofyear
The ordinal day of the year

pandas.DatetimeIndex.weekofyear

DatetimeIndex.weekofyear
The week ordinal of the year

pandas.DatetimeIndex.week

DatetimeIndex.week
The week ordinal of the year

pandas.DatetimeIndex.dayofweek

DatetimeIndex.dayofweek
The day of the week with Monday=0, Sunday=6

pandas.DatetimeIndex.weekday

DatetimeIndexweekday
The day of the week with Monday=0, Sunday=6

pandas.DatetimeIndex.quarter

DatetimeIndex.quarter
The quarter of the date

pandas.DatetimeIndex.tz

DatetimeIndex.tz = None

pandas.DatetimeIndex.freq

DatetimeIndex.freq
get/set the frequncy of the Index
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pandas.DatetimeIndex.freqstr

DatetimeIndex.freqstr
return the frequency object as a string if its set, otherwise None

pandas.DatetimeIndex.is_month_start

DatetimeIndex.is_month_start
Logical indicating if first day of month (defined by frequency)

pandas.DatetimeIndex.is_month_end

DatetimeIndex.is_month_end
Logical indicating if last day of month (defined by frequency)

pandas.DatetimeIndex.is_quarter_start

DatetimeIndex.is_quarter_start
Logical indicating if first day of quarter (defined by frequency)

pandas.DatetimeIndex.is_quarter_end

DatetimeIndex.is_quarter_end
Logical indicating if last day of quarter (defined by frequency)

pandas.DatetimeIndex.is_year_start

DatetimeIndex.is_year_start
Logical indicating if first day of year (defined by frequency)

pandas.DatetimeIndex.is_year_end

DatetimeIndex.is_year_end
Logical indicating if last day of year (defined by frequency)

pandas.DatetimeIndex.inferred_freq

DatetimeIndex.inferred_freq = None

34.9.3 Selecting

<table>
<thead>
<tr>
<th>DatetimeIndex.indexer_at_time(time[, asof])</th>
<th>Select values at particular time of day (e.g. 9:00-9:30AM)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DatetimeIndex.indexer_between_time(...[, ...])</td>
<td>Select values between particular times of day (e.g. 9:00-9:30AM)</td>
</tr>
</tbody>
</table>
**pandas.DatetimeIndex.indexer_at_time**

```python
DatetimeIndex.indexer_at_time(time, asof=False)
```

Select values at particular time of day (e.g. 9:30AM)

- **Parameters**
  - `time`: datetime.time or string
- **Returns**
  - `values_at_time`: TimeSeries

**pandas.DatetimeIndex.indexer_between_time**

```python
DatetimeIndex.indexer_between_time(start_time, end_time, include_start=True, include_end=True)
```

Select values between particular times of day (e.g., 9:00-9:30AM)

- **Parameters**
  - `start_time`: datetime.time or string
  - `end_time`: datetime.time or string
  - `include_start`: boolean, default True
  - `include_end`: boolean, default True
  - `tz`: string or pytz.timezone or dateutil.tz.tzfile, default None

- **Returns**
  - `values_between_time`: TimeSeries

### 34.9.4 Time-specific operations

- **DatetimeIndex.normalize**
  - Return DatetimeIndex with times to midnight. Length is unaltered
  - **Returns**
    - `normalized`: DatetimeIndex

- **DatetimeIndex.strftime**(date_format)
  - Return an array 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 the python string format doc
  - **Parameters**
    - `date_format`: str
date format string (e.g. “%Y-%m-%d”)
  - **Returns**
    - ndarray of formatted strings

- **DatetimeIndex.snap([freq])**
  - Snap time stamps to nearest occurring frequency

- **DatetimeIndex.tz_convert**(tz)
  - Convert tz-aware DatetimeIndex from one time zone to another (using pytz/dateutil)

- **DatetimeIndex.tz_localize**(args, **kwargs)
  - Localize tz-naive DatetimeIndex to given time zone (using pytz/dateutil)
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pandas.DatetimeIndex.snap

DatetimeIndex.snap(freq='S')
Snap time stamps to nearest occurring frequency

pandas.DatetimeIndex.tz_convert

DatetimeIndex.tz_convert(tz)
Convert tz-aware DatetimeIndex from one time zone to another (using pytz/dateutil)

Parameters tz : string, pytz.timezone, dateutil.tz.tzfile or None
   Time zone for time. Corresponding timestamps would be converted to time zone of
   the TimeSeries. None will remove timezone holding UTC time.

Returns normalized : DatetimeIndex

Raises TypeError
   If DatetimeIndex is tz-naive.

pandas.DatetimeIndex.tz_localize

DatetimeIndex.tz_localize(*args, **kwargs)
Localize tz-naive DatetimeIndex to given time zone (using pytz/dateutil), or remove timezone from tz-aware
DatetimeIndex

Parameters tz : string, pytz.timezone, dateutil.tz.tzfile or None
   Time zone for time. Corresponding timestamps would be converted to time zone of
   the TimeSeries. None will remove timezone holding local time.

ambiguous : ‘infer’, bool-ndarray, ‘NaT’, default ‘raise’
   ‘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

infer_dst : boolean, default False (DEPRECATED)
   Attempt to infer fall dst-transition hours based on order

Returns localized : DatetimeIndex

Raises TypeError
   If the DatetimeIndex is tz-aware and tz is not None.

34.9.5 Conversion

DatetimeIndex.to_datetime([dayfirst])
Cast to PeriodIndex at a particular frequency

DatetimeIndex.to_period([freq])
Calculates TimedeltaIndex of difference between index values and index converted

Continued on next page
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Table 34.110 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DatetimeIndex.to_pydatetime</td>
<td>Return DatetimeIndex as object ndarray of datetime.datetime objects</td>
</tr>
<tr>
<td>DatetimeIndex.to_series(keep_tz)</td>
<td>Create a Series with both index and values equal to the index keys</td>
</tr>
</tbody>
</table>

pandas.DatetimeIndex.to_datetime

DatetimeIndex.to_datetime(dayfirst=False)

pandas.DatetimeIndex.to_period

DatetimeIndex.to_period(freq=None)

  Cast to PeriodIndex at a particular frequency

pandas.DatetimeIndex.to_perioddelta

DatetimeIndex.to_perioddelta(freq)

  Calculates TimedeltaIndex of difference between index values and index converted to PeriodIndex at specified
  freq. Used for vectorized offsets

  New in version 0.17.0.

  Parameters freq : Period frequency

  Returns y : TimedeltaIndex

pandas.DatetimeIndex.to_pydatetime

DatetimeIndex.to_pydatetime()

  Return DatetimeIndex as object ndarray of datetime.datetime objects

  Returns datetimes : ndarray

pandas.DatetimeIndex.to_series

DatetimeIndex.to_series(keep_tz=False)

  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 False.

  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.

  Returns Series
34.10 TimedeltaIndex

TimedeltaIndex  Immutable ndarray of timedelta64 data, represented internally as int64, and which can be boxed to timedelta objects

34.10.1 pandas.TimedeltaIndex

class pandas.TimedeltaIndex

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 : a frequency for the index, optional

- copy : bool
  Make a copy of input ndarray

- start : starting value, timedelta-like, optional
  If data is None, start is used as the start point in generating regular timedelta data.

- periods : int, optional, > 0
  Number of periods to generate, if generating index. Takes precedence over end argument

- end : end time, timedelta-like, optional
  If periods is none, generated index will extend to first conforming time on or just past end argument

- closed : string or None, default None
  Make the interval closed with respect to the given frequency to the ‘left’, ‘right’, or both sides (None)

- name : object
  Name to be stored in the index

Attributes

- T
  return the transpose, which is by definition self

- asi8
  asobject
  base
  components
  data
days
dtype

  return the base object if the memory of the underlying data is shared
  Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds)
  return the data pointer of the underlying data
  Number of days for each element.
<table>
<thead>
<tr>
<th>attribute</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>dtype_str</td>
<td>return the frequency object as a string if its set, otherwise None</td>
</tr>
<tr>
<td>flags</td>
<td></td>
</tr>
<tr>
<td>freq</td>
<td></td>
</tr>
<tr>
<td>freqstr</td>
<td></td>
</tr>
<tr>
<td>has_duplicates</td>
<td></td>
</tr>
<tr>
<td>hasnans</td>
<td></td>
</tr>
<tr>
<td>inferred_freq</td>
<td>alias for is_monotonic_increasing (deprecated)</td>
</tr>
<tr>
<td>inferred_type</td>
<td>return if the index is monotonic decreasing (only equal or</td>
</tr>
<tr>
<td>is_all_dates</td>
<td>return if the index is monotonic increasing (only equal or</td>
</tr>
<tr>
<td>is_monotonic</td>
<td>return if the index is monotonic decreasing (only equal or</td>
</tr>
<tr>
<td>is_monotonic_decreasing</td>
<td>return if the index is monotonic increasing (only equal or</td>
</tr>
<tr>
<td>is_monotonic_increasing</td>
<td>return if the index is monotonic increasing (only equal or</td>
</tr>
<tr>
<td>is_unique</td>
<td>return the size of the dtype of the item of the underlying data</td>
</tr>
<tr>
<td>itemsize</td>
<td>Number of microseconds (&gt;= 0 and less than 1 second) 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>name</td>
<td></td>
</tr>
<tr>
<td>names</td>
<td></td>
</tr>
<tr>
<td>nanoseconds</td>
<td>Number of nanoseconds (&gt;= 0 and less than 1 microsecond) for each element.</td>
</tr>
<tr>
<td>nbytes</td>
<td>return the number of bytes in the underlying data</td>
</tr>
<tr>
<td>ndim</td>
<td>return the number of dimensions of the underlying data, by definition 1</td>
</tr>
<tr>
<td>nlevels</td>
<td></td>
</tr>
<tr>
<td>resolution</td>
<td></td>
</tr>
<tr>
<td>seconds</td>
<td>Number of seconds (&gt;= 0 and less than 1 day) for each element.</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>strides</td>
<td>return the strides of the underlying data</td>
</tr>
<tr>
<td>values</td>
<td>return the underlying data as an ndarray</td>
</tr>
</tbody>
</table>

**pandas.TimedeltaIndex.T**

TimedeltaIndex.T

return the transpose, which is by definition self

**pandas.TimedeltaIndex.asi8**

TimedeltaIndex.asi8

**pandas.TimedeltaIndex.asobject**

TimedeltaIndex.asobject

**pandas.TimedeltaIndex.base**

TimedeltaIndex.base

return the base object if the memory of the underlying data is shared

**pandas.TimedeltaIndex.components**

TimedeltaIndex.components

Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds,)
nanoseconds) of the Timedeltas.

Returns a DataFrame

**pandas.TimedeltaIndex.data**

TimedeltaIndex.data

return the data pointer of the underlying data

**pandas.TimedeltaIndex.days**

TimedeltaIndex.days

Number of days for each element.

**pandas.TimedeltaIndex.dtype**

TimedeltaIndex.dtype

**pandas.TimedeltaIndex.dtype_str**

TimedeltaIndex.dtype_str = None

**pandas.TimedeltaIndex.flags**

TimedeltaIndex.flags

**pandas.TimedeltaIndex.freq**

TimedeltaIndex.freq = None

**pandas.TimedeltaIndex.freqstr**

TimedeltaIndex.freqstr

return the frequency object as a string if its set, otherwise None

**pandas.TimedeltaIndex.has_duplicates**

TimedeltaIndex.has_duplicates

**pandas.TimedeltaIndex.hasnans**

TimedeltaIndex.hasnans = None

**pandas.TimedeltaIndex.inferred_freq**

TimedeltaIndex.inferred_freq = None
pandas.TimedeltaIndex.inferred_type
TimedeltaIndex.inferred_type

pandas.TimedeltaIndex.is_all_dates
TimedeltaIndex.is_all_dates

pandas.TimedeltaIndex.is_monotonic
TimedeltaIndex.is_monotonic
    alias for is_monotonic_increasing (deprecated)

pandas.TimedeltaIndex.is_monotonic_decreasing
TimedeltaIndex.is_monotonic_decreasing
    return if the index is monotonic decreasing (only equal or decreasing) values.

pandas.TimedeltaIndex.is_monotonic_increasing
TimedeltaIndex.is_monotonic_increasing
    return if the index is monotonic increasing (only equal or increasing) values.

pandas.TimedeltaIndex.is_unique
TimedeltaIndex.is_unique = None

pandas.TimedeltaIndex.itemsize
TimedeltaIndex.itemsize
    return the size of the dtype of the item of the underlying data

pandas.TimedeltaIndex.microseconds
TimedeltaIndex.microseconds
    Number of microseconds (>= 0 and less than 1 second) for each element.

pandas.TimedeltaIndex.name
TimedeltaIndex.name = None

pandas.TimedeltaIndex.names
TimedeltaIndex.names
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**pandas.TimedeltaIndex.nanoseconds**

TimedeltaIndex.nanoseconds

Number of nanoseconds (>= 0 and less than 1 microsecond) for each element.

**pandas.TimedeltaIndex.nbytes**

TimedeltaIndex.nbytes

return the number of bytes in the underlying data

**pandas.TimedeltaIndex.ndim**

TimedeltaIndex.ndim

return the number of dimensions of the underlying data, by definition 1

**pandas.TimedeltaIndex.nlevels**

TimedeltaIndex.nlevels

**pandas.TimedeltaIndex.resolution**

TimedeltaIndex.resolution = None

**pandas.TimedeltaIndex.seconds**

TimedeltaIndex.seconds

Number of seconds (>= 0 and less than 1 day) for each element.

**pandas.TimedeltaIndex.shape**

TimedeltaIndex.shape

return a tuple of the shape of the underlying data

**pandas.TimedeltaIndex.size**

TimedeltaIndex.size

return the number of elements in the underlying data

**pandas.TimedeltaIndex.strides**

TimedeltaIndex.strides

return the strides of the underlying data

**pandas.TimedeltaIndex.values**

TimedeltaIndex.values

return the underlying data as an ndarray
Methods

all([other])
any([other])
append(other)
argmax([axis])
argmin([axis])
argsort(*args, **kwargs)
asof(label)
asof_locs(where, mask)
astype(dtype)
copy([names, name, dtype, deep])
delete(loc)
diff(*args, **kwargs)
difference(other)
drop_duplicates(*args, **kwargs)
duplicated(*args, **kwargs)
equals(other)
factorize([sort, na_sentinel])
format([name, formatter])
get_duplicates()
get_indexer(target[, method, limit, tolerance])
get_indexer_for(target, **kwargs)
get_indexer_non_unique(target)
get_level_values(level)
gequal_indexer(key[, method, tolerance])
get_slice_bound(label, side, kind)
get_value(series, key)
get_value_maybe_box(series, key)
get_values()
groupby(f)
holds_integer()
identical(other)
insert(loc, item)
intersection(other)
is_(other)
is_boolean()
is_categorical()
is_floating()
is_integer()
is_lexsorted_for_tuple(tup)
is_mixed()
is_numeric()
is_object()
is_type_compatible(typ)
isin(values)
item()
join(other[, how, level, return_indexers])
map(f)
max([axis])
min([axis])

Append a collection of Index options together
return a ndarray of the maximum argument indexer
return a ndarray of the minimum argument indexer
For a sorted index, return the most recent label up to and including the passed label, where : array of timestamps
Make a copy of this object.
Make a new DatetimeIndex with passed location(s) deleted.
Compute sorted set difference of two Index objects
Make new Index with passed list of labels deleted
Return Index with duplicate values removed
Return boolean np.array denoting duplicate values
Determines if two Index objects contain the same elements.
Encode the object as an enumerated type or categorical variable
Render a string representation of the Index
Compute indexer and mask for new index given the current index.
guaranteed return of an indexer even when non-unique
return an indexer suitable for taking from a non unique index
Return vector of label values for requested level, equal to the length
Get integer location for requested label
Calculate slice bound that corresponds to given label.
Fast lookup of value from 1-dimensional ndarray.
return the underlying data as an ndarray
Similar to equals, but check that other comparable attributes are
Make new Index inserting new item at location
Specialized intersection for TimedeltaIndex objects.
More flexible, faster check like is but that works through views
Compute boolean array of whether each index value is found in the
return the first element of the underlying data as a python scalar
See Index.join
return the maximum value of the Index
return the minimum value of the Index
Table 34.113 – continued from previous page

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>nunique([dropna])</td>
<td>Return number of unique elements in the object.</td>
</tr>
<tr>
<td>order([return_indexer, ascending])</td>
<td>Return sorted copy of Index</td>
</tr>
<tr>
<td>putmask(mask, value)</td>
<td>return a new Index of the values set with the mask</td>
</tr>
<tr>
<td>ravel([order])</td>
<td>return an ndarray of the flattened values of the underlying data</td>
</tr>
<tr>
<td>reindex(target[, method, level, limit, ...])</td>
<td>Create index with target’s values (move/add/delete values as necessary)</td>
</tr>
<tr>
<td>rename(name[, inplace])</td>
<td>Set new names on index.</td>
</tr>
<tr>
<td>repeat(repeats[, axis])</td>
<td>Analogous to ndarray.repeat</td>
</tr>
<tr>
<td>searchsorted(key[, side])</td>
<td>Set new names on index.</td>
</tr>
<tr>
<td>set_names(names[, level, inplace])</td>
<td>Fast lookup of value from 1-dimensional ndarray.</td>
</tr>
<tr>
<td>set_value(arr, key, value)</td>
<td>Specialized shift which produces a DatetimeIndex</td>
</tr>
<tr>
<td>slice_indexer([start, end, step, kind])</td>
<td>For an ordered Index, compute the slice indexer for input labels and</td>
</tr>
<tr>
<td>slice_locs([start, end, step, kind])</td>
<td>Compute slice locations for input labels.</td>
</tr>
<tr>
<td>sort(*args, **kwargs)</td>
<td>Return sorted copy of Index</td>
</tr>
<tr>
<td>sort_values([return_indexer, ascending])</td>
<td>For internal compatibility with with the Index API</td>
</tr>
<tr>
<td>str</td>
<td>alias of StringMethods</td>
</tr>
<tr>
<td>summary([name])</td>
<td>return a summarized representation</td>
</tr>
<tr>
<td>sym_diff(other[, result_name])</td>
<td>Compute the sorted symmetric difference of two Index objects.</td>
</tr>
<tr>
<td>take(indices[, axis])</td>
<td>Analogous to ndarray.take</td>
</tr>
<tr>
<td>to_datetime([dayfirst])</td>
<td>For an Index containing strings or datetime.datetime objects, attempt</td>
</tr>
<tr>
<td>to_native_types([slicer])</td>
<td>Return TimedeltaIndex as object ndarray of datetime.timedelta objects</td>
</tr>
<tr>
<td>to_pytimedelta</td>
<td>Create a Series with both index and values equal to the index keys</td>
</tr>
<tr>
<td>to_series(**kwargs)</td>
<td>return a list of the underlying data</td>
</tr>
<tr>
<td>total_seconds()</td>
<td>Total duration of each element expressed in seconds.</td>
</tr>
<tr>
<td>transpose()</td>
<td>return the transpose, which is by definition self</td>
</tr>
<tr>
<td>union(other)</td>
<td>Specialized union for TimedeltaIndex objects.</td>
</tr>
<tr>
<td>unique()</td>
<td>Index.unique with handling for DatetimeIndex/PeriodIndex metadata</td>
</tr>
<tr>
<td>value_counts([normalize, sort, ascending, ...])</td>
<td>Returns object containing counts of unique values.</td>
</tr>
<tr>
<td>view([cls])</td>
<td></td>
</tr>
</tbody>
</table>
pandas.TimedeltaIndex.argmax

TimedeltaIndex.argmax (axis=None)
return a ndarray of the maximum argument indexer

See also:
numpy.ndarray.argmax

pandas.TimedeltaIndex.argmin

TimedeltaIndex.argmin (axis=None)
return a ndarray of the minimum argument indexer

See also:
numpy.ndarray.argmin

pandas.TimedeltaIndex.argsort

TimedeltaIndex.argsort (*args, **kwargs)
return an ndarray indexer of the underlying data

See also:
numpy.ndarray.argsort

pandas.TimedeltaIndex.asof

TimedeltaIndex.asof (label)
For a sorted index, return the most recent label up to and including the passed label. Return NaN if not found.

See also:
get_loc
asof is a thin wrapper around get_loc with method='pad'

pandas.TimedeltaIndex.asof_locs

TimedeltaIndex.asof_locs (where, mask)
where : array of timestamps mask : array of booleans where data is not NA

pandas.TimedeltaIndex.astype

TimedeltaIndex.astype (dtype)

pandas.TimedeltaIndex.copy

TimedeltaIndex.copy (names=None, name=None, dtype=None, deep=False)
Make a copy of this object. Name and dtype sets those attributes on the new object.

Parameters name : string, optional
dtype : numpy dtype or pandas type
**Returns**  
`copy` : Index

**Notes**

In most cases, there should be no functional difference from using `deep`, but if `deep` is passed it will attempt to deepcopy.

### pandas.TimedeltaIndex.delete

TimedeltaIndex.delete(loc)

Make a new DatetimeIndex with passed location(s) deleted.

**Parameters**  
`loc` : int, slice or array of ints  
Indicate which sub-arrays to remove.

**Returns**  
`new_index` : TimedeltaIndex

### pandas.TimedeltaIndex.diff

TimedeltaIndex.diff(*args, **kwargs)

### pandas.TimedeltaIndex.difference

TimedeltaIndex.difference(other)

Compute sorted set difference of two Index objects

**Parameters**  
`other` : Index or array-like

**Returns**  
`diff` : Index

**Notes**

One can do either of these and achieve the same result

```python
>>> index.difference(index2)
```

### pandas.TimedeltaIndex.drop

TimedeltaIndex.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
pandas.TimedeltaIndex.drop_duplicates

TimedeltaIndex.drop_duplicates(*args, **kwargs)
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.

take_last : deprecated

Returns deduplicated : Index

pandas.TimedeltaIndex.duplicated

TimedeltaIndex.duplicated(*args, **kwargs)
Return boolean np.array denoting duplicate values

Parameters keep: {‘first’, ‘last’, False}, default ‘first’
  • 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.

take_last : deprecated

Returns duplicated : np.array

pandas.TimedeltaIndex.equals

TimedeltaIndex.equals(other)
Determines if two Index objects contain the same elements.

pandas.TimedeltaIndex.factorize

TimedeltaIndex.factorize(sort=False, na_sentinel=-1)
Encode the object as an enumerated type or categorical variable

Parameters sort : boolean, default False
  Sort by values

na_sentinel : int, default -1
  Value to mark “not found”

Returns labels : the indexer to the original array
  uniques : the unique Index

pandas.TimedeltaIndex.format

TimedeltaIndex.format(name=False, formatter=None, **kwargs)
Render a string representation of the Index
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pandas.TimedeltaIndex.get_duplicates

TimedeltaIndex.get_duplicates()

pandas.TimedeltaIndex.get_indexer

TimedeltaIndex.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 $\text{abs}(\text{index}[\text{indexer}] - \text{target}) \leq \text{tolerance}$.

New in version 0.17.0.

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
>>> indexer = index.get_indexer(new_index)
>>> new_values = cur_values.take(indexer)
```

pandas.TimedeltaIndex.get_indexer_for

TimedeltaIndex.get_indexer_for(target, **kwargs)

guaranteed return of an indexer even when non-unique

pandas.TimedeltaIndex.get_indexer_non_unique

TimedeltaIndex.get_indexer_non_unique(target)

return an indexer suitable for taking from a non unique index return the labels in the same order as the target, and return a missing indexer into the target (missing are marked as -1 in the indexer); target must be an iterable
pandas.TimedeltaIndex.get_level_values

TimedeltaIndex.get_level_values(level)
Return vector of label values for requested level, equal to the length of the index

Parameters level : int

Returns values : ndarray

pandas.TimedeltaIndex.get_loc

TimedeltaIndex.get_loc(key, method=None, tolerance=None)
Get integer location for requested label

Returns loc : int

pandas.TimedeltaIndex.get_slice_bound

TimedeltaIndex.get_slice_bound(label, side, kind)
Calculate slice bound that corresponds to given label.

Returns leftmost (one-past-the-rightmost if side=='right') position of given label.

Parameters label : object
side : {'left', 'right'}
kind : string / None, the type of indexer

pandas.TimedeltaIndex.get_value

TimedeltaIndex.get_value(series, key)
Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you’re doing

pandas.TimedeltaIndex.get_value_maybe_box

TimedeltaIndex.get_value_maybe_box(series, key)

pandas.TimedeltaIndex.get_values

TimedeltaIndex.get_values()
return the underlying data as an ndarray

pandas.TimedeltaIndex.groupby

TimedeltaIndex.groupby(f)

pandas.TimedeltaIndex.holds_integer

TimedeltaIndex.holds_integer()
pandas.TimedeltaIndex.identical

TimedeltaIndex.identical(other)
Similar to equals, but check that other comparable attributes are also equal

pandas.TimedeltaIndex.insert

TimedeltaIndex.insert(loc, item)
Make new Index inserting new item at location
Parameters
loc : int
item : object
    if not either a Python datetime or a numpy integer-like, returned Index dtype will be object rather than datetime.
Returns
new_index : Index

pandas.TimedeltaIndex.intersection

TimedeltaIndex.intersection(other)
Specialized intersection for TimedeltaIndex objects. May be much faster than Index.intersection
Parameters
other : TimedeltaIndex or array-like
Returns
y : Index or TimedeltaIndex

pandas.TimedeltaIndex.is

TimedeltaIndex.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
True if both have same underlying data, False otherwise : bool

pandas.TimedeltaIndex.is_boolean

TimedeltaIndex.is_boolean()

pandas.TimedeltaIndex.is_categorical

TimedeltaIndex.is_categorical()

pandas.TimedeltaIndex.is_floating

TimedeltaIndex.is_floating()
pandas.TimedeltaIndex.is_integer

TimedeltaIndex.is_integer()

pandas.TimedeltaIndex.is_lexsorted_for_tuple

TimedeltaIndex.is_lexsorted_for_tuple(tup)

pandas.TimedeltaIndex.is_mixed

TimedeltaIndex.is_mixed()

pandas.TimedeltaIndex.is_numeric

TimedeltaIndex.is_numeric()

pandas.TimedeltaIndex.is_object

TimedeltaIndex.is_object()

pandas.TimedeltaIndex.is_type_compatible

TimedeltaIndex.is_type_compatible(typ)

pandas.TimedeltaIndex.isin

TimedeltaIndex.isin(values)

Compute boolean array of whether each index value is found in the passed set of values

Parameters values : set or sequence of values

Returns is_contained : ndarray (boolean dtype)

pandas.TimedeltaIndex.item

TimedeltaIndex.item()

return the first element of the underlying data as a python scalar

pandas.TimedeltaIndex.join

TimedeltaIndex.join(other, how='left', level=None, return_indexers=False)

See Index.join

pandas.TimedeltaIndex.map

TimedeltaIndex.map(f)
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**pandas.TimedeltaIndex.max**

TimedeltaIndex.max(axis=None)
return the maximum value of the Index

See also:
numpy.ndarray.max

**pandas.TimedeltaIndex.min**

TimedeltaIndex.min(axis=None)
return the minimum value of the Index

See also:
numpy.ndarray.min

**pandas.TimedeltaIndex.nunique**

TimedeltaIndex.nunique(dropna=True)
Return number of unique elements in the object.
Excludes NA values by default.

Parameters dropna : boolean, default True
Don’t include NaN in the count.

Returns nunique : int

**pandas.TimedeltaIndex.order**

TimedeltaIndex.order(return_indexer=False, ascending=True)
Return sorted copy of Index

DEPRECATED: use Index.sort_values()

**pandas.TimedeltaIndex.putmask**

TimedeltaIndex.putmask(mask, value)
return a new Index of the values set with the mask

See also:
numpy.ndarray.putmask

**pandas.TimedeltaIndex.ravel**

TimedeltaIndex.ravel(order='C')
return an ndarray of the flattened values of the underlying data

See also:
numpy.ndarray.ravel
**pandas.TimedeltaIndex.reindex**

TimedeltaIndex.reindex (target, method=None, level=None, limit=None, tolerance=None)
Create index with target’s values (move/add/delete values as necessary)

**Parameters**
- **target**: an iterable

**Returns**
- **new_index**: pd.Index
  - Resulting index
- **indexer**: np.ndarray or None
  - Indices of output values in original index

**pandas.TimedeltaIndex.rename**

TimedeltaIndex.rename (name, inplace=False)
Set new names on index. Defaults to returning new index.

**Parameters**
- **name**: str or list
  - name to set
- **inplace**: bool
  - if True, mutates in place

**Returns**
- new index (of same type and class...etc) [if inplace, returns None]

**pandas.TimedeltaIndex.repeat**

TimedeltaIndex.repeat (repeats, axis=None)
Analogous to ndarray.repeat

**pandas.TimedeltaIndex.searchsorted**

TimedeltaIndex.searchsorted (key, side='left')

**pandas.TimedeltaIndex.set_names**

TimedeltaIndex.set_names (names, level=None, inplace=False)
Set new names on index. Defaults to returning new index.

**Parameters**
- **names**: str or sequence
  - name(s) to set
- **level**: int or level name, or sequence of int / level names (default None)
  - If the index is a MultiIndex (hierarchical), level(s) to set (None for all levels)
  - Otherwise level must be None
- **inplace**: bool
  - if True, mutates in place

**Returns**
- new index (of same type and class...etc) [if inplace, returns None]
Examples

>>> Index([1, 2, 3, 4]).set_names('foo')
Int64Index([1, 2, 3, 4], dtype='int64')

>>> Index([1, 2, 3, 4]).set_names(['foo'])
Int64Index([1, 2, 3, 4], dtype='int64')

>>> idx = MultiIndex.from_tuples(((1, u'one'), (1, u'two'),
                               (2, u'one'), (2, u'two')),
                               names=['foo', 'bar'])

>>> idx.set_names(['baz', 'quz'])
MultiIndex(levels=[[1, 2], [u'one', u'two']],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
           names=[u'baz', u'quz'])

>>> idx.set_names('baz', level=0)
MultiIndex(levels=[[1, 2], [u'one', u'two']],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
           names=[u'baz', u'bar'])

pandas.TimedeltaIndex.set_value

TimedeltaIndex.set_value(arr, key, value)

Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you’re doing

pandas.TimedeltaIndex.shift

TimedeltaIndex.shift(n, freq=None)

Specialized shift which produces a DatetimeIndex

Parameters n : int

   Periods to shift by

   freq : DateOffset or timedelta-like, optional

Returns shifted : DatetimeIndex

pandas.TimedeltaIndex.slice_indexer

TimedeltaIndex.slice_indexer(start=None, end=None, step=None, kind=None)

For an ordered Index, compute the slice indexer for input labels and step

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 : string, default None

Returns indexer : ndarray or slice
Notes

This function assumes that the data is sorted, so use at your own peril

**pandas.TimedeltaIndex.slice_locs**

TimedeltaIndex.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**: string, defaults None

Returns
- **start, end**: int

**pandas.TimedeltaIndex.sort**

TimedeltaIndex.sort(*args, **kwargs)

**pandas.TimedeltaIndex.sort_values**

TimedeltaIndex.sort_values(return_indexer=False, ascending=True)

Return sorted copy of Index

**pandas.TimedeltaIndex.sortlevel**

TimedeltaIndex.sortlevel(level=None, ascending=True, sort_remaining=None)

Sort the Index. This is for compat with MultiIndex

Parameters
- **ascending**: boolean, default True
  - False to sort in descending order

level, sort_remaining are compat paramaters

Returns
- **sorted_index**: Index

**pandas.TimedeltaIndex.str**

TimedeltaIndex.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.str.split('_')
>>> s.str.replace('_', '')
```

**pandas.TimedeltaIndex.summary**

`TimedeltaIndex.summary(name=None)`

Return a summarized representation

**pandas.TimedeltaIndex.sym_diff**

`TimedeltaIndex.sym_diff(other, result_name=None)`

Compute the sorted symmetric difference of two Index objects.

**Parameters**
- `other`: Index or array-like
- `result_name`: str

**Returns**
- `sym_diff`: Index

**Notes**

`sym_diff` contains elements that appear in either `idx1` or `idx2` but not both. Equivalent to the Index created by `(idx1 - idx2) + (idx2 - idx1)` with duplicates dropped.

The sorting of a result containing NaN values is not guaranteed across Python versions. See GitHub issue #6444.

**Examples**

```python
>>> idx1 = Index([1, 2, 3, 4])
>>> idx2 = Index([2, 3, 4, 5])
>>> idx1.sym_diff(idx2)
Int64Index([1, 5], dtype='int64')
```

You can also use the `^` operator:

```python
>>> idx1 ^ idx2
Int64Index([1, 5], dtype='int64')
```

**pandas.TimedeltaIndex.take**

`TimedeltaIndex.take(indices, axis=0, **kwargs)`

Analogous to ndarray.take

**pandas.TimedeltaIndex.to_datetime**

`TimedeltaIndex.to_datetime(dayfirst=False)`

For an Index containing strings or datetime.datetime objects, attempt conversion to DatetimeIndex
**pandas.TimedeltaIndex.to_native_types**

TimedeltaIndex.to_native_types(slicer=None, **kwargs)
slice and dice then format

**pandas.TimedeltaIndex.to_pytimedelta**

TimedeltaIndex.to_pytimedelta()
Return TimedeltaIndex as object ndarray of datetime.timedelta objects

**pandas.TimedeltaIndex.to_series**

TimedeltaIndex.to_series(**kwargs)
Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index

**pandas.TimedeltaIndex.tolist**

TimedeltaIndex.tolist()
return a list of the underlying data

**pandas.TimedeltaIndex.total_seconds**

TimedeltaIndex.total_seconds()
Total duration of each element expressed in seconds.

New in version 0.17.0.

**pandas.TimedeltaIndex.transpose**

TimedeltaIndex.transpose()
return the transpose, which is by definition self

**pandas.TimedeltaIndex.union**

TimedeltaIndex.union(other)
Specialized union for TimedeltaIndex objects. If combine overlapping ranges with the same DateOffset, will be much faster than Index.union

**Parameters**
other : TimedeltaIndex or array-like

**Returns**
y : Index or TimedeltaIndex
pandas.TimedeltaIndex.unique

TimedeltaIndex.unique()

Index.unique with handling for DatetimeIndex/PeriodIndex metadata

Returns result: DatetimeIndex or PeriodIndex

pandas.TimedeltaIndex.value_counts

TimedeltaIndex.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)

Returns object 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 : boolean, default False

If True then the object returned will contain the relative frequencies of the unique values.

sort : boolean, default True

Sort by values

ascending : boolean, default False

Sort in ascending order

bins : integer, optional

Rather than count values, group them into half-open bins, a convenience for pd.cut, only works with numeric data

dropna : boolean, default True

Don’t include counts of NaN.

Returns counts : Series

pandas.TimedeltaIndex.view

TimedeltaIndex.view(cls=None)

34.10.2 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 Timedelta.</td>
</tr>
<tr>
<td>TimedeltaIndex.inferred_freq</td>
<td></td>
</tr>
</tbody>
</table>
pandas.TimedeltaIndex.seconds

TimedeltaIndex.seconds

Number of seconds (>= 0 and less than 1 day) for each element.

pandas.TimedeltaIndex.microseconds

TimedeltaIndex.microseconds

Number of microseconds (>= 0 and less than 1 second) for each element.

pandas.TimedeltaIndex.nanoseconds

TimedeltaIndex.nanoseconds

Number of nanoseconds (>= 0 and less than 1 microsecond) for each element.

pandas.TimedeltaIndex.components

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 = None

34.10.3 Conversion

TimedeltaIndex.to_pytimedelta() Return TimedeltaIndex as object ndarray of datetime.timedelta objects

TimedeltaIndex.to_series(**kwargs) Create a Series with both index and values equal to the index keys

pandas.TimedeltaIndex.to_pytimedelta

TimedeltaIndex.to_pytimedelta()

Return TimedeltaIndex as object ndarray of datetime.timedelta objects

Returns datetimes : ndarray

pandas.TimedeltaIndex.to_series

TimedeltaIndex.to_series(**kwargs)

Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index

Returns Series : dtype will be based on the type of the Index values.
34.11 GroupBy

GroupBy objects are returned by groupby calls: pandas.DataFrame.groupby(), pandas.Series.groupby(), etc.

34.11.1 Indexing, iteration

- GroupBy.__iter__() GroupBy iterator
- GroupBy.groups dict {group name -> group labels}
- GroupBy.indices dict {group name -> group indices}
- GroupBy.get_group(name[, obj]) Constructs NDFrame 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

GroupBy.groups
dict {group name -> group labels}

pandas.core.groupby.GroupBy.indices

GroupBy.indices
dict {group name -> group indices}

pandas.core.groupby.GroupBy.get_group

GroupBy.get_group(name, obj=None)
Constructs NDFrame from group with provided name

Parameters

- name : object
  the name of the group to get as a DataFrame

- obj : NDFrame, default None
  the NDFrame to take the DataFrame out of. If it is None, the object groupby was called on will be used

Returns

- group : type of obj

Grouper([key, level, freq, axis, sort]) A Grouper allows the user to specify a groupby instruction for a target object
pandas: powerful Python data analysis toolkit, Release 0.17.0

pandas.Grouper

class pandas.Grouper (key=None, level=None, freq=None, axis=0, sort=False)
A Grouper allows the user to specify a groupby instruction for a target 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.

These are local specifications and will override ‘global’ settings, that is the parameters axis and level which are passed to the groupby itself.

Parameters

key : string, 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 : string / 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 : number/name of the axis, defaults to 0

sort : boolean, default to False
  whether to sort the resulting labels

additional kwargs to control time-like groupers (when freq is passed)

closed : closed end of interval; left or right

label : interval boundary to use for labeling; left or right

convention : {'start', 'end', 'e', 's'}

If grouper is PeriodIndex

Returns
A specification for a groupby instruction

Examples

Syntactic sugar for df.groupby('A')

>>> df.groupby(Grouper(key='A'))

Specify a resample operation on the column ‘date’

>>> df.groupby(Grouper(key='date', freq='60s'))

Specify a resample operation on the level ‘date’ on the columns axis with a frequency of 60s

>>> df.groupby(Grouper(level='date', freq='60s', axis=1))

Attributes

ax
groups
34.11.2 Function application

GroupBy.apply(func, *args, **kwargs)
Apply function and combine results together in an intelligent way. The split-apply-combine combination rules attempt to be as common sense based as possible. For example:

- case 1: group DataFrame apply aggregation function (f(chunk) -> Series) yield DataFrame, with group axis having group labels
- case 2: group DataFrame apply transform function ((f(chunk) -> DataFrame with same indexes) yield DataFrame with resulting chunks glued together
- case 3: group Series apply function with f(chunk) -> DataFrame yield DataFrame with result of chunks glued together

Parameters

- func : function

Returns

- applied : type depending on grouped object and function

See also:
aggregate, transform

Notes

See online documentation for full exposition on how to use apply.

In the current implementation apply calls func twice on the first group to decide whether it can take a fast or slow code path. This can lead to unexpected behavior if func has side-effects, as they will take effect twice for the first group.
34.11.3 Computation / Descriptive Stats

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<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.first()</code></td>
<td>Compute first of group values</td>
</tr>
<tr>
<td><code>GroupBy.last()</code></td>
<td>Compute last of group values</td>
</tr>
<tr>
<td><code>GroupBy.max()</code></td>
<td>Compute max of group values</td>
</tr>
<tr>
<td><code>GroupBy.mean()</code></td>
<td>Compute mean of groups, excluding missing values</td>
</tr>
<tr>
<td><code>GroupBy.median()</code></td>
<td>Compute median of groups, excluding missing values</td>
</tr>
<tr>
<td><code>GroupBy.min()</code></td>
<td>Compute min of group values</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 sum of values, excluding missing values</td>
</tr>
<tr>
<td><code>GroupBy.prod()</code></td>
<td>Compute prod of group values</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()</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>Returns last n rows of each group</td>
</tr>
</tbody>
</table>

**pandas.core.groupby.GroupBy.count**

`GroupBy.count()`  
Compute count of group, excluding missing values

**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: Series(np.arange(len(x)), x.index))
```

**Parameters**  
- `ascending`: bool, default True  
  If False, number in reverse, from length of group - 1 to 0.

**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
```
```python
1  1
2  2
3  0
4  1
5  3
dtype: int64
>>> df.groupby('A').cumcount(ascending=False)
  0  3
  1  2
  2  1
  3  1
  4  0
  5  0
dtype: int64
```

### pandas.core.groupby.GroupBy.first

`GroupBy.first()`

Compute first of group values

### pandas.core.groupby.GroupBy.head

`GroupBy.head(n=5)`

Returns first n rows of each group.

Essentially equivalent to `.apply(lambda x: x.head(n))`, except ignores `as_index` flag.

**Examples**

```python
>>> df = DataFrame([[1, 2], [1, 4], [5, 6]],
                  columns=['A', 'B'])
>>> df.groupby('A', as_index=False).head(1)
   A  B
0  1  2
2  5  6
```

### pandas.core.groupby.GroupBy.last

`GroupBy.last()`

Compute last of group values

### pandas.core.groupby.GroupBy.max

`GroupBy.max()`

Compute max of group values
pandas.core.groupby.GroupBy.mean

GroupBy.mean()
Compute mean of groups, excluding missing values
For multiple groupings, the result index will be a MultiIndex

pandas.core.groupby.GroupBy.median

GroupBy.median()
Compute median of groups, excluding missing values
For multiple groupings, the result index will be a MultiIndex

pandas.core.groupby.GroupBy.min

GroupBy.min()
Compute min of group values

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 Truthy (if a Series) or ‘all’, ‘any’ (if a DataFrame); 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’

Examples

```python
>>> df = DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=['A', 'B'])
>>> g = df.groupby('A')
>>> g.nth(0)
   A  B
0  1 NaN
2  5  6
>>> g.nth(1)
   A  B
1  1  4
>>> g.nth(-1)
   A  B
1  1  4
2  5  6
>>> g.nth(0, dropna='any')
   B
A
   1  4
```
```python
>>> g.nth(1, dropna='any')  # NaNs denote group exhausted when using dropna
B
A
1 NaN
5 NaN
```

**pandas.core.groupby.GroupBy.ohlc**

GroupBy.ohlc()  
Compute sum of values, excluding missing values For multiple groupings, the result index will be a MultiIndex

**pandas.core.groupby.GroupBy.prod**

GroupBy.prod()  
Compute prod of group values

**pandas.core.groupby.GroupBy.size**

GroupBy.size()  
Compute group sizes

**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

**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

**pandas.core.groupby.GroupBy.sum**

GroupBy.sum()  
Compute sum of group values

**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
pandas.core.groupby.GroupBy.tail

GroupBy.tail(n=5)
    Returns last n rows of each group

    Essentially equivalent to apply(lambda x: x.tail(n)), except ignores as_index flag.

Examples

```python
df = DataFrame([['a', 1], ['a', 2], ['b', 1], ['b', 2]],
               columns=['A', 'B'])

>>> df.groupby('A').tail(1)
   A  B
0  a  2
1  b  2

>>> df.groupby('A').head(1)
   A  B
0  a  1
1  b  1
```

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.

```
DataFrameGroupBy.bfill([axis, inplace, ...]) Synonym for NDFrame.fillna(method='bfill')
DataFrameGroupBy.cummax([axis, dtype, out, ...]) Return cumulative max over requested axis.
DataFrameGroupBy.cummin([axis, dtype, out, ...]) Return cumulative min over requested axis.
DataFrameGroupBy.cumprod([axis, dtype, out, ...]) Return cumulative prod over requested axis.
DataFrameGroupBy.cumsum([axis, dtype, out, ...]) Return cumulative sum over requested axis.
DataFrameGroupBy.describe([percentiles, ...]) Generate various summary statistics, excluding NaN values.
DataFrameGroupBy.all([axis, bool_only, ...]) Return whether all elements are True over requested axis
DataFrameGroupBy.any([axis, bool_only, ...]) Return whether any element is True over requested axis
DataFrameGroupBy.corr([method, min_periods]) Compute pairwise correlation of columns, excluding NA/null values
DataFrameGroupBy.cov([min_periods]) Compute pairwise covariance of columns, excluding NA/null values
DataFrameGroupBy.diff([periods, axis]) 1st discrete difference of object
DataFrameGroupBy.ffill([axis, inplace, ...]) Synonym for NDFrame.fillna(method='ffill')
DataFrameGroupBy.fillna([value, method, ...]) Fill NA/NaN values using the specified method
DataFrameGroupBy.hist([data[, column, by, ...]]) Draw histogram of the DataFrame’s series using matplotlib / ptylab.
DataFrameGroupBy.idxmax([axis, skipna]) Return index of first occurrence of maximum over requested axis.
DataFrameGroupBy.idxmin([axis, skipna]) Return index of first occurrence of minimum over requested axis.
DataFrameGroupBy.mad([axis, skipna]) Return the mean absolute deviation of the values for the requested axis.
DataFrameGroupBy.pct_change([periods, axis]) Percent change over given number of periods.
DataFrameGroupBy.plot Class implementing the .plot attribute for groupby objects
DataFrameGroupBy.quantile([q, axis, ...]) Return values at the given quantile over requested axis, a la numpy.percentile
DataFrameGroupBy.rank([axis, numeric_only, ...]) Compute numerical data ranks (1 through n) along axis.
DataFrameGroupBy.resample([rule[, how, axis, ...]]) Convenience method for frequency conversion and resampling of regular
DataFrameGroupBy.shift([periods, freq, axis]) Shift index by desired number of periods with an optional time freq
DataFrameGroupBy.skew([axis, skipna]) Return unbiased skew over requested axis
DataFrameGroupBy.take(indices[, axis, ...]) Analogous to ndarray.take
DataFrameGroupBy.tshift([periods, freq, axis]) Shift the time index, using the index’s frequency if available
```
pandas.core.groupby.DataFrameGroupBy.bfill

```
DataFrameGroupBy.bfill (axis=None, inplace=False, limit=None, downcast=None)

Synonym for NDFrame.fillna(method='bfill')
```

pandas.core.groupby.DataFrameGroupBy.cummax

```
DataFrameGroupBy.cummax (axis=None, dtype=None, out=None, skipna=True, **kwargs)

Return cumulative max over requested axis.

Parameters axis : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns max : Series
```

pandas.core.groupby.DataFrameGroupBy.cummin

```
DataFrameGroupBy.cummin (axis=None, dtype=None, out=None, skipna=True, **kwargs)

Return cumulative min over requested axis.

Parameters axis : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns min : Series
```

pandas.core.groupby.DataFrameGroupBy.cumprod

```
DataFrameGroupBy.cumprod (axis=None, dtype=None, out=None, skipna=True, **kwargs)

Return cumulative prod over requested axis.

Parameters axis : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns prod : Series
```

pandas.core.groupby.DataFrameGroupBy.cumsum

```
DataFrameGroupBy.cumsum (axis=None, dtype=None, out=None, skipna=True, **kwargs)

Return cumulative sum over requested axis.

Parameters axis : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns prod : Series
```
**Returns**`sum` : Series

**pandas.core.groupby.DataFrameGroupBy.describe**

`DataFrameGroupBy.describe(percentiles=None, include=None, exclude=None)`

Generate various summary statistics, excluding NaN values.

**Parameters**

- `percentiles` : array-like, optional
  The percentiles to include in the output. Should all be in the interval [0, 1]. By default `percentiles` is [.25, .5, .75], returning the 25th, 50th, and 75th percentiles.

- `include, exclude` : list-like, ‘all’, or None (default)
  Specify the form of the returned result. Either:
  - None to both (default). The result will include only numeric-typed columns or, if none are, only categorical columns.
  - A list of dtypes or strings to be included/excluded. To select all numeric types use `numpy` `numpy.number`. To select categorical objects use `type` object. See also the `select_dtypes` documentation. eg. `df.describe(include=['O'])`
  - If include is the string ‘all’, the output column-set will match the input one.

**Returns** `summary` : NDFrame of summary statistics

**See also:**
`DataFrame.select_dtypes`

**Notes**

The output DataFrame index depends on the requested dtypes:

For numeric dtypes, it will include: count, mean, std, min, max, and lower, 50, and upper percentiles.

For object dtypes (e.g. timestamps or strings), the index will include the count, unique, most common, and frequency of the most common. Timestamps also include the first and last items.

For mixed dtypes, the index will be the union of the corresponding output types. Non-applicable entries will be filled with NaN. Note that mixed-dtype outputs can only be returned from mixed-dtype inputs and appropriate use of the include/exclude arguments.

If multiple values have the highest count, then the `count` and `most common` pair will be arbitrarily chosen from among those with the highest count.

The include, exclude arguments are ignored for Series.

**pandas.core.groupby.DataFrameGroupBy.all**

`DataFrameGroupBy.all(axis=None, bool_only=None, skipna=None, level=None, **kwargs)`

Return whether all elements are True over requested axis

**Parameters**

- `axis` : {index (0), columns (1)}
- `skipna` : boolean, 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

**bool_only** : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only
boolean data

**Returns** all : Series or DataFrame (if level specified)

**pandas.core.groupby.DataFrameGroupBy.any**

DataFrameGroupBy.**any** *(axis=None, bool_only=None, skipna=None, level=None, **kwargs)*

Return whether any element is True over requested axis

**Parameters**

**axis** : {index (0), columns (1)}

**skipna** : boolean, 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

**bool_only** : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only
boolean data

**Returns** any : Series or DataFrame (if level specified)

**pandas.core.groupby.DataFrameGroupBy.corr**

DataFrameGroupBy.**corr** *(method='pearson', min_periods=1)*

Compute pairwise correlation of columns, excluding NA/null values

**Parameters**

**method** : {'pearson', 'kendall', 'spearman'}

• pearson : standard correlation coefficient

• kendall : Kendall Tau correlation coefficient

• spearman : Spearman rank correlation

**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** y : DataFrame

**pandas.core.groupby.DataFrameGroupBy.cov**

DataFrameGroupBy.**cov** *(min_periods=None)*

Compute pairwise covariance of columns, excluding NA/null values

**Parameters**

**min_periods** : int, optional

Minimum number of observations required per pair of columns to have a valid result.
**Returns** y : DataFrame

**Notes**

y contains the covariance matrix of the DataFrame’s time series. The covariance is normalized by N-1 (unbiased estimator).

**pandas.core.groupby.DataFrameGroupBy.diff**

DataFrameGroupBy.diff(periods=1, axis=0)

1st discrete difference of object

**Parameters** periods : int, default 1

Periods to shift for forming difference

axis : {0 or ‘index’, 1 or ‘columns’}, default 0

Take difference over rows (0) or columns (1).

**Returns** diffed : DataFrame

**pandas.core.groupby.DataFrameGroupBy.ffill**

DataFrameGroupBy.ffill(axis=None, inplace=False, limit=None, downcast=None)

Synonym for NDFrame.fillna(method='ffill')

**pandas.core.groupby.DataFrameGroupBy.fillna**

DataFrameGroupBy.fillna(value=None, method=None, axis=None, inplace=False, limit=None, downcast=None, **kwargs)

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 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, 1, ‘index’, ‘columns’}

inplace : boolean, 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.

**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**

*filled*: DataFrame

**See also:**

reindex, asfreq

---

**pandas.core.groupby.DataFrameGroupBy.hist**

DataframeGroupBy.hist(data, 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, **kwds)

Draw histogram of the DataFrame’s series using matplotlib / pylab.

**Parameters**

**data**: DataFrame

**column**: string 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**: boolean, 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

**ax**: matplotlib axes object, default None

**sharex**: boolean, 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 subplots in a figure!

**sharey**: boolean, default False

In case subplots=True, share y axis and set some y axis labels to invisible

**figsize**: tuple
The size of the figure to create in inches by default

layout: (optional) a tuple (rows, columns) for the layout of the histograms

bins: integer, default 10
Number of histogram bins to be used

kwds: other plotting keyword arguments
To be passed to hist function

**pandas.core.groupby.DataFrameGroupBy.idxmax**

DataFrameGroupBy.\[\texttt{idxmax}\] (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
0 or ‘index’ for row-wise, 1 or ‘columns’ for column-wise

skipna: boolean, default True
Exclude NA/null values. If an entire row/column is NA, the result will be first index.

**Returns**
\texttt{idxmax}: Series

**See also:**
Series.idxmax

**Notes**
This method is the DataFrame version of \texttt{ndarray.argmax}.

**pandas.core.groupby.DataFrameGroupBy.idxmin**

DataFrameGroupBy.\[\texttt{idxmin}\] (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
0 or ‘index’ for row-wise, 1 or ‘columns’ for column-wise

skipna: boolean, default True
Exclude NA/null values. If an entire row/column is NA, the result will be NA

**Returns**
\texttt{idxmin}: Series

**See also:**
Series.idxmin

**Notes**
This method is the DataFrame version of \texttt{ndarray.argmin}.
pandas.core.groupby.DataFrameGroupBy.mad

DataFrameGroupBy.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)}
skipna : boolean, 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
numeric_only : boolean, default None
Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns
mad : Series or DataFrame (if level specified)

pandas.core.groupby.DataFrameGroupBy.pct_change

DataFrameGroupBy.pct_change(periods=1, fill_method=’pad’, limit=None, freq=None, **kwargs)
Percent change over given number of periods.

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 offset alias string, optional
Increment to use from time series API (e.g. ‘M’ or BDay())

Returns
chg : NDFrame

Notes

By default, the percentage change is calculated along the stat axis: 0, or Index, for DataFrame and 1, or minor for Panel. You can change this with the axis keyword argument.

pandas.core.groupby.DataFrameGroupBy.plot

DataFrameGroupBy.plot
Class implementing the .plot attribute for groupby objects
pandas.core.groupby.DataFrameGroupBy.quantile

DataFrameGroupBy.quantile(q=0.5, axis=0, numeric_only=True)

Return values at the given quantile over requested axis, a la numpy.percentile.

Parameters q : float or array-like, default 0.5 (50% quantile)
    0 <= q <= 1, the quantile(s) to compute

axis : {0, 1, ‘index’, ‘columns’} (default 0)
    0 or ‘index’ for row-wise, 1 or ‘columns’ for column-wise

Returns quantiles : 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.

Examples

>>> df = DataFrame(np.array([[1, 1], [2, 10], [3, 100], [4, 100]]),
                  columns=['a', 'b'])
>>> df.quantile(.1)
a  1.3  
b  3.7  
dtype: float64
>>> df.quantile([.1, .5])
a  b
0.1 1.3 3.7
0.5 2.5 55.0

pandas.core.groupby.DataFrameGroupBy.rank

DataFrameGroupBy.rank(axis=0, numeric_only=None, method='average', na_option='keep', ascending=True, pct=False)

Compute numerical data ranks (1 through n) along axis. 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
    Ranks over columns (0) or rows (1)

numeric_only : boolean, default None
    Include only float, int, boolean data

method : {'average', 'min', 'max', 'first', 'dense'}
    • 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

na_option : {'keep', 'top', 'bottom'}
    • keep: leave NA values where they are
pandas: powerful Python data analysis toolkit, Release 0.17.0

- top: smallest rank if ascending
- bottom: smallest rank if descending

**ascending**: boolean, default True

False for ranks by high (1) to low (N)

**pct**: boolean, default False

Computes percentage rank of data

**Returns**

**ranks**: DataFrame

---

**pandas.core.groupby.DataFrameGroupBy.resample**

DataFrameGroupBy. **resample** *(rule, how=None, axis=0, fill_method=None, closed=None, label=None, convention='start', kind=None, loffset=None, limit=None, base=0)*

Convenience method for frequency conversion and resampling of regular time-series data.

**Parameters**

- **rule**: string
  the offset string or object representing target conversion

- **how**: string
  method for down- or re-sampling, default to ‘mean’ for downsampling

- **axis**: int, optional, default 0

- **fill_method**: string, default None
  fill_method for upsampling

- **closed**: {'right', 'left'}
  Which side of bin interval is closed

- **label**: {'right', 'left'}
  Which bin edge label to label bucket with

- **convention**: {'start', 'end', 's', 'e'}

- **kind**: “period”/“timestamp”

- **loffset**: timedelta
  Adjust the resampled time labels

- **limit**: int, default None
  Maximum size gap to when reindexing with fill_method

- **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

**Examples**

Start by creating a series with 9 one minute timestamps.
Downsample the series into 3 minute bins and sum the values of the timestamps falling into a bin.

```python
>>> series.resample('3T', how='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', how='sum', label='right')
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', how='sum', label='right', closed='right')
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')[0:5]  # select first 5 rows
2000-01-01 00:00:00    0
2000-01-01 00:00:30   NaN
2000-01-01 00:01:00    1
2000-01-01 00:01:30   NaN
2000-01-01 00:02:00    2
Freq: 30S, dtype: float64
```

Upsample the series into 30 second bins and fill the NaN values using the pad method.

```python
>>> series.resample('30S', fill_method='pad')[0:5]
2000-01-01 00:00:00    0
2000-01-01 00:00:30    0
```

34.11. GroupBy
Upsample the series into 30 second bins and fill the NaN values using the `bfill` method.

```python
>>> series.resample('30S', fill_method='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 to `how`.

```python
>>> def custom_resampler(array_like):
...     return np.sum(array_like)+5

>>> series.resample('3T', how=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
```

### pandas.core.groupby.DataFrameGroupBy.shift

**DataFrameGroupBy.shift**(periods=1, freq=None, axis=0)

Shift index by desired number of periods with an optional time freq

- **Parameters**
  - **periods**: int
    - Number of periods to move, can be positive or negative
  - **freq**: DateOffset, timedelta, or time rule string, optional
    - Increment to use from datetools module or time rule (e.g. ‘EOM’). See Notes.
  - **axis**: {0, 1, ‘index’, ‘columns’}

- **Returns**
  - **shifted**: DataFrame

- **Notes**
  - 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.

### pandas.core.groupby.DataFrameGroupBy.skew

**DataFrameGroupBy.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)}
  - **skipna**: boolean, 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

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns skew : Series or DataFrame (if level specified)

**pandas.core.groupby.DataFrameGroupBy.take**

DataFrameGroupBy.take (indices, axis=0, convert=True, is_copy=True)

Analogous to ndarray.take

- **Parameters**
  - indices : list / array of ints
  - axis : int, default 0
  - convert : translate neg to pos indices (default)
  - is_copy : mark the returned frame as a copy

Returns taken : type of caller

**pandas.core.groupby.DataFrameGroupBy.tshift**

DataFrameGroupBy.tshift (periods=1, freq=None, axis=0)

Shift the time index, using the index’s frequency if available

- **Parameters**
  - periods : int
    Number of periods to move, can be positive or negative
  - freq : DateOffset, timedelta, or time rule string, default None
    Increment to use from datetools module or time rule (e.g. ‘EOM’)  
  - axis : int or basestring
    Corresponds to the axis that contains the Index

Returns shifted : NDFrame

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>SeriesGroupBy.nlargest(*args, **kwargs)</td>
<td>Return the largest n elements.</td>
</tr>
<tr>
<td>SeriesGroupBy.nsmallest(*args, **kwargs)</td>
<td>Return the smallest n elements.</td>
</tr>
<tr>
<td>SeriesGroupBy.nunique([dropna])</td>
<td>Return array of unique values in the object.</td>
</tr>
<tr>
<td>SeriesGroupBy.unique()</td>
<td></td>
</tr>
<tr>
<td>SeriesGroupBy.value_counts([normalize, ...])</td>
<td></td>
</tr>
</tbody>
</table>
**pandas.core.groupby.SeriesGroupBy.nlargest**

SeriesGroupBy.nlargest(*args, **kwargs)

Return the largest \( n \) elements.

**Parameters**

\( n \) : int

Return this many descending sorted values

**keep** : {'first', 'last', False}, default 'first'

Where there are duplicate values: - first: take the first occurrence. - last: take the last occurrence.

**take_last** : deprecated

**Returns**

\( \text{top}_n \) : Series

The \( n \) largest values in the Series, in sorted order

**See also:**

Series.nsmallest

**Notes**

Faster than .sort_values(ascending=False).head(n) for small \( n \) relative to the size of the Series object.

**Examples**

```python
>>> import pandas as pd
>>> import numpy as np
>>> s = pd.Series(np.random.randn(1e6))
>>> s.nlargest(10)  # only sorts up to the N requested
```

**pandas.core.groupby.SeriesGroupBy.nsmallest**

SeriesGroupBy.nsmallest(*args, **kwargs)

Return the smallest \( n \) elements.

**Parameters**

\( n \) : int

Return this many ascending sorted values

**keep** : {'first', 'last', False}, default 'first'

Where there are duplicate values: - first: take the first occurrence. - last: take the last occurrence.

**take_last** : deprecated

**Returns**

\( \text{bottom}_n \) : Series

The \( n \) smallest values in the Series, in sorted order

**See also:**

Series.nlargest
Notes

Faster than `.sort_values().head(n)` for small $n$ relative to the size of the `Series` object.

Examples

```python
>>> import pandas as pd
>>> import numpy as np

>>> s = pd.Series(np.random.randn(1e6))
>>> s.nsmallest(10)  # only sorts up to the N requested

pandas.core.groupby.SeriesGroupBy.nunique

SeriesGroupBy.nunique(dropna=True)

pandas.core.groupby.SeriesGroupBy.unique

SeriesGroupBy.unique()

Return array of unique values in the object. Significantly faster than numpy.unique. Includes NA values.

Returns uniques : ndarray

pandas.core.groupby.SeriesGroupBy.value_counts

SeriesGroupBy.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)

The following methods are available only for `DataFrameGroupBy` objects.

- DataFrameGroupBy.corrwith(other[, axis, drop]) : Compute pairwise correlation between rows or columns of two DataFrame objects.
- DataFrameGroupBy.boxplot(grouped[, ...]) : Make box plots from `DataFrameGroupBy` data.

pandas.core.groupby.DataFrameGroupBy.corrwith

DataFrameGroupBy.corrwith(other[, axis, drop])

Compute pairwise correlation between rows or columns of two DataFrame objects.

Parameters other : DataFrame
    
    Compute pairwise correlation between rows or columns of two DataFrame objects.

Returns correls : Series
    
    Drop missing indices from result, default returns union of all
pandas.core.groupby.DataFrameGroupBy.boxplot

`DataFrameGroupBy.boxplot(grouped, subplots=True, column=None, fontsize=None, rot=0, grid=True, ax=None, figsize=None, layout=None, **kwds)`

Make box plots from DataFrameGroupBy data.

**Parameters**

- **grouped**: Grouped DataFrame

  **subplots**:
  - 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 string

- **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)
  (rows, columns) for the layout of the plot

- **kwds**: other plotting keyword arguments to be passed to matplotlib boxplot function

**Returns**

dict of key/value = group key/DataFrame.boxplot return value

or DataFrame.boxplot return value in case subplots=figures=False

**Examples**

```python
>>> import pandas
>>> import numpy as np
>>> import itertools

>>> tuples = [t for t in itertools.product(range(1000), range(4))]
>>> index = pandas.MultiIndex.from_tuples(tuples, names=['lvl0', 'lvl1'])
>>> data = np.random.randn(len(index), 4)
>>> df = pandas.DataFrame(data, columns=list('ABCD'), index=index)

>>> grouped = df.groupby(level='lvl1')
>>> boxplot_frame_groupby(grouped)

>>> grouped = df.unstack(level='lvl1').groupby(level=0, axis=1)
>>> boxplot_frame_groupby(grouped, subplots=False)
```

### 34.12 General utility functions

#### 34.12.1 Working with options
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<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>describe_option</code></td>
<td>Prints the description for one or more registered options.</td>
</tr>
<tr>
<td><code>reset_option</code></td>
<td>Reset one or more options to their default value.</td>
</tr>
<tr>
<td><code>get_option</code></td>
<td>Retrieves the value of the specified option.</td>
</tr>
<tr>
<td><code>set_option</code></td>
<td>Sets the value of the specified option.</td>
</tr>
<tr>
<td><code>option_context</code></td>
<td>Context manager to temporarily set options in the with statement context.</td>
</tr>
</tbody>
</table>

**pandas.describe_option**

```python
pandas.describe_option(pat, _print_desc=False) = <pandas.core.config.CallableDynamicDoc object at 0xb559f24c>
```

Prints the description for one or more registered options. Call with no arguments to get a listing for all registered options.

Available options:

- `display.chop_threshold`, `colheader_justify`, `column_space`, `date_dayfirst`, `date_yearfirst`, `encoding`, `expand_frame_repr`, `float_format`, `height`, `large_repr`, `line_width`, `max_categories`, `max_columns`, `max_colwidth`, `max_info_columns`, `max_info_rows`, `max_rows`, `max_seq_items`, `memory_usage`, `mpl_style`, `multi_sparse`, `notebook_repr_html`, `pprint_nest_depth`, `precision`, `show_dimensions`
- `display.unicode.ambiguous_as_wide`, `east_asian_width`
- `display.[width]`
- `io.excel.xls.[writer]`
- `io.excel.xlsm.[writer]`
- `io.excel.xltx.[writer]`
- `io.hdf.[default_format, dropna_table]`
- `mode.[chained_assignment, sim_interactive, use_inf_as_null]`

**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:

- `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 core.format.EngFormatter for an example. [default: None] [currently: None]
display.height [int] Deprecated. [default: 60] [currently: 15] (Deprecated, use display.max_rows instead.)
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.line_width [int] Deprecated. [default: 80] [currently: 80] (Deprecated, use display.width instead.)
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: 20] [currently: 20]
display.max_colwidth [int] 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. [default: 50] [currently: 50]
display.max_info_columns [int or None] 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 then 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 or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. [default: True] [currently: True]
**display.mpl_style** [bool] Setting this to ‘default’ will modify the rcParams used by matplotlib to give plots a more pleasing visual style by default. Setting this to None/False restores the values to their initial value. [default: None] [currently: None]

**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_null** [boolean] True means treat None, NaN, INF, -INF as null (old way), False means None and NaN are null, but INF, -INF are not null (new way). [default: False] [currently: False]

**pandas.reset_option**

**pandas.reset_option**(pat) = <pandas.core.config.CallableDynamicDoc object at 0xb559f22c>

Reset one or more options to their default value.
Pass “all” as argument to reset all options.

Available options:

- `display.chop_threshold`, `colheader_justify`, `column_space`, `date_dayfirst`, `date_yearfirst`, `encoding`, `expand_frame_repr`, `float_format`, `height`, `large_repr`, `line_width`, `max_categories`, `max_columns`, `max_colwidth`, `max_info_columns`, `max_info_rows`, `max_rows`, `max_seq_items`, `memory_usage`, `mpl_style`, `multi_sparse`, `notebook_repr_html`, `pprint_nest_depth`, `precision`, `show_dimensions`
- `display.unicode.ambiguous_as_wide`, `display.unicode.east_asian_width`
- `display.width`
- `io.excel.xls.writer`
- `io.excel.xlsm.writer`
- `io.excel.xlsx.writer`
- `io.hdf.default_format`, `dropna_table`
- `mode.chained_assignment`, `sim_interactive`, `use_inf_as_null`

**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 their descriptions:

- **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 core.format.EngFormatter for an example. [default: None] [currently: None]

- **display.height**  
  [int] Deprecated.  
  [default: 60] [currently: 15] (Deprecated, use `display.max_rows` instead.)
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.line_width [int] Deprecated. [default: 80] [currently: 80] (Deprecated, use display.width instead.)

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: 20] [currently: 20]

display.max_colwidth [int] 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. [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 then 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 or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. [default: True] [currently: True]

display.mpl_style [bool] Setting this to ‘default’ will modify the rcParams used by matplotlib to give plots a more pleasing visual style by default. Setting this to None/False restores the values to their initial value. [default: None] [currently: None]

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 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 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_null [boolean] True means treat None, NaN, INF, -INF as null (old way), False means None and NaN are null, but INF, -INF are not null (new way).  [default: False]  [currently: False]

pandas.get_option

pandas.get_option(pat) = <pandas.core.config.CallableDynamicDoc object at 0xb559f1ec>
Retrieves the value of the specified option.

Available options:

- display.chop_threshold, colheader_justify, column_space, date_dayfirst, date_yearfirst, encoding, expand_frame_repr, float_format, height, large_repr, line_width, max_categories, max_columns, max_colwidth, max_info_columns, max_info_rows, max_rows, max_seq_items, memory_usage, mpl_style, multi_sparse, notebook_repr_html, pprint_nest_depth, precision, show_dimensions
- display.unicode.ambiguous_as_wide, east_asian_width
- display.width
- io.excel.xls.[writer]
- io.excel.xlsm.[writer]
- io.excel.xlsx.[writer]
- io.hdf.[default_format, dropna_table]
- mode.[chained_assignment, sim_interactive, use_inf_as_null]
**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 their descriptions:

- `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 core.format.EngFormatter for an example. [default: None] [currently: None]
- `display.height` [int] Deprecated. [default: 60] [currently: 15] (Deprecated, use `display.max_rows` instead.)
- `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.line_width` [int] Deprecated. [default: 80] [currently: 80] (Deprecated, use `display.width` instead.)
- `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: 20] [currently: 20]

- `display.max_colwidth` [int] 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. [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 then 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 or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. [default: True] [currently: True]

**display.mpl_style** [bool] Setting this to ‘default’ will modify the rcParams used by matplotlib to give plots a more pleasing visual style by default. Setting this to None/False restores the values to their initial value. [default: None] [currently: None]

**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_null  [boolean] True means treat None, NaN, INF, -INF as null (old way), False means None and NaN are null, but INF, -INF are not null (new way). [default: False] [currently: False]

pandas.set_option

pandas.set_option(pat, value) = <pandas.core.config.CallableDynamicDoc object at 0xb559f20c>
Sets the value of the specified option.

Available options:

•display.[chop_threshold, colheader_justify, column_space, date_dayfirst, date_yearfirst, encoding, expand_frame_repr, float_format, height, large_repr, line_width, max_categories, max_columns, max_colwidth, max_info_columns, max_info_rows, max_rows, max_seq_items, memory_usage, mpl_style, multi_sparse, notebook_repr_html, pprint_nest_depth, precision, show_dimensions]

•display.unicode.[ambiguous_as_wide, east_asian_width]

•display.[width]

•io.excel.xls.[writer]

•io.excel.xlsm.[writer]

•io.excel.xlsx.[writer]

•io.hdf.[default_format, dropna_table]

•mode.[chained_assignment, sim_interactive, use_inf_as_null]

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 :

new value of option.

Returns None

Raises OptionError if no such option exists

Notes

The available options with its descriptions:
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 core.format.EngFormatter for an example. [default: None] [currently: None]

display.height [int] Deprecated. [default: 60] [currently: 15] (Deprecated, use display.max_rows instead.)

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.line_width [int] Deprecated. [default: 80] [currently: 80] (Deprecated, use display.width instead.)

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: 20] [currently: 20]

display.max_colwidth [int] 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. [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 then 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 or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. [default: True] [currently: True]

display.mpl_style [bool] Setting this to ‘default’ will modify the rcParams used by matplotlib to give plots a more pleasing visual style by default. Setting this to None/False restores the values to their initial value. [default: None] [currently: None]

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 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 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_null** [boolean] True means treat None, NaN, INF, -INF as null (old way). False means None and NaN are null, but INF, -INF are not null (new way). [default: False] [currently: False]

**pandas.option_context**

```python
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

   >>> with option_context('display.max_rows', 10, 'display.max_columns', 5):
   ...  
```
This section will provide a look into some of pandas internals.

### 35.1 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 in64 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

### 35.1.1 MultiIndex

Internally, the MultiIndex consists of a few things: the **levels**, the integer **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(levels=[[0, 1, 2], [u'one', u'two']], labels=[[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]], names=[u'first', u'second'])
```

```
In [3]: index.levels
Out[3]: FrozenList([[0, 1, 2], [u'one', u'two']])
```

```
In [4]: index.labels
Out[4]: FrozenList([[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]])
```

```
In [5]: index.names
Out[5]: FrozenList([u'first', u'second'])
```

You can probably guess that the labels 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 labels 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 labels yourself, please be careful.

### 35.2 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.

This section describes how to subclass pandas data structures to meet more specific needs. There are 2 points which need attention:

1. Override constructor properties.
2. Define original properties

**Note**: You can find a nice example in geopandas project.
35.2.1 Override Constructor Properties

Each data structure has constructor properties to specifying data constructors. By overriding these properties, you can retain defined-classes through pandas data manipulations.

There are 3 constructors to be defined:

- `__constructor`: Used when a manipulation result has the same dimesions 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() and DataFrame.to_panel().

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>
<th>Panel</th>
</tr>
</thead>
<tbody>
<tr>
<td>__constructor</td>
<td>Series</td>
<td>DataFrame</td>
<td>Panel</td>
</tr>
<tr>
<td>__constructor_sliced</td>
<td>NotImplemented</td>
<td>Series</td>
<td>Panel</td>
</tr>
<tr>
<td>__constructor_expanddim</td>
<td>NotImplemented</td>
<td>DataFrame</td>
<td>NotImplemented</td>
</tr>
</tbody>
</table>

Below example shows how to define SubclassedSeries and SubclassedDataFrame overriding constructor properties.

class SubclassedSeries(Series):

    @property
    def __constructor(self):
        return SubclassedSeries

    @property
    def __constructor_expanddim(self):
        return SubclassedDataFrame

class SubclassedDataFrame(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
1  2  5  8
2  3  6  9
35.2.2 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 2 original properties, “internal_cache” as a temporary property and “added_property” as a normal property

```python
class SubclassedDataFrame2(DataFrame):
    
    # temporary properties
    _internal_names = pd.DataFrame._internal_names + ['internal_cache']
    _internal_names_set = set(_internal_names)

    # normal properties
    _metadata = ['added_property']

    @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
```
>>> 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
This is the list of changes to pandas between each release. For full details, see the commit logs at http://github.com/pydata/pandas

What is it

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.

Where to get it

- Source code: http://github.com/pydata/pandas
- Binary installers on PyPI: http://pypi.python.org/pypi/pandas
- Documentation: http://pandas.pydata.org

36.1 pandas 0.17.0

Release date: (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.

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 unparsable 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 datetimelikes, 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 (GH8316)

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)

See the v0.17.0 Whatsnew overview for an extensive list of all enhancements and bugs that have been fixed in 0.17.0.

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- Safia Abdalla
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- Sebastian Pölsterl
- Sebastian Rubbert
- Sheppard, Kevin
- Sinhrks
- Siu Kwan Lam
- Skipper Seabold
- Spencer Carrucci
- Stephan Hoyer
- Stephen Hoover
- Stephen Pascoe
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- Tjerk Santegoeds
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- agijsberts
- ajcr
- behzad nouri
- cel4
- cyrusmaher
- davidovitch
- ganego
- jreback
36.2 pandas 0.16.2

Release date: (June 12, 2015)

This is a minor release from 0.16.1 and includes a large number of bug fixes along with several new features, enhancements, and performance improvements.

Highlights include:

• A new `pipe` method, see [here](#)
• Documentation on how to use numba with pandas, see [here](#)

See the v0.16.2 Whatsnew overview for an extensive list of all enhancements and bugs that have been fixed in 0.16.2.

36.2.1 Thanks

• Andrew Rosenfeld
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This is a minor release from 0.16.0 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.

See the v0.16.1 Whatsnew overview for an extensive list of all API changes, enhancements and bugs that have been fixed in 0.16.1.

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36.4 pandas 0.16.0

Release date: (March 22, 2015)

This is a major release from 0.15.2 and includes a number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes.

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](#)
- The `pandas.tools.rplot`, `pandas.sandbox.qtpandas` and `pandas.rpy` modules are deprecated. We refer users to external packages like `seaborn`, `pandas-qt` and `rpy2` for similar or equivalent functionality, see [here](#)

See the v0.16.0 Whatsnew overview or the issue tracker on GitHub for an extensive list of all API changes, enhancements and bugs that have been fixed in 0.16.0.

36.4.1 Thanks

- Aaron Toth
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36.5 pandas 0.15.2

Release date: (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.

See the v0.15.2 Whatsnew overview for an extensive list of all API changes, enhancements and bugs that have been fixed in 0.15.2.

36.5.1 Thanks

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• Matthew Brett
• Phillip Cloud
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• broessli
• charalampos papaloizou
• immerrr
• jnmclarty
• jreback
• mgilbert
• onesandzeroes
• peadarcoyle
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36.6 pandas 0.15.1

**Release date:** (November 9, 2014)

This is a minor 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.

See the v0.15.1 Whatsnew overview for an extensive list of all API changes, enhancements and bugs that have been fixed in 0.15.1.

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- Aaron Staple
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- WANG Aiyong
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- immerrr
- jnmclarty
- jreback
- pallav-fdsi
- unutbu
36.7 pandas 0.15.0

**Release date:** (October 18, 2014)

This is a major release from 0.14.1 and includes a number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes.

Highlights include:

- Drop support for numpy < 1.7.0 (GH7711)
- 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 DataFrame default display for df.info() to include memory usage, see Memory Usage
- New datetimelike properties accessor .dt for Series, see Datetimelike Properties
- Split indexing documentation into Indexing and Selecting Data and MultiIndex / Advanced Indexing
- Split out string methods documentation into Working with Text Data
- read_csv will now by default ignore blank lines when parsing, see here
- API change in using Indexes in set operations, 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)

See the v0.15.0 Whatsnew overview or the issue tracker on GitHub for an extensive list of all API changes, enhancements and bugs that have been fixed in 0.15.0.

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- Aaron Schumacher
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- dlovell
• DSM
• dsm054
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36.8 pandas 0.14.1

Release date: (July 11, 2014)

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.

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 \texttt{read\_csv()} text parser.
• New documentation section on \textit{Options and Settings}.
• Lots of bug fixes.

See the \texttt{v0.14.1 \textit{Whatsnew}} overview or the issue tracker on GitHub for an extensive list of all API changes, enhancements and bugs that have been fixed in 0.14.1.

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36.9 pandas 0.14.0

Release date: (May 31, 2014)

This is a major release from 0.13.1 and includes a number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes.

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 multi-indexed 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

See the v0.14.0 Whatsnew overview or the issue tracker on GitHub for an extensive list of all API changes, enhancements and bugs that have been fixed in 0.14.0.
36.9.1 Thanks

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• Noah Spies
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• Randy Carnevale
• ribonuous
• Robert Gibboni
• rockg
• sinhrks
• Skipper Seabold
• SplashDance
• Stephan Hoyer
• Tim Cera
• Tobias Brandt
• Todd Jennings
• TomAugspurger
• Tom Augspurger
• unutbu
• westurner
• Yaroslav Halchenko
• y-p
• zach powers

36.10 pandas 0.13.1

Release date: (February 3, 2014)

36.10.1 New Features

• Added date_format and datetime_format attribute to ExcelWriter. (GH4133)

36.10.2 API Changes

• Series.sort will raise a ValueError (rather than a TypeError) on sorting an object that is a view of another (GH5856, GH5853)
• Raise/Warn SettingWithCopyError (according to the option chained_assignment in more cases, when detecting chained assignment, related (GH5938, GH6025)
• `DataFrame.head(0)` returns self instead of empty frame (GH5846)

• `autocorrelation_plot` now accepts `**kwargs` (GH5623)

• `convert_objects` now accepts a `convert_timedeltas='coerce'` argument to allow forced dtype conversion of timedeltas (GH5458, issue: 5689)

• Add `-NaN` and `-nan` to the default set of NA values (GH5952). See NA Values.

• `NDFrame` now has an `equals` method. (GH5283)

• `DataFrame.apply` will use the `reduce` argument to determine whether a Series or a DataFrame should be returned when the DataFrame is empty (GH6007).

### 36.10.3 Experimental Features

### 36.10.4 Improvements to existing features

• perf improvements in Series datetime/timedelta binary operations (GH5801)

• `option_context` context manager now available as top-level API (GH5752)

• `df.info()` view now display dtype info per column (GH5682)

• `df.info()` now honors option max_info_rows, disable null counts for large frames (GH5974)

• perf improvements in 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)

• support `dtypes` property on `Series/Panel/Panel4D`

• extend `Panel.apply` to allow arbitrary functions (rather than only ufuncs) (GH1148) allow multiple axes to be used to operate on slabs of a Panel

• The `ArrayFormatter` for `datetime` and `timedelta64` now intelligently limit precision based on the values in the array (GH3401)

• `pd.show_versions()` is now available for convenience when reporting issues.

• perf improvements to `Series.str.extract` (GH5944)

• perf improvements in `dtypes/ftypes` methods (GH5968)

• perf improvements in indexing with object dtypes (GH5968)

• improved dtype inference for `timedelta` like passed to constructors (GH5458, GH5689)

• escape special characters when writing to latex (:issue: 5374)

• perf improvements in `DataFrame.apply` (GH6013)

• `pd.read_csv` and `pd.to_datetime` learned a new `infer_datetime_format` keyword which greatly improves parsing perf in many cases. Thanks to @lexual for suggesting and @danbirken for rapidly implementing. (GH5490, issue: 6021)

• add ability to recognize ‘%p’ format code (am/pm) to date parsers when the specific format is supplied (GH5361)

• Fix performance regression in JSON IO (GH5765)

• performance regression in Index construction from Series (GH6150)
36.10.5 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 `NaN` comparison if a mixed datetime/np.datetime64 with `NaN` 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 multi-index via `ix` (GH6018)
• Bug in Series.xs with a multi-index (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 propogating _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 datafarm 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 multi-indexed columns to an existing table (GH6167)
• Consistency with dtypes in setting an empty DataFrame (GH6171)
• Bug in selecting on a multi-index 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)

36.11 pandas 0.13.0

Release date: January 3, 2014

36.11.1 New Features

• 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)
• Added isin method to DataFrame (GH4211)
• df.to_clipboard() learned a new excel keyword that let’s you paste df data directly into excel (enabled by default). (GH5070).
• Clipboard functionality now works with PySide (GH4282)
• New extract string method returns regex matches more conveniently (GH4685)
• Auto-detect field widths in read_fwf when unspecified (GH4488)
• to_csv() now outputs datetime objects according to a specified format string via the date_format keyword (GH4313)
• Added LastWeekOfMonth DateOffset (GH4637)
• Added cumcount groupby method (GH4646)
• Added FY5253, and FY5253Quarter DateOffsets (GH4511)
• Added mode() method to Series and DataFrame to get the statistical mode(s) of a column/series. (GH5367)

36.11.2 Experimental Features

• The new eval() function implements expression evaluation using numexpr behind the scenes. This results in large speedups for complicated expressions involving large DataFrames/Series.
• DataFrame has a new eval() that evaluates an expression in the context of the DataFrame; allows inline expression assignment
• A query() method has been added that allows you to select elements of a DataFrame using a natural query syntax nearly identical to Python syntax.
• pd.eval and friends now evaluate operations involving datetime64 objects in Python space because numexpr cannot handle NaT values (GH4897).
• Add msgpack support via pd.read_msgpack() and pd.to_msgpack() / df.to_msgpack() for serialization of arbitrary pandas (and python objects) in a lightweight portable binary format (GH686, GH5506)
• Added PySide support for the qtpandas DataFrameModel and DataFrameWidget.
• Added pandas.io.gbq for reading from (and writing to) Google BigQuery into a DataFrame. (GH4140)

36.11.3 Improvements to existing features

• read_html now raises a URLError instead of catching and raising a ValueError (GH4303, GH4305)
• read_excel now supports an integer in its sheetname argument giving the index of the sheet to read in (GH4301).
• get_dummies works with NaN (GH4446)
• Added a test for read_clipboard() and to_clipboard() (GH4282)
• Added bins argument to value_counts (GH3945), also sort and ascending, now available in Series method as well as top-level function.
• Text parser now treats anything that reads like inf (“inf”, “Inf”, “-Inf”, “iNf”, etc.) to infinity. (GH4220, GH4219), affecting read_table, read_csv, etc.
• Added a more informative error message when plot arguments contain overlapping color and style arguments (GH4402)
• Significant table writing performance improvements in HDFStore
• JSON date serialization now performed in low-level C code.
• JSON support for encoding datetime.time
• Expanded JSON docs, more info about orient options and the use of the numpy param when decoding.
• Add drop_level argument to xs (GH4180)
• Can now resample a DataFrame with ohlc (GH2320)
• Index.copy() and MultiIndex.copy() now accept keyword arguments to change attributes (i.e., names, levels, labels) (GH4039)
• Add rename and set_names methods to Index as well as set_names, set_levels, set_labels to MultiIndex. (GH4039) with improved validation for all (GH4039, GH4794)
• A Series of dtype timedelta64[ns] can now be divided/multiplied by an integer series (GH4521)
• A Series of dtype timedelta64[ns] can now be divided by another timedelta64[ns] object to yield a float64 dtype Series. This is frequency conversion; astyping is also supported.
• Timedelta64 support fillna/ffill/bfill with an integer interpreted as seconds, or a timedelta (GH3371)
• Box numeric ops on timedelta Series (GH4984)
• Datetime64 support ffill/bfill
• Performance improvements with __getitem__ on DataFrames with when the key is a column
• Support for using a DatetimeIndex/PeriodsIndex directly in a datelike calculation e.g. s-s.index (GH4629)
• Better/cleaned up exceptions in core/common, io/excel and core/format (GH4721, GH3954), as well as cleaned up test cases in tests/test_frame, tests/test_multilevel (GH4732).
• Performance improvement of timeseries plotting with PeriodIndex and added test to vbench (GH4705 and GH4722)
• Add axis and level keywords to where, so that the other argument can now be an alignable pandas object.
• to_datetime with a format of ‘%Y%m%d’ now parses much faster
• It’s now easier to hook new Excel writers into pandas (just subclass ExcelWriter and register your engine). You can specify an engine in to_excel or in ExcelWriter. You can also specify which writers you want to use by default with config options io.excel.xlsx.writer and io.excel.xls.writer. (GH4745, GH4750)
• Panel.to_excel() now accepts keyword arguments that will be passed to its DataFrame's to_excel() methods. (GH4750)
• Added XlsxWriter as an optional ExcelWriter engine. This is about 5x faster than the default openpyxl xlsx writer and is equivalent in speed to the xlwt xls writer module. (GH4542)
• allow DataFrame constructor to accept more list-like objects, e.g. list of collections.Sequence and array.Array objects (GH3783, GH4297, GH4851), thanks @lgautier
• DataFrame constructor now accepts a numpy masked record array (GH3478), thanks @jnothman
• __getitem__ with tuple key (e.g., [:, 2]) on Series without MultiIndex raises ValueError (GH4759, GH4837)
• read_json now raises a (more informative) ValueError when the dict contains a bad key and orient='split' (GH4730, GH4838)
- read_stata now accepts Stata 13 format (GH4291)
- ExcelWriter and ExcelFile can be used as contextmanagers. (GH3441, GH4933)
- pandas is now tested with two different versions of statsmodels (0.4.3 and 0.5.0) (GH4981).
- Better string representations of MultiIndex (including ability to roundtrip via repr). (GH3347, GH4935)
- Both ExcelFile and read_excel to accept an XLRD.Book for the io (formerly path_or_buf) argument; this requires engine to be set. (GH4961).
- concat now gives a more informative error message when passed objects that cannot be concatenated (GH4608).
- Add halflife option to exponentially weighted moving functions (PR GH4998)
- to_dict now takes records as a possible outtype. Returns an array of column-keyed dictionaries. (GH4936)
- tz_localize can infer a fall daylight savings transition based on the structure of unlocalized data (GH4230)
- DatetimeIndex is now in the API documentation
- Improve support for converting R datasets to pandas objects (more informative index for timeseries and numeric, support for factors, dist, and high-dimensional arrays).
- read_html() now supports the parse_dates, tupleize_cols and thousands parameters (GH4770).
- json_normalize() is a new method to allow you to create a flat table from semi-structured JSON data. See the docs (GH1067)
- DataFrame.from_records() will now accept generators (GH4910)
- DataFrame.interpolate() and Series.interpolate() have been expanded to include interpolation methods from scipy. (GH4434, GH1892)
- Series now supports to_frame method to convert it to a single-column DataFrame (GH5164)
- DatetimeIndex (and date_range) can now be constructed in a left- or right-open fashion using the closed parameter (GH4579)
- Python csv parser now supports usecols (GH4335)
- Added support for Google Analytics v3 API segment IDs that also supports v2 IDs. (GH5271)
- NDFrame.drop() now accepts names as well as integers for the axis argument. (GH5354)
- Added short docstrings to a few methods that were missing them + fixed the docstrings for Panel flex methods. (GH5336)
- NDFrame.drop(), NDFrame.dropna(), and .drop_duplicates() all accept inplace as a keyword argument; however, this only means that the wrapper is updated inplace, a copy is still made internally. (GH1960, GH5247, GH5628, and related GH2325 [still not closed])
- Fixed bug in tools.plotting.andrews_curves so that lines are drawn grouped by color as expected.
- read_excel() now tries to convert integral floats (like 1.0) to int by default. (GH5394)
- Excel writers now have a default option merge_cells into_excel() to merge cells in MultiIndex and Hierarchical Rows. Note: using this option it is no longer possible to round trip Excel files with merged MultiIndex and Hierarchical Rows. Set the merge_cells to False to restore the previous behaviour. (GH5254)
- The FRED DataReader now accepts multiple series (issue`3413`)
- StataWriter adjusts variable names to Stata’s limitations (GH5709)
36.11.4 API Changes

- DataFrame.reindex() and forward/backward filling now raises ValueError if either index is not monotonic (GH4483, GH4484).

- 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)

- deprecated iterkv, which will be removed in a future release (was just an alias of iteritems used to get around 2to3’s changes). (GH4384, GH4375, GH4372)

- Series.get with negative indexers now returns the same as [] (GH4390)

- allow ix/loc for Series/DataFrame/Panel to set on any axis even when the single-key is not currently contained in the index for that axis (GH2578, GH5226, GH5632, GH5720, GH5744, GH5756)

- Default export for to_clipboard is now csv with a sep of | for compat (GH3368)

- at now will enlarge the object inplace (and return the same) (GH2578)

- DataFrame.plot will scatter plot x versus y by passing kind='scatter' (GH2215)

- HDFStore
  - append_to_multiple automatically synchronizes writing rows to multiple tables and adds a dropna kwarg (GH4698)
  - handle a passed Series in table format (GH4330)
  - 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
  - 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)
  - 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)
  - the format keyword now replaces the table keyword; allowed values are fixed(f)|table(t) the Storer format has been renamed to Fixed
  - a column multi-index will be recreated properly (GH4710); raise on trying to use a multi-index with data_columns on the same axis
  - select_as_coordinates will now return an Int64Index of the resultant selection set
-- support timedelta64[ns] as a serialization type (GH3577)
-- store datetime.date objects as ordinals rather then timetuples to avoid timezone issues (GH2852), thanks @tavismorph and @numpand
-- numexpr 2.2.2 fixes incompatibility in PyTables 2.4 (GH4908)
-- flush now accepts an fsync parameter, which defaults to False (GH5364)
-- unicode indices not supported on table formats (GH5386)
-- pass thru store creation arguments; can be used to support in-memory stores

- JSON
-- added date_unit parameter to specify resolution of timestamps. Options are seconds, milliseconds, microseconds and nanoseconds. (GH4362, GH4498).
-- added default_handler parameter to allow a callable to be passed which will be responsible for handling otherwise unserializable objects. (GH5138)

- Index and MultiIndex changes (GH4039):
  -- Setting levels and labels directly on MultiIndex is now deprecated. Instead, you can use the set_levels() and set_labels() methods.
  -- levels, labels and names properties no longer return lists, but instead return containers that do not allow setting of items (‘mostly immutable’)
  -- levels, labels and names are validated upon setting and are either copied or shallow-copied.
  -- inplace setting of levels or labels now correctly invalidates the cached properties. (GH5238).
  -- __deepcopy__ now returns a shallow copy (currently: a view) of the data - allowing metadata changes.
  -- MultiIndex.astype() now only allows np.object_-like dtypes and now returns a MultiIndex rather than an Index. (GH4039)
  -- Added is_ method to Index that allows fast equality comparison of views (similar to np.may_share_memory but no false positives, and changes on levels and labels setting on MultiIndex). (GH4859, GH4909)
  -- Aliased __iadd__ to __add__. (GH4996)
  -- Added is_ method to Index that allows fast equality comparison of views (similar to np.may_share_memory but no false positives, and changes on levels and labels setting on MultiIndex). (GH4859, GH4909)

- Infer and downcast dtpe 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. Add .bool() method to NDFrame objects to facilitate evaluating of single-element boolean Series
- DataFrame.update() no longer raises a DataConflictError, it now will raise a ValueError instead (if necessary) (GH4732)
- Series.isin() and DataFrame.isin() now raise a TypeError when passed a string (GH4763). Pass a list of one element (containing the string) instead.
- Remove undocumented/unused kind keyword argument from read_excel, and ExcelFile. (GH4713, GH4712)
- The method argument of NDFrame.replace() is valid again, so that a a list can be passed to to_replace (GH4743).
• provide automatic dtype conversions on _reduce operations (GH3371)
• exclude non-numerics if mixed types with datelike in _reduce operations (GH3371)
• default for tupleize_cols is now False for both to_csv and read_csv. Fair warning in 0.12 (GH3604)
• moved timedeltas support to pandas.tseries.timedeltas.py; add timedeltas string parsing, add top-level to_timedelta function
• NDFrame now is compatible with Python’s toplevel abs() function (GH4821).
• raise a TypeError on invalid comparison ops on Series/DataFrame (e.g. integer/datetime) (GH4968)
• 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. 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 raise a TypeError, e.g. Series(range(5)) [3.5:4.5] (GH263, issue:5375)
• Make Categorical repr nicer (GH4368)
• Remove deprecated Factor (GH3650)
• Remove deprecated set_printoptions/reset_printoptions (issue:3046)
• Remove deprecated _verbose_info (GH3215)
• Begin removing methods that don’t make sense on GroupBy objects (GH4887).
• Remove deprecated read_clipboard/to_clipboard/ExcelFile/ExcelWriter from pandas.io.parsers (GH3717)
• 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)
• Arithmetic func factories are now passed real names (suitable for using with super) (GH5240)
• Provide numpy compatibility with 1.7 for a calling convention like np.prod(pandas_object) as numpy call with additional keyword args (GH4435)
• Provide __dir__ method (and local context) for tab completion / remove ipython completers code (GH4501)
• Support non-unique axes in a Panel via indexing operations (GH4960)
• .truncate will raise a ValueError if invalid before and afters dates are given (GH5242)
• Timestamp now supports now/today/utcnow class methods (GH5339)
• default for display.max_seq_len is now 100 rather then None. This activates truncated display (“...”) of long sequences in various places. (GH3391)
• All division with NDFrame - likes is now truedivision, regardless of the future import. You can use // and floordiv to do integer division.

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])
In [6]: pd.Series(arr) / pd.Series(arr2) # no future import required
Out[6]:
<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.200000</td>
</tr>
<tr>
<td>1</td>
<td>0.666667</td>
</tr>
<tr>
<td>2</td>
<td>1.500000</td>
</tr>
<tr>
<td>3</td>
<td>4.000000</td>
</tr>
</tbody>
</table>

dtype: float64

- raise/warn SettingWithCopyError/Warning exception/warning when setting of a copy thru chained assignment is detected, settable via option mode.chained_assignment
- test the list of NA values in the csv parser. add N/A, #NA as independent default na values (GH5521)
- The refactoring involving “Series” deriving from NDFrame breaks rpy2<=2.3.8. an Issue has been opened against rpy2 and a workaround is detailed in GH5698. Thanks @JanSchulz.
- 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)

### 36.11.5 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) See Internal Refactoring

- 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)
  - isnull/notnull now available on NDFrame objects
- 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 same API as original DataFrame filter
- fillna refactored to core/generic.py, while > 3ndim is NotImplemented
• Series now inherits from NDFrame rather than directly from ndarray. There are several minor changes that affect the API.

• numpy functions that do not support the array interface will now return ndarrays rather than series, e.g. np.diff, np.ones_like, np.where

• Series(0.5) would previously return the scalar 0.5, this is no longer supported

• 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 now have a _prop_attributes, which can be used to indicate various values to propagate to a new object from an existing (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 in Series update where the parent frame is not updating its cache based on changes (GH4080, GH5216) or types (GH3217), fillna (GH3386)

• Indexing with dtype conversions fixed (GH4463, GH4204)

• Refactor Series.reindex to core/generic.py (GH4604, GH4618), allow method= in reindexing on a Series to work

• Series.copy no longer accepts the order parameter and is now consistent with NDFrame copy

• Refactor rename methods to core/generic.py; fixes Series.rename for (GH4605), and adds rename with the same signature for Panel

• Series (for index) / Panel (for items) now as attribute access to its elements (GH1903)

• Refactor clip methods to core/generic.py (GH4798)

• Refactor of _get_numeric_data/_get_bool_data to core/generic.py, allowing Series/Panel functionality

• Refactor of Series arithmetic with time-like objects (datetime/timedelta/time etc.) into a separate, cleaned up wrapper class. (GH4613)

• Complex compat for Series with ndarray. (GH4819)

• Removed unnecessary rwproperty from codebase in favor of builtin property. (GH4843)

• Refactor object level numeric methods (mean/sum/min/max...) from object level modules to core/generic.py (GH4435).
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• Refactor cum objects to core/generic.py (GH4435), note that these have a more numpy-like function signature.
• read_html() now uses TextParser to parse HTML data from bs4/lxml (GH4770).
• Removed the keep_internal keyword parameter in pandas/core/groupby.py because it wasn’t being used (GH5102).
• Base DateOffsets are no longer all instantiated on importing pandas, instead they are generated and cached on the fly. The internal representation and handling of DateOffsets has also been clarified. (GH5189, related GH5004)
• MultiIndex constructor now validates that passed levels and labels are compatible. (GH5213, GH5214)
• Unity dropna for Series/DataFrame signature (GH5250), tests from GH5234, courtesy of @rockg
• Rewrite assert_almost_equal() in cython for performance (GH4398)
• Added an internal _update_inplace method to facilitate updating NDFrame wrappers on inplace ops (only is for convenience of caller, doesn’t actually prevent copies). (GH5247)

36.11.6 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 pytz3 (GH5441)
  – Validate levels in a multi-index 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 cparsers 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 multi-index 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 date-times (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 indcies (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 multi-indexing 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 multi-index 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/numpy.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 c 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 multi-index 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 seg fault 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 multi-index 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 (GH5538)

• Bug in getitem with a multi-index 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 multi-index selection in PY3 when using certain keys (GH5725)

• Row-wise concat of differing dtypes failing in certain cases (GH5754)

36.12 pandas 0.12.0

Release date: 2013-07-24

36.12.1 New Features

• pd.read_html() can now parse HTML strings, files or urls and returns a list of DataFrame s courtesy of @cpcloud. (GH3477, GH3605, GH3606)

• Support for reading Amazon S3 files. (GH3504)

• Added module for reading and writing JSON strings/files: pandas.io.json includes to_json DataFrame/Series method, and a read_json top-level reader various issues (GH1226, GH3804, GH3876, GH3867, GH1305)

• Added module for reading and writing Stata files: pandas.io.stata (GH1512) includes to_stata DataFrame method, and a read_stata top-level reader
• Added support for writing in `to_csv` and reading in `read_csv`, multi-index columns. The `header` option in `read_csv` now accepts a list of the rows from which to read the index. Added the option, `tupleize_cols` to provide compatibility for the pre 0.12 behavior of writing and reading multi-index 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 multi-index column. Note: The default value will change in 0.12 to make the default to write and read multi-index columns in the new format. (GH3571, GH1651, GH3141)

• Add iterator to `Series.str` (GH3638)

• `pd.set_option()` now allows N option, value pairs (GH3667).

• Added keyword parameters for different types of scatter_matrix subplots

• A `filter` method on grouped Series or DataFrames returns a subset of the original (GH3680, GH919)

• Access to historical Google Finance data in pandas.io.data (GH3814)

• DataFrame plotting methods can sample column colors from a Matplotlib colormap via the `colormap` keyword. (GH3860)

36.12.2 Improvements to existing features

• Fixed various issues with internal pprinting code, the repr() for various objects including TimeStamp and Index now produces valid python code strings and can be used to recreate the object, (GH3038, GH3379, GH3251, GH3460)

• `convert_objects` now accepts a `copy` parameter (defaults to True)

• `HDFStore`
  – will retain index attributes (freq,tz,name) on recreation (GH3499,issue:4098)
  – 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)
  – table writing performance improvements.
  – support python3 (via PyTables 3.0.0) (GH3750)

• Add modulo operator to Series, DataFrame

• Add `date` method to DatetimeIndex

• Add `dropna` argument to pivot_table (:issue: 3820)

• Simplified the API and added a describe method to Categorical

• `melt` now accepts the optional parameters `var_name` and `value_name` to specify custom column names of the returned DataFrame (GH3649), thanks @hoechenberger. If `var_name` is not specified and `dataframe.columns.name` is not None, then this will be used as the `var_name` (GH4144). Also support for MultiIndex columns.

• clipboard functions use pyperclip (no dependencies on Windows, alternative dependencies offered for Linux) (GH3837).

• 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.

• Added Faq section on repr display options, to help users customize their setup.
• where operations that result in block splitting are much faster (GH3733)
• Series and DataFrame hist methods now take a figsize argument (GH3834)
• DatetimeIndexes no longer try to convert mixed-integer indexes during join operations (GH3877)
• Add unit keyword to Timestamp and to_datetime to enable passing of integers or floats that are in an epoch unit of D, s, ms, us, ns, thanks @mtkini (GH3969) (e.g. unix timestamps or epoch s, with fractional seconds allowed) (GH3540)
• DataFrame corr method (spearman) is now cythonized.
• 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)
• read_csv will now throw a more informative error message when a file contains no columns, e.g., all newline characters
• Added layout keyword to DataFrame.hist() for more customizable layout (GH4050)
• 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)

36.12.3 API Changes

• HDFStore
  – When removing an object, remove(key) raises KeyError if the key is not a valid store object.
  – raise a TypeError on passing where or columns to select with a Storer; these are invalid parameters at this time (GH4189)
  – can now specify an encoding option to append/put to enable alternate encodings (GH3750)
  – enable support for iterator/chunksize with read_hdf
• The repr() for (Multi)Index now obeys display.max_seq_items rather then numpy threshold print options. (GH3426, GH3466)
• Added mangle_dupe_cols option to read_table/csv, allowing users to control legacy behaviour re dupe cols (A, A.1, A.2 vs A, A) (GH3468) Note: The default value will change in 0.12 to the “no mangle” behaviour, If your code relies on this behaviour, explicitly specify mangle_dupe_cols=False in your calls.
• 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
• Do not allow datetimelike/timedelta-like creation except with valid types (e.g. cannot pass datetime64[ms]) (GH3423)
• Add squeeze keyword to groupby to allow reduction from DataFrame -> Series if groups are unique. Regression from 0.10.1, partial revert on (GH2893) with (GH3596)
• 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)

36.12. pandas 0.12.0 1713
• The raise_on_error option to plotting methods is obviated by GH3572, so it is removed. Plots now always raise when data cannot be plotted or the object being plotted has a dtype of object.

• 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)

• Deprecated display.height, display.width is now only a formatting option does not control triggering of summary, similar to < 0.11.0.

• 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)

• io API changes
  – added pandas.io.api for i/o imports
  – removed Excel support to pandas.io.excel
  – added top-level pd.read_sql and to_sql DataFrame methods
  – removed clipboard support to pandas.io.clipboard
  – replace top-level and instance methods save and load with top-level read_pickle and to_pickle instance method, save and load will give deprecation warning.

• the method and axis arguments of DataFrame.replace() are deprecated

• set FutureWarning to require data_source, and to replace year/month with expiry date in pandas.io options. This is in preparation to add options data from Google (GH3822)

• the method and axis arguments of DataFrame.replace() are deprecated

• Implement __nonzero__ for NDFrame objects (GH3691, GH3696)

• as_matrix with mixed signed and unsigned dtypes will result in 2 x the lcd of the unsigned as an int, maxing with int64, to avoid precision issues (GH3733)

• na_values in a list provided to read_csv/read_excel will match string and numeric versions e.g. na_values=['99'] will match 99 whether the column ends up being int, float, or string (GH3611)

• 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

• more consistency in the to_datetime return types (give string/array of string inputs) (GH3888)

• The internal pandas class hierarchy has changed (slightly). The previous PandasObject now is called PandasContainer and a new PandasObject has become the baseclass 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)

36.12.4 Experimental Features

• Added experimental CustomBusinessDay class to support DateOffsets with custom holiday calendars and custom weekmasks. (GH2301)
36.12.5 Bug Fixes

- Fixed an esoteric excel reading bug. xlrd>= 0.9.0 now required for excel support. Should provide python3 support (for reading) which has been lacking. (GH3164)
- Disallow Series constructor called with MultiIndex which caused segfault (GH4187)
- Allow unioning of date ranges sharing a timezone (GH3491)
- Fix to_csv issue when having a large number of rows and NaT in some columns (GH3437)
- .loc was not raising when passed an integer list (GH3449)
- Unordered time series selection was misbehaving when using label slicing (GH3448)
- Fix sorting in a frame with a list of columns which contains datetime64[ns] dtypes (GH3461)
- DataFrames fetched via FRED now handle ‘.’ as a NaN. (GH3469)
- Fix regression in a DataFrame apply with axis=1, objects were not being converted back to base dtypes correctly (GH3480)
- Fix issue when storing uint dtypes in an HDFStore. (GH3493)
- Non-unique index support clarified (GH3468)
  - Addressed handling of dupe columns in df.to_csv new and old (GH3454, GH3457)
  - 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)
  - Fix to_csv to handle non-unique columns (GH3495)
  - Duplicate indexes with getitem 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)
  - 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)
- Fixed bug in groupby with empty series referencing a variable before assignment. (GH3510)
- Allow index name to be used in groupby for non MultiIndex (GH4014)
- Fixed bug in mixed-frame assignment with aligned series (GH3492)
Fixed bug in selecting month/quarter/year from a series would not select the time element on the last day (GH3546)

Fixed a couple of MultiIndex rendering bugs in df.to_html() (GH3547, GH3553)

Properly convert np.datetime64 objects in a Series (GH3416)

Raise a TypeError on invalid datetime/timedelta operations e.g. add datetimes, multiple timedelta x datetime

Fix .diff on datelike and timedelta operations (GH3100)

combine_first not returning the same dtype in cases where it can (GH3552)

Fixed bug with Panel.transpose argument aliases (GH3556)

Fixed platform bug in PeriodIndex.take (GH3579)

Fixed bug in incorrect conversion of datetime64[ns] in combine_first (GH3593)

Fixed bug in reset_index with NaN in a multi-index (GH3586)

fillna methods now raise a TypeError when the value parameter is a list or tuple.

Fixed bug where a time-series was being selected in preference to an actual column name in a frame (GH3594)

Make secondary_y work properly for bar plots (GH3598)

Fix modulo and integer division on Series,DataFrames to act simialry to float dtypes to return np.nan or np.inf as appropriate (GH3590)

Fix incorrect dtype on groupby with as_index=False (GH3610)

Fix read_csv/read_excel to correctly encode identical na_values, e.g. na_values=[-999.0,-999] was failing (GH3611)

Disable HTML output in qtconsole again. (GH3657)

Reworked the new repr display logic, which users found confusing. (GH3663)

Fix indexing issue in ndim >= 3 with iloc (GH3617)

Correctly parse date columns with embedded (nan/NaT) into datetime64[ns] dtype in read_csv when parse_dates is specified (GH3062)

Fix not consolidating before to_csv (GH3624)

Fix alignment issue when setitem in a DataFrame with a piece of a DataFrame (GH3626) or a mixed DataFrame and a Series (GH3668)

Fix plotting of unordered DatetimeIndex (GH3601)

sql.write_frame failing when writing a single column to sqlite (GH3628), thanks to @stonebig

Fix pivoting with nan in the index (GH3558)

Fix running of bs4 tests when it is not installed (GH3605)

Fix parsing of html table (GH3606)

read_html() now only allows a single backend: html5lib (GH3616)

convert_objects with convert_dates='coerce' was parsing some single-letter strings into today's date

DataFrame.from_records did not accept empty recarrays (GH3682)

DataFrame.to_csv will succeed with the deprecated option nanRep. @tdsmith

DataFrame.to_html and DataFrame.to_latex now accept a path for their first argument (GH3702)
• Fix file tokenization error with r delimiter and quoted fields (GH3453)
• Groupby transform with item-by-item not upcasting correctly (GH3740)
• Incorrectly read a HDFStore multi-index Frame with a column specification (GH3748)
• read_html now correctly skips tests (GH3741)
• PandasObjects raise TypeError when trying to hash (GH3882)
• Fix incorrect arguments passed to concat that are not list-like (e.g. concat(df1,df2)) (GH3481)
• Correctly parse when passed the dtype=str (or other variable-len string dtypes) in read_csv (GH3795)
• Fix index name not propagating when using loc/ix (GH3880)
• Fix groupby when applying a custom function resulting in a returned DataFrame was not converting dtypes (GH3911)
• Fixed a bug where DataFrame.replace with a compiled regular expression in the to_replace argument wasn’t working (GH3907)
• Fixed __truediv__ in Python 2.7 with numexpr installed to actually do true division when dividing two integer arrays with at least 10000 cells total (GH3764)
• Indexing with a string with seconds resolution not selecting from a time index (GH3925)
• csv parsers would loop infinitely if iterator=True but no chunksize was specified (GH3967), python parser failing with chunksize=1
• Fix index name not propagating when using shift
• Fixed dropna=False being ignored with multi-index stack (GH3997)
• Fixed flattening of columns when renaming MultiIndex columns DataFrame (GH4004)
• Fix Series.clip for datetime series. NA/NaN threshold values will now throw ValueError (GH3996)
• Fixed insertion issue into DataFrame, after rename (GH4032)
• 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)
• Fix bug where HDFStore will fail to append because of a different block ordering on-disk (GH4096)
• Better error messages on inserting incompatible columns to a frame (GH4107)
• Fixed bug in DataFrame.replace where a nested dict wasn’t being iterated over when regex=False (GH4115)
• Fixed bug in convert_objects(convert_numeric=True) where a mixed numeric and object Series/Frame was not converting properly (GH4119)
• Fixed bugs in multi-index selection with column multi-index and duplicates (GH4145, GH4146)
• 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 Series.where where broadcasting a single element input vector to the length of the series resulted in multiplying the value inside the input (GH4192)
- 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)

### 36.13 pandas 0.11.0

**Release date:** 2013-04-22

#### 36.13.1 New Features

- New documentation section, 10 Minutes to Pandas
- New documentation section, Cookbook
- Allow mixed dtypes (e.g float32/float64/int32/int16/int8) to coexist in DataFrames and propagate in operations
- Add function to pandas.io.data for retrieving stock index components from Yahoo! finance (GH2795)
- Support slicing with time objects (GH2681)
- Added `.iloc` attribute, to support strict integer based indexing, analogous to `.ix` (GH2922)
- Added `.loc` attribute, to support strict label based indexing, analogous to `.ix` (GH3053)
- Added `.iat` attribute, to support fast scalar access via integers (replaces `iget_value/iset_value`)
- Added `.at` attribute, to support fast scalar access via labels (replaces `get_value/set_value`)
- Moved functionality from `irow,icol,iget_value/iset_value` to `.iloc` indexer (via `_ixs` methods in each object)
- Added support for expression evaluation using the `numexpr` library
- Added `convert=boolean` to take routines to translate negative indices to positive, defaults to True
- Added `to_series()` method to indices, to facilitate the creation of indexers (GH3275)

#### 36.13.2 Improvements to existing features

- Improved performance of `df.to_csv()` by up to 10x in some cases. (GH3059)
- Added `blocks` attribute to DataFrames, to return a dict of dtypes to homogeneously dtyped DataFrames
- Added keyword `convert_numeric` to `convert_objects()` to try to convert object dtypes to numeric types (default is False)
- `convert_dates` in `convert_objects` can now be `coerce` which will return a `datetime64[ns]` dtype with non-convertibles set as NaT; will preserve an all-nan object (e.g. strings), default is True (to perform soft-conversion)

- Series print output now includes the dtype by default

- Optimize internal reindexing routines (GH2819, GH2867)

- `describe_option()` now reports the default and current value of options.

- Add `format` option to `pandas.to_datetime` with faster conversion of strings that can be parsed with `datetime.strptime`

- Add `axes` property to `Series` for compatibility

- Add `xs` function to `Series` for compatibility

- Allow `setitem` in a frame where only mixed numerics are present (e.g. int and float), (GH3037)

- `HDFStore`
  - 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)
  - Support `read_hdf/to_hdf` API similar to `read_csv/to_csv` (GH3222)

- Add `squeeze` method to possibly remove length 1 dimensions from an object.

```python
In [1]: 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'])
...:

In [2]: p
Out[2]:
<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

In [3]: p.reindex(items=['ItemA']).squeeze()
Out[3]:
          A         B         C         D
2001-01-02  0.469112 -0.282863 -1.509059 -1.135632
2001-01-03  1.212112 -0.173215  0.119209 -1.044236
2001-01-04 -0.861849 -2.104569 -0.494929  1.071804
2001-01-05  0.721555 -0.706771 -1.039575  0.271860

In [4]: p.reindex(items=['ItemA'],minor=['B']).squeeze()
Out[4]:
          A         B
2001-01-02 -0.282863
2001-01-03 -0.173215
2001-01-04 -2.104569
2001-01-05 -0.706771
Freq: D, Name: B, dtype: float64
```

- Improvement to Yahoo API access in `pd.io.data.Options` (GH2758)

- 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.

• Allow selection semantics via a string with a datelike index to work in both Series and DataFrames (GH3070)

```python
In [5]: idx = pd.date_range("2001-10-1", periods=5, freq='M')

In [6]: ts = pd.Series(np.random.rand(len(idx)),index=idx)

In [7]: ts['2001']
Out[7]:
2001-10-31  0.838796
2001-11-30  0.897333
2001-12-31  0.732592
Freq: M, dtype: float64

In [8]: df = pd.DataFrame(dict(A = ts))

In [9]: df['2001']
Out[9]:
   A
2001-10-31  0.838796
2001-11-30  0.897333
2001-12-31  0.732592
```

• added option `display.mpl_style` providing a sleeker visual style for plots. Based on https://gist.github.com/huyng/816622 (GH3075).

• Improved performance across several core functions by taking memory ordering of arrays into account. Courtesy of @stephenwlin (GH3130)

• Improved performance of groupby transform method (GH2121)

• Handle “ragged” CSV files missing trailing delimiters in rows with missing fields when also providing explicit list of column names (so the parser knows how many columns to expect in the result) (GH2981)

• On a mixed DataFrame, allow setting with indexers with ndarray/DataFrame on rhs (GH3216)

• Treat boolean values as integers (values 1 and 0) for numeric operations. (GH2641)

• Add `time` method to DatetimeIndex (GH3180)

• Return NA when using Series.str[...] for values that are not long enough (GH3223)

• Display cursor coordinate information in time-series plots (GH1670)

• `to_html()` now accepts an optional “escape” argument to control reserved HTML character escaping (enabled by default) and escapes & in addition to < and >. (GH2919)

### 36.13.3 API Changes

• Do not automatically upcast numeric specified dtypes to `int64` or `float64` (GH622 and GH797)

• DataFrame construction of lists and scalars, with no dtype present, will result in casting to `int64` or `float64`, regardless of platform. This is not an apparent change in the API, but noting it.

• Guarantee that `convert_objects()` for Series/DataFrame always returns a copy.
• groupby operations will respect dtypes for numeric float operations (float32/float64); other types will be operated on, and will try to cast back to the input dtype (e.g. if an int is passed, as long as the output doesn’t have nans, then an int will be returned)

• backfill/pad/take/diff/ohlc will now support float32/int16/int8 operations

• Block types will upcast as needed in where/masking operations (GH2793)

• Series now automatically will try to set the correct dtype based on passed datetimelike objects (date-time/Timestamp)
  – timedelta64 are returned in appropriate cases (e.g. Series - Series, when both are datetime64)
  – mixed datetimes and objects (GH2751) in a constructor will be cast correctly
  – astype on datetimes to object are now handled (as well as NaT conversions to np.nan)
  – all timedelta like objects will be correctly assigned to timedelta64 with mixed NaN and/or NaT allowed

• arguments to DataFrame.clip were inconsistent to numpy and Series clipping (GH2747)

• util.testing.assert_frame_equal now checks the column and index names (GH2964)

• Constructors will now return a more informative ValueError on failures when invalid shapes are passed

• Don’t suppress TypeError in GroupBy.agg (GH3238)

• Methods return None when inplace=True (GH1893)

• 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 will now automatically create data_columns for passed keys

• Downcast on pivot if possible (GH3283), adds argument downcast to fillna

• Introduced options display.height/width for explicitly specifying terminal height/width in characters. Deprecated display.line_width, now replaced by display.width. These defaults are in effect for scripts as well, so unless disabled, previously very wide output will now be output as “expand_repr” style wrapped output.

• Various defaults for options (including display.max_rows) have been revised, after a brief survey concluded they were wrong for everyone. Now at w=80,h=60.

• HTML repr output in IPython qtconsole is once again controlled by the option display.notebook_repr_html, and on by default.

### 36.13.4 Bug Fixes

• Fix seg fault on empty data frame when fillna with pad or backfill (GH2778)

• Single element ndarrays of datetimelike objects are handled (e.g. np.array(datetime(2001,1,1,0,0))), w/o dtype being passed

• 0-dim ndarrays with a passed dtype are handled correctly (e.g. np.array(0.,dtype='float32'))

• Fix some boolean indexing inconsistencies in Series._getitem_/__setitem__ (GH2776)

• Fix issues with DataFrame and Series constructor with integers that overflow int64 and some mixed typed type lists (GH2845)

• HDFStore
- Fix weird PyTables error when using too many selectors in a where also correctly filter on any number of values in a Term expression (so not using numexpr filtering, but isin filtering)
- Internally, change all variables to be private-like (now have leading underscore)
- Fixes for query parsing to correctly interpret boolean and != (GH2849, GH2973)
- Fixes for pathological case on SparseSeries with 0-len array and compression (GH2931)
- Fixes bug with writing rows if part of a block was all-nan (GH3012)
- Exceptions are now ValueError or TypeError as needed
- A table will now raise if min_itemsize contains fields which are not queryables

- Bug showing up in applymap where some object type columns are converted (GH2909) had an incorrect default in convert_objects

- TimeDeltas
  - Series ops with a Timestamp on the rhs was throwing an exception (GH2898) added tests for Series ops with datetimes, timedeltas, Timestamps, and datelike Series on both lhs and rhs
  - Fixed subtle timedelta64 inference issue on py3 & numpy 1.7.0 (GH3094)
  - Fixed some formatting issues on timedelta when negative
  - Support null checking on timedelta64, representing (and formatting) with NaT
  - Support setitem with np.nan value, converts to NaT
  - Support min/max ops in a Dataframe (abs not working, nor do we error on non-supported ops)
  - Support idxmin/idxmax/abs/max/min in a Series (GH2989, GH2982)

- Bug on in-place putmasking on an integer series that needs to be converted to float (GH2746)
- Bug in argsort of datetime64[ns] Series with NaT (GH2967)
- Bug in value_counts of datetime64[ns] Series (GH3002)
- Fixed printing of NaT in an index
- Bug in idxmin/idxmax of datetime64[ns] Series with NaT (GH2982)
- Bug in icol, take with negative indicies was producing incorrect return values (see GH2922, GH2892), also check for out-of-bounds indices (GH3029)
- Bug in DataFrame column insertion when the column creation fails, existing frame is left in an irrecoverable state (GH3010)
- Bug in DataFrame update, combine_first where non-specified values could cause dtype changes (GH3016, GH3041)
- Bug in groupby with first/last where dtypes could change (GH3041, GH2763)
- Formatting of an index that has nan was inconsistent or wrong (would fill from other values), (GH2850)
- Unstack of a frame with no nans would always cause dtype upcasting (GH2929)
- Fix scalar datetime.datetime parsing bug in read_csv (GH3071)
- Fixed slow printing of large Dataframes, due to inefficient dtype reporting (GH2807)
- Fixed a segfault when using a function as grouper in groupby (GH3035)
- Fix pretty-printing of infinite data structures (closes GH2978)
- Fixed exception when plotting timeseries bearing a timezone (closes GH2877)
str.contains ignored na argument (GH2806)
Substitute warning for segfault when grouping with categorical grouper of mismatched length (GH3011)
Fix exception in SparseSeries.density (GH2083)
Fix upsampling bug with closed=’left’ and daily to daily data (GH3020)
Fixed missing tick bars on scatter_matrix plot (GH3063)
Fixed bug in Timestamp(d,tz=foo) when d is date() rather then datetime() (GH2993)
series.plot(kind=’bar’) now respects pylab color schem (GH3115)
Fixed bug in reshape if not passed correct input, now raises TypeError (GH2719)
Fixed a bug where Series ctor did not respect ordering if OrderedDict passed in (GH3282)
Fix NameError issue on RESO_US (GH2787)
Allow selection in an unordered timeseries to work similary to an ordered timeseries (GH2437).
Fix implemented .xs when called with axes=1 and a level parameter (GH2903)
Timestamp now supports the class method fromordinal similar to datetimes (GH3042)
Fix issue with indexing a series with a boolean key and specifying a 1-len list on the rhs (GH2745) or a list on the rhs (GH3235)
Fixed bug in groupby apply when kernel generate list of arrays having unequal len (GH1738)
fixed handling of rolling_corr with center=True which could produce corr>1 (GH3155)
Fixed issues where indices can be passed as ‘index/column’ in addition to 0/1 for the axis parameter
PeriodIndex.tolist now boxes to Period (GH3178)
PeriodIndex.get_loc KeyError now reports Period instead of ordinal (GH3179)
df.to_records bug when handling MultiIndex (GH3189)
Fix Series.__getitem__ segfault when index less than -length (GH3168)
Fix bug when using Timestamp as a date parser (GH2932)
Fix bug creating date range from Timestamp with time zone and passing same time zone (GH2926)
Add comparison operators to Period object (GH2781)
Fix bug when concatenating two Series into a DataFrame when they have the same name (GH2797)
Fix automatic color cycling when plotting consecutive timeseries without color arguments (GH2816)
fixed bug in the pickling of PeriodIndex (GH2891)
Upcast/split blocks when needed in a mixed DataFrame when setitem with an indexer (GH3216)
Invoking df.applymap on a dataframe with dupe cols now raises a ValueError (GH2786)
Apply with invalid returned indices raise correct Exception (GH2808)
Fixed a bug in plotting log-scale bar plots (GH3247)
df.plot() grid on/off now obeys the mpl default style, just like series.plot(). (GH3233)
Fixed a bug in the legend of plotting.andrews_curves() (GH3278)
Produce a series on apply if we only generate a singular series and have a simple index (GH2893)
Fix Python ASCII file parsing when integer falls outside of floating point spacing (GH3258)
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- fixed pretty priniting of sets (GH3294)
- Panel() and Panel.from_dict() now respects ordering when give OrderedDict (GH3303)
- DataFrame where with a datetimelike incorrectly selecting (GH3311)
- Ensure index casts work even in Int64Index
- Fix set_index segfault when passing MultiIndex (GH3308)
- Ensure pickles created in py2 can be read in py3
- Insert ellipsis in MultiIndex summary repr (GH3348)
- Groupby will handle mutation among an input groups columns (and fallback to non-fast apply) (GH3380)
- Eliminated unicode errors on FreeBSD when using MPL GTK backend (GH3360)
- Period.strftime should return unicode strings always (GH3363)
- Respect passed read_* chunksize in get_chunk function (GH3406)

36.14 pandas 0.10.1

Release date: 2013-01-22

36.14.1 New Features

- Add data interface to World Bank WDI pandas.io.wb (GH2592)

36.14.2 API Changes

- Restored inplace=True behavior returning self (same object) with deprecation warning until 0.11 (GH1893)
- HDFStore
  - refactored HDFStore to deal with non-table stores as objects, will allow future enhancements
  - removed keyword compression from put (replaced by keyword complib to be consistent across library)
  - warn PerformanceWarning if you are attempting to store types that will be pickled by PyTables

36.14.3 Improvements to existing features

- HDFStore
  - enables storing of multi-index dataframes (closes GH1277)
  - support data column indexing and selection, via data_columns keyword in append
  - support write chunking to reduce memory footprint, via chunksize keyword to append
  - support automatic indexing via index keyword to append
  - support expectedrows keyword in append toinform PyTables about the expected tablesize
  - support start and stop keywords in select to limit the row selection space
  - added get_store context manager to automatically import with pandas
- added column filtering via `columns` keyword in `select`
- added methods `append_to_multiple/select_as_multiple/select_as_coordinates` to do multiple-table append/selection
- added support for `datetime64` in columns
- added method `unique` to select the unique values in an indexable or data column
- added method `copy` to copy an existing store (and possibly upgrade)
- show the shape of the data on disk for non-table stores when printing the store
- added ability to read PyTables flavor tables (allows compatibility to other HDF5 systems)

- Add `logx` option to DataFrame/Series.plot (GH2327, GH2565)
- Support reading gzipped data from file-like object
- `pivot_table aggfunc` can be anything used in `GroupBy.aggregate` (GH2643)
- Implement DataFrame merges in case where set cardinalities might overflow 64-bit integer (GH2690)
- Raise exception in C file parser if integer dtype specified and have NA values. (GH2631)
- Attempt to parse ISO8601 format dates when `parse_dates=True` in `read_csv` for major performance boost in such cases (GH2698)
- Add methods `neg` and `inv` to Series
- Implement `kind` option in ExcelFile to indicate whether it’s an XLS or XLSX file (GH2613)
- Documented a fast-path in `pd.read_csv` when parsing iso8601 datetime strings yielding as much as a 20x speedup. (GH5993)

### 36.14.4 Bug Fixes

- Fix `read_csv/read_table` multithreading issues (GH2608)
- HDFStore
  - correctly handle `nan` elements in string columns; serialize via the `nan_rep` keyword to append
  - raise correctly on non-implemented column types (unicode/date)
  - handle correctly `Term` passed types (e.g. `index<1000, when index is Int64`), (closes GH512)
  - handle `Timestamp` correctly in `data_columns` (closes GH2637)
  - contains correctly matches on non-natural names
  - correctly store `float32` dtypes in tables (if not other float types in the same table)
- Fix DataFrame.info bug with UTF8-encoded columns. (GH2576)
- Fix DatetimeIndex handling of FixedOffset tz (GH2604)
- More robust detection of being in IPython session for wide DataFrame console formatting (GH2585)
- Fix platform issues with `file:///` in unit test (GH2564)
- Fix bug and possible segfault when grouping by hierarchical level that contains NA values (GH2616)
- Ensure that MultiIndex tuples can be constructed with NAs (GH2616)
- Fix int64 overflow issue when unstacking MultiIndex with many levels (GH2616)
- Exclude non-numeric data from DataFrame.quantile by default (GH2625)
• Fix a Cython C int64 boxing issue causing read_csv to return incorrect results (GH2599)
• Fix groupby summing performance issue on boolean data (GH2692)
• Don’t bork Series containing datetime64 values with to_datetime (GH2699)
• Fix DataFrame.from_records corner case when passed columns, index column, but empty record list (GH2633)
• Fix C parser-tokenizer bug with trailing fields. (GH2668)
• Don’t exclude non-numeric data from GroupBy.max/min (GH2700)
• Don’t lose time zone when calling DatetimeIndex.drop (GH2621)
• Fix setitem on a Series with a boolean key and a non-scalar as value (GH2686)
• Box datetime64 values in Series.apply/map (GH2627, GH2689)
• Upconvert datetime + datetime64 values when concatenating frames (GH2624)
• Raise a more helpful error message in merge operations when one DataFrame has duplicate columns (GH2649)
• Fix partial date parsing issue occurring only when code is run at EOM (GH2618)
• Prevent MemoryError when using counting sort in sortlevel with high-cardinality MultiIndex objects (GH2684)
• Fix Period resampling bug when all values fall into a single bin (GH2070)
• Fix buggy interaction with usecols argument in read_csv when there is an implicit first index column (GH2654)
• Fix bug in index.summary() where string format methods were being called incorrectly. (GH3869)

36.15 pandas 0.10.0

Release date: 2012-12-17

36.15.1 New Features

• Brand new high-performance delimited file parsing engine written in C and Cython. 50% or better performance in many standard use cases with a fraction as much memory usage. (GH407, GH821)
• Many new file parser (read_csv, read_table) features:
  – Support for on-the-fly gzip or bz2 decompression (compression option)
  – Ability to get back numpy.recarray instead of DataFrame (as_recarray=True)
  – dtype option: explicit column dtypes
  – usecols option: specify list of columns to be read from a file. Good for reading very wide files with many irrelevant columns (GH1216 GH926, GH2465)
  – Enhanced unicode decoding support via encoding option
  – skipinitialspace dialect option
  – Can specify strings to be recognized as True (true_values) or False (false_values)
  – High-performance delim_whitespace option for whitespace-delimited files; a preferred alternative to the ‘s+’ regular expression delimiter
  – Option to skip “bad” lines (wrong number of fields) that would otherwise have caused an error in the past (error_bad_lines and warn_bad_lines options)
- Substantially improved performance in the parsing of integers with thousands markers and lines with comments
- Easy of European (and other) decimal formats (*decimal option*) (GH584, GH2466)
- Custom line terminators (e.g. lineterminator='~') (GH2457)
- Handling of no trailing commas in CSV files (GH2333)
- Ability to handle fractional seconds in date_converters (GH2209)
- read_csv allow scalar arg to na_values (GH1944)
- Explicit column dtype specification in read_* functions (GH1858)
- Easier CSV dialect specification (GH1743)
- Improve parser performance when handling special characters (GH1204)

- Google Analytics API integration with easy oauth2 workflow (GH2283)
- Add error handling to Series.str.encode/decode (GH2276)
- Add where and mask to Series (GH2337)
- Grouped histogram via by keyword in Series/DataFrame.hist (GH2186)
- Support optional min_periods keyword in corr and cov for both Series and DataFrame (GH2002)
- Add duplicated and drop_duplicates functions to Series (GH1923)
- Add docs for HDFStore table format
- 'density' property in SparseSeries (GH2384)
- Add ffill and bfill convenience functions for forward- and backfilling time series data (GH2284)
- New option configuration system and functions set_option, get_option, describe_option, and reset_option. Deprecate set_printoptions and reset_printoptions (GH2393). You can also access options as attributes via pandas.options.X
- Wide DataFrames can be viewed more easily in the console with new expand_frame_repr and line_width configuration options. This is on by default now (GH2436)
- Scikits.timeseries-like moving window functions via rolling_window (GH1270)

### 36.15.2 Experimental Features

- Add support for Panel4D, a named 4 Dimensional structure
- Add support for ndpanel factory functions, to create custom, domain-specific N-Dimensional containers

### 36.15.3 API Changes

- The default binning/labeling behavior for resample has been changed to closed=’left’, label=’left’ for daily and lower frequencies. This had been a large source of confusion for users. See “what’s new” page for more on this. (GH2410)
- Methods with inplace option now return None instead of the calling (modified) object (GH1893)
- The special case DataFrame - TimeSeries doing column-by-column broadcasting has been deprecated. Users should explicitly do e.g. df.sub(ts, axis=0) instead. This is a legacy hack and can lead to subtle bugs.
• inf/-inf are no longer considered as NA by isnull/notnull. To be clear, this is legacy cruft from early pandas. This behavior can be globally re-enabled using the new option `mode.use_inf_as_null` (GH2050, GH1919)

• `pandas.merge` will now default to `sort=False`. For many use cases sorting the join keys is not necessary, and doing it by default is wasteful

• Specify `header=0` explicitly to replace existing column names in file in read_* functions.

• Default column names for header-less parsed files (yielded by read_csv, etc.) are now the integers 0, 1, ... A new argument `prefix` has been added; to get the v0.9.x behavior specify `prefix='X'` (GH2034). This API change was made to make the default column names more consistent with the DataFrame constructor’s default column names when none are specified.

• DataFrame selection using a boolean frame now preserves input shape

• If function passed to Series.apply yields a Series, result will be a DataFrame (GH2316)

• Values like YES/NO/yes/no will not be considered as boolean by default any longer in the file parsers. This can be customized using the new `true_values` and `false_values` options (GH2360)

• `obj.fillna()` is no longer valid; make `method='pad'` no longer the default option, to be more explicit about what kind of filling to perform. Add `ffill/bfill` convenience functions per above (GH2284)

• `HDFStore.keys()` now returns an absolute path-name for each key

• `to_string()` now always returns a unicode string. (GH2224)

• File parsers will not handle NA sentinel values arising from passed converter functions

### 36.15.4 Improvements to existing features

• Add `nrows` option to DataFrame.from_records for iterators (GH1794)

• Unstack/reshape algorithm rewrite to avoid high memory use in cases where the number of observed key-tuples is much smaller than the total possible number that could occur (GH2278). Also improves performance in most cases.

• Support duplicate columns in DataFrame.from_records (GH2179)

• Add `normalize` option to Series/DataFrame.asfreq (GH2137)

• SparseSeries and SparseDataFrame construction from empty and scalar values now no longer create dense ndarrays unnecessarily (GH2322)

• `HDFStore` now supports hierarchical keys (GH2397)

• Support multiple query selection formats for HDFStore tables (GH1996)

• Support `del store['df']` syntax to delete HDFStores

• Add `multi-dtype` support for HDFStore tables

• `min_itemsize` parameter can be specified in HDFStore table creation

• Indexing support in HDFStore tables (GH698)

• Add `line_terminator` option to DataFrame.to_csv (GH2383)

• added implementation of `str(x)/unicode(x)/bytes(x)` to major pandas data structures, which should do the right thing on both py2.x and py3.x. (GH2224)

• Reduce groupby.apply overhead substantially by low-level manipulation of internal NumPy arrays in DataFrames (GH535)

• Implement `value_vars` in `melt` and add `melt` to pandas namespace (GH2412)
• Added boolean comparison operators to Panel
• Enable Series.str.strip/lstrip/rstrip methods to take an argument (GH2411)
• The DataFrame ctor now respects column ordering when given an OrderedDict (GH2455)
• Assigning DatetimeIndex to Series changes the class to TimeSeries (GH2139)
• Improve performance of .value_counts method on non-integer data (GH2480)
• get_level_values method for MultiIndex return Index instead of ndarray (GH2449)
• convert_to_r_dataframe conversion for datetime values (GH2351)
• Allow DataFrame.to_csv to represent inf and nan differently (GH2026)
• Add min_i argument to nancorr to specify minimum required observations (GH2002)
• Add inplace option to sortlevel / sort functions on DataFrame (GH1873)
• Enable DataFrame to accept scalar constructor values like Series (GH1856)
• DataFrame.from_records now takes optional size parameter (GH1794)
• include iris dataset (GH1709)
• No datetime64 DataFrame column conversion of datetime.datetime with tzinfo (GH1581)
• Micro-optimizations in DataFrame for tracking state of internal consolidation (GH217)
• Format parameter in DataFrame.to_csv (GH1525)
• Partial string slicing for DatetimeIndex for daily and higher frequencies (GH2306)
• Implement col_space parameter in to_html and to_string in DataFrame (GH1000)
• Override Series.tolist and box datetime64 types (GH2447)
• Optimize unstack memory usage by compressing indices (GH2278)
• Fix HTML repr in IPython qtconsole if opening window is small (GH2275)
• Escape more special characters in console output (GH2492)
• df.select now invokes bool on the result of crit(x) (GH2487)

36.15.5 Bug Fixes

• Fix major performance regression in DataFrame.iteritems (GH2273)
• Fixes bug when negative period passed to Series/DataFrame.diff (GH2266)
• Escape tabs in console output to avoid alignment issues (GH2038)
• Properly box datetime64 values when retrieving cross-section from mixed-dtype DataFrame (GH2272)
• Fix concatenation bug leading to GH2057, GH2257
• Fix regression in Index console formatting (GH2319)
• Box Period data when assigning PeriodIndex to frame column (GH2243, GH2281)
• Raise exception on calling reset_index on Series with inplace=True (GH2277)
• Enable setting multiple columns in DataFrame with hierarchical columns (GH2295)
• Respect dtype=object in DataFrame constructor (GH2291)
• Fix DatetimeIndex.join bug with tz-aware indexes and how='outer’ (GH2317)
• pop(...) and del works with DataFrame with duplicate columns (GH2349)
• Treat empty strings as NA in date parsing (rather than let dateutil do something weird) (GH2263)
• Prevent uint64 -> int64 overflows (GH2355)
• Enable joins between MultiIndex and regular Index (GH2024)
• Fix time zone metadata issue when unioning non-overlapping DatetimeIndex objects (GH2367)
• Raise/handle int64 overflows in parsers (GH2247)
• Deleting of consecutive rows in HDFstore tables‘ is much faster than before
• Appending on a HDFStore would fail if the table was not first created via put
• Use col_space argument as minimum column width in DataFrame.to_html (GH2328)
• Fix tz-aware DatetimeIndex.to_period (GH2232)
• Fix DataFrame row indexing case with MultiIndex (GH2314)
• Fix to_excel exporting issues with Timestamp objects in index (GH2294)
• Fixes assigning scalars and array to hierarchical column chunk (GH1803)
• Fixed a UnicodeDecodeError with series tidy_repr (GH2225)
• Fixed issues with duplicate keys in an index (GH2347, GH2380)
• Fixed issues re: Hash randomization, default on starting w/ py3.3 (GH2331)
• Fixed issue with missing attributes after loading a pickled dataframe (GH2431)
• Fix Timestamp formatting with tzoffset time zone in dateutil 2.1 (GH2443)
• Fix GroupBy.apply issue when using BinGrouper to do ts binning (GH2300)
• Fix issues resulting from datetime.datetime columns being converted to datetime64 when calling DataFrame.apply. (GH2374)
• Raise exception when calling to_panel on non uniquely-indexed frame (GH2441)
• Improved detection of console encoding on IPython zmq frontends (GH2458)
• Preserve time zone when .append-ing two time series (GH2260)
• Box timestamps when calling reset_index on time-zone-aware index rather than creating a tz-less datetime64 column (GH2262)
• Enable searching non-string columns in DataFrame.filter(like=...) (GH2467)
• Fixed issue with losing nanosecond precision upon conversion to DatetimeIndex(GH2252)
• Handle timezones in Datetime.normalize (GH2338)
• Fix test case where dtype specification with endianness causes failures on big endian machines (GH2318)
• Fix plotting bug where upsampling causes data to appear shifted in time (GH2448)
• Fix read_csv failure for UTF-16 with BOM and skiprows(GH2298)
• read_csv with names arg not implicitly setting header=None(GH2459)
• Unrecognized compression mode causes segfault in read_csv(GH2474)
• In read_csv, header=0 and passed names should discard first row(GH2269)
• Correctly route to stdout/stderr in read_table (GH2071)
• Fix exception when Timestamp.to_datetime is called on a Timestamp with tzoffset (GH2471)
• Fixed unintentional conversion of datetime64 to long in groupby.first() (GH2133)
• Union of empty DataFrames now return empty with concatenated index (GH2307)
• DataFrame.sort_index raises more helpful exception if sorting by column with duplicates (GH2488)
• DataFrame.to_string formatters can be list, too (GH2520)
• DataFrame.combine_first will always result in the union of the index and columns, even if one DataFrame is length-zero (GH2525)
• Fix several DataFrame.iloc/iorow with duplicate indices issues (GH2228, GH2259)
• Use Series names for column names when using concat with axis=1 (GH2489)
• Raise Exception if start, end, periods all passed to date_range (GH2538)
• Fix Panel resampling issue (GH2537)

36.16 pandas 0.9.1

Release date: 2012-11-14

36.16.1 New Features

• Can specify multiple sort orders in DataFrame/Series.sort/sort_index (GH928)
• New top and bottom options for handling NAs in rank (GH1508, GH2159)
• Add where and mask functions to DataFrame (GH2109, GH2151)
• Add at_time and between_time functions to DataFrame (GH2149)
• Add flexible pow and rpow methods to DataFrame (GH2190)

36.16.2 API Changes

• Upsampling period index “spans” intervals. Example: annual periods upsampled to monthly will span all months in each year
• Period.end_time will yield timestamp at last nanosecond in the interval (GH2124, GH2125, GH1764)
• File parsers no longer coerce to float or bool for columns that have custom converters specified (GH2184)

36.16.3 Improvements to existing features

• Time rule inference for week-of-month (e.g. WOM-2FRI) rules (GH2140)
• Improve performance of datetime + business day offset with large number of offset periods
• Improve HTML display of DataFrame objects with hierarchical columns
• Enable referencing of Excel columns by their column names (GH1936)
• DataFrame.dot can accept ndarrays (GH2042)
• Support negative periods in Panel.shift (GH2164)
• Make .drop(...) work with non-unique indexes (GH2101)
• Improve performance of Series/DataFrame.diff (re: GH2087)
• Support unary ~ (__invert__) in DataFrame (GH2110)
• Turn off pandas-style tick locators and formatters (GH2205)
• DataFrame[DataFrame] uses DataFrame.where to compute masked frame (GH2230)

### 36.16.4 Bug Fixes

• Fix some duplicate-column DataFrame constructor issues (GH2079)
• Fix bar plot color cycle issues (GH2082)
• Fix off-center grid for stacked bar plots (GH2157)
• Fix plotting bug if inferred frequency is offset with N > 1 (GH2126)
• Implement comparisons on date offsets with fixed delta (GH2078)
• Handle inf/-inf correctly in read_* parser functions (GH2041)
• Fix matplotlib unicode interaction bug
• Make WLS r-squared match statsmodels 0.5.0 fixed value
• Fix zero-trimming DataFrame formatting bug
• Correctly compute/box datetime64 min/max values from Series.min/max (GH2083)
• Fix unstacking edge case with unrepresented groups (GH2100)
• Fix Series.str failures when using pipe pattern ‘\|’ (GH2119)
• Fix pretty-printing of dict entries in Series, DataFrame (GH2144)
• Cast other datetime64 values to nanoseconds in DataFrame ctor (GH2095)
• Alias Timestamp.astimezone to tz_convert, so will yield Timestamp (GH2060)
• Fix timedelta64 formatting from Series (GH2165, GH2146)
• Handle None values gracefully in dict passed to Panel constructor (GH2075)
• Box datetime64 values as Timestamp objects in Series/DataFrame.iget (GH2148)
• Fix Timestamp indexing bug in DatetimeIndex.insert (GH2155)
• Use index name(s) (if any) in DataFrame.to_records (GH2161)
• Don’t lose index names in Panel.to_frame/DataFrame.to_panel (GH2163)
• Work around length-0 boolean indexing NumPy bug (GH2096)
• Fix partial integer indexing bug in DataFrame.xs (GH2107)
• Fix variety of cut/qcut string-bin formatting bugs (GH1978, GH1979)
• Raise Exception when xs view not possible of MultiIndex’d DataFrame (GH2117)
• Fix groupby(...) .first() issue with datetime64 (GH2133)
• Better floating point error robustness in some rolling_* functions (GH2114, GH2527)
• Fix ewma NA handling in the middle of Series (GH2128)
• Fix numerical precision issues in diff with integer data (GH2087)
• Fix bug in MultiIndex.__getitem__ with NA values (GH2008)
• Fix DataFrame.from_records dict-arg bug when passing columns (GH2179)
• Fix Series and DataFrame.diff for integer dtypes (GH2087, GH2174)
• Fix bug when taking intersection of DatetimeIndex with empty index (GH2129)
• Pass through timezone information when calling DataFrame.align (GH2127)
• Properly sort when joining on datetime64 values (GH2196)
• Fix indexing bug in which False/True were being coerced to 0/1 (GH2199)
• Many unicode formatting fixes (GH2201)
• Fix improper MultiIndex conversion issue when assigning e.g. DataFrame.index (GH2200)
• Fix conversion of mixed-type DataFrame to ndarray with dup columns (GH2236)
• Fix duplicate columns issue (GH2218, GH2219)
• Fix SparseSeries.__pow__ issue with NA input (GH2220)
• Fix icol with integer sequence failure (GH2228)
• Fixed resampling tz-aware time series issue (GH2245)
• SparseDataFrame.icol was not returning SparseSeries (GH2227, GH2229)
• Enable ExcelWriter to handle PeriodIndex (GH2240)
• Fix issue constructing DataFrame from empty Series with name (GH2234)
• Use console-width detection in interactive sessions only (GH1610)
• Fix parallel_coordinates legend bug with mpl 1.2.0 (GH2237)
• Make tz_localize work in corner case of empty Series (GH2248)

36.17 pandas 0.9.0

Release date: 10/7/2012

36.17.1 New Features

• Add str.encode and str.decode to Series (GH1706)
• Add to_latex method to DataFrame (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)
• Recognize and convert more boolean values in file parsing (Yes, No, TRUE, FALSE, variants thereof) (GH1691, GH1295)
• Add Panel.update method, analogous to DataFrame.update (GH1999, GH1988)
36.17.2 Improvements to existing features

- Proper handling of NA values in merge operations (GH1990)
- Add flags option for re.compile in some Series.str methods (GH1659)
- Parsing of UTC date strings in read_* functions (GH1693)
- Handle generator input to Series (GH1679)
- Add na_action='ignore' to Series.map to quietly propagate NAs (GH1661)
- Add args/kwds options to Series.apply (GH1829)
- Add inplace option to Series/DataFrame.reset_index (GH1797)
- Add level parameter to Series.reset_index
- Add quoting option for DataFrame.to_csv (GH1902)
- Indicate long column value truncation in DataFrame output with ... (GH1854)
- DataFrame.dot will not do data alignment, and also work with Series (GH1915)
- Add na option for missing data handling in some vectorized string methods (GH1689)
- If index_label=False in DataFrame.to_csv, do not print fields/commas in the text output. Results in easier importing into R (GH1583)
- Can pass tuple/list of axes to DataFrame.dropna to simplify repeated calls (dropping both columns and rows) (GH924)
- Improve DataFrame.to_html output for hierarchically-indexed rows (do not repeat levels) (GH1929)
- TimeSeries.between_time can now select times across midnight (GH1871)
- Enable skip footer parameter in ExcelFile.parse (GH1843)

36.17.3 API Changes

- Change default header names in read_* functions to more Pythonic X0, X1, etc. instead of X.1, X.2. (GH2000)
- Deprecated day_of_year API removed from PeriodIndex, use dayofyear (GH1723)
- Don’t modify NumPy suppress printoption 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 over-ride default NAs unless keep_default_na is set to false explicitly (GH1657)
- Enable skipfooter parameter in text parsers as an alias for skip_footer
36.17.4 Bug Fixes

- Perform arithmetic column-by-column in mixed-type DataFrame to avoid type upcasting issues. Caused downstream DataFrame.diff bug (GH1896)
- Fix matplotlib auto-color assignment when no custom spectrum passed. Also respect passed color keyword argument (GH1711)
- Fix resampling logical error with closed='left' (GH1726)
- Fix critical DatetimeIndex.union bugs (GH1730, GH1719, GH1745, GH1702, GH1753)
- Fix critical DatetimeIndex.intersection bug with unanchored offsets (GH1708)
- Fix MM-YYYY time series indexing case (GH1672)
- Fix case where Categorical group key was not being passed into index in GroupBy result (GH1701)
- Handle Ellipsis in Series.__getitem__/__setitem__ (GH1721)
- Fix some bugs with handling datetime64 scalars of other units in NumPy 1.6 and 1.7 (GH1717)
- Fix performance issue in MultiIndex.format (GH1746)
- Fixed GroupBy bugs interacting with DatetimeIndex asof / map methods (GH1677)
- Handle factors with NAs in pandas.rpy (GH1615)
- Fix statsmodels import in pandas.stats.var (GH1734)
- Fix DataFrame repr/info summary with non-unique columns (GH1700)
- Fix Series.iget_value for non-unique indexes (GH1694)
- Don’t lose tzinfo when passing DatetimeIndex as DataFrame column (GH1682)
- Fix tz conversion with time zones that haven’t had any DST transitions since first date in the array (GH1673)
- Fix field access with UTC->local conversion on unsorted arrays (GH1756)
- Fix isnan handling of array-like (list) inputs (GH1755)
- Fix regression in handling of Series in Series constructor (GH1671)
- Fix comparison of Int64Index with DatetimeIndex (GH1681)
- Fix min_periods handling in new rolling_max/min at array start (GH1695)
- Fix errors with how=’median’ and generic NumPy resampling in some cases caused by SeriesBinGrouper (GH1648, GH1688)
- When grouping by level, exclude unobserved levels (GH1697)
- Don’t lose tzinfo in DatetimeIndex when shifting by different offset (GH1683)
- Hack to support storing data with a zero-length axis in HDFStore (GH1707)
- Fix DatetimeIndex tz-aware range generation issue (GH1674)
- Fix method=’time’ interpolation with intraday data (GH1698)
- Don’t plot all-NA DataFrame columns as zeros (GH1696)
- Fix bug in scatter_plot with by option (GH1716)
- Fix performance problem in infer_freq with lots of non-unique stamps (GH1686)
- Fix handling of PeriodIndex as argument to create MultiIndex (GH1705)
- Fix re: unicode MultiIndex level names in Series/DataFrame repr (GH1736)
- Handle PeriodIndex in to_datetime instance method (GH1703)
- Support StaticTzInfo in DatetimeIndex infrastructure (GH1692)
- Allow MultiIndex setops with length-0 other type indexes (GH1727)
- Fix handling of DatetimeIndex in DataFrame.to_records (GH1720)
- Fix handling of general objects in isnull on which bool(...) fails (GH1749)
- Fix .ix indexing with MultiIndex ambiguity (GH1678)
- Fix .ix setting logic error with non-unique MultiIndex (GH1750)
- Basic indexing now works on MultiIndex with > 1000000 elements, regression from earlier version of pandas (GH1757)
- Handle non-float64 dtypes in fast DataFrame.corr/cov code paths (GH1761)
- Fix DatetimeIndex.isin to function properly (GH1763)
- Fix conversion of array of tz-aware datetime.datetime to DatetimeIndex with right time zone (GH1777)
- Fix DST issues with generating unsynchronized date ranges (GH1778)
- Fix issue calling sort on result of Series.unique (GH1807)
- Fix numerical issue leading to square root of negative number in rolling_std (GH1840)
- Let Series.str.split accept no arguments (like str.split) (GH1859)
- Allow user to have dateutil 2.1 installed on a Python 2 system (GH1851)
- Catch ImportError less aggressively in pandas/__init__.py (GH1845)
- Fix pip source installation bug when installing from GitHub (GH1805)
- Fix error when window size > array size in rolling_apply (GH1850)
- Fix pip source installation issues via SSH from GitHub
- Fix OLS.summary when column is a tuple (GH1837)
- Fix bug in __doc__ patching when -OO passed to interpreter (GH1792 GH1741 GH1774)
- Fix unicode console encoding issue in IPython notebook (GH1782, GH1768)
- Fix unicode formatting issue with Series.name (GH1782)
- Fix bug in DataFrame.duplicated with datetime64 columns (GH1833)
- Fix bug in Panel internals resulting in error when doing fillna after truncate not changing size of panel (GH1823)
- Prevent segfault due to MultiIndex not being supported in HDFStore table format (GH1848)
- Fix UnboundLocalError in Panel.__setitem__ and add better error (GH1826)
- Fix to_csv issues with list of string entries. Isnull works on list of strings now too (GH1791)
- Fix Timestamp comparisons with datetime values outside the nanosecond range (1677-2262)
- Revert to prior behavior of normalize_date with datetime.date objects (return datetime)
- Fix broken interaction between np.nansum and Series.any/all
- Fix bug with multiple column date parsers (GH1866)
- DatetimeIndex.union(Int64Index) was broken
- Make plot x vs y interface consistent with integer indexing (GH1842)
• set_index inplace modified data even if unique check fails (GH1831)
• Only use Q-OCT/NOV/DEC in quarterly frequency inference (GH1789)
• Upcast to dtype=object when unstacking boolean DataFrame (GH1820)
• Fix float64/float32 merging bug (GH1849)
• Fixes to Period.start_time for non-daily frequencies (GH1857)
• Fix failure when converter used on index_col in read_csv (GH1835)
• Implement PeriodIndex.append so that pandas.concat works correctly (GH1815)
• Avoid Cython out-of-bounds access causing segfault sometimes in pad_2d, backfill_2d
• Fix resampling error with intraday times and anchored target time (like AS-DEC) (GH1772)
• Fix .ix indexing bugs with mixed-integer indexes (GH1799)
• Respect passed color keyword argument in Series.plot (GH1890)
• Fix rolling_min/max when the window is larger than the size of the input array. Check other malformed inputs (GH1899, GH1897)
• Rolling variance / standard deviation with only a single observation in window (GH1884)
• Fix unicode sheet name failure in to_excel (GH1828)
• Override DatetimeIndex.min/max to return Timestamp objects (GH1895)
• Fix column name formatting issue in length-truncated column (GH1906)
• Fix broken handling of copying Index metadata to new instances created by view(...) calls inside the NumPy infrastructure
• Support datetime.date again in DateOffset.rollback/rollforward
• Raise Exception if set passed to Series constructor (GH1913)
• Add TypeError when appending HDFStore table w/ wrong index type (GH1881)
• Don’t raise exception on empty inputs in EW functions (e.g. ewma) (GH1900)
• Make asof work correctly with PeriodIndex (GH1883)
• Fix extlinks in doc build
• Fill boolean DataFrame with NaN when calling shift (GH1814)
• Fix setuptools bug causing pip not to Cythonize .pyx files sometimes
• Fix negative integer indexing regression in .ix from 0.7.x (GH1888)
• Fix error while retrieving timezone and utc offset from subclasses of datetime.tzinfo without .zone and ._utcoffset attributes (GH1922)
• Fix DataFrame formatting of small, non-zero FP numbers (GH1911)
• Various fixes by upcasting of date -> datetime (GH1395)
• Raise better exception when passing multiple functions with the same name, such as lambdas, to GroupBy.aggregate
• Fix DataFrame.apply with axis=1 on a non-unique index (GH1878)
• Proper handling of Index subclasses in pandas.unique (GH1759)
• Set index names in DataFrame.from_records (GH1744)
• Fix time series indexing error with duplicates, under and over hash table size cutoff (GH1821)
• Handle list keys in addition to tuples in DataFrame.xs when partial-indexing a hierarchically-indexed DataFrame (GH1796)
• Support multiple column selection in DataFrame.__getitem__ with duplicate columns (GH1943)
• Fix time zone localization bug causing improper fields (e.g. hours) in time zones that have not had a UTC transition in a long time (GH1946)
• Fix errors when parsing and working with fixed offset timezones (GH1922, GH1928)
• Fix text parser bug when handling UTC datetime objects generated by dateutil (GH1693)
• Fix plotting bug when ‘B’ is the inferred frequency but index actually contains weekends (GH1668, GH1669)
• Fix plot styling bugs (GH1666, GH1665, GH1658)
• Fix plotting bug with index/columns with unicode (GH1685)
• Fix DataFrame constructor bug when passed Series with datetime64 dtype in a dict (GH1680)
• Fixed regression in generating DatetimeIndex using timezone aware datetime.datetime (GH1676)
• Fix DataFrame bug when printing concatenated DataFrames with duplicated columns (GH1675)
• Fixed bug when plotting time series with multiple intraday frequencies (GH1732)
• Fix bug in DataFrame.duplicated to enable iterables other than list-types as input argument (GH1773)
• Fix resample bug when passed list of lambdas as how argument (GH1808)
• Repr fix for MultiIndex level with all NAs (GH1971)
• Fix PeriodIndex slicing bug when slice start/end are out-of-bounds (GH1977)
• Fix read_table bug when parsing unicode (GH1975)
• Fix BlockManager.iget bug when dealing with non-unique MultiIndex as columns (GH1970)
• Fix reset_index bug if both drop and level are specified (GH1957)
• Work around unsafe NumPy object->int casting with Cython function (GH1987)
• Fix datetime64 formatting bug in DataFrame.to_csv (GH1993)
• Default start date in pandas.io.data to 1/1/2000 as the docs say (GH2011)

36.18 pandas 0.8.1

Release date: July 22, 2012

36.18.1 New Features

• Add vectorized, NA-friendly string methods to Series (GH1621, GH620)
• Can pass dict of per-column line styles to DataFrame.plot (GH1559)
• Selective plotting to secondary y-axis on same subplot (GH1640)
• Add new bootstrap_plot plot function
• Add new parallel_coordinates plot function (GH1488)
• Add radviz plot function (GH1566)
36.18.2 Improvements to existing features

- Use moving min/max algorithms from Bottleneck in rolling_min/rolling_max for > 100x speedup. (GH1504, GH50)
- Add Cython group median method for >15x speedup (GH1358)
- Drastically improve to_datetime performance on ISO8601 datetime strings (with no time zones) (GH1571)
- Improve single-key groupby performance on large data sets, accelerate use of groupby with a Categorical variable
- Add ability to append hierarchical index levels with set_index and to drop single levels with reset_index (GH1569, GH1577)
- Always apply passed functions in resample, even if upsampling (GH1596)
- Avoid unnecessary copies in DataFrame constructor with explicit dtype (GH1572)
- Cleaner DatetimeIndex string representation with 1 or 2 elements (GH1611)
- Improve performance of array-of-Period to PeriodIndex, convert such arrays to PeriodIndex inside Index (GH1215)
- More informative string representation for weekly Period objects (GH1503)
- Accelerate 3-axis multi data selection from homogeneous Panel (GH979)
- Add adjust option to ewma to disable adjustment factor (GH1584)
- Add new matplotlib converters for high frequency time series plotting (GH1599)
- Handling of tz-aware datetime.datetime objects in to_datetime; raise Exception unless utc=True given (GH1581)

36.18.3 Bug Fixes

- Fix NA handling in DataFrame.to_panel (GH1582)
- Handle TypeError issues inside PyObject_RichCompareBool calls in khash (GH1318)
- Fix resampling bug to lower case daily frequency (GH1588)
- Fix kendall/spearman DataFrame.corr bug with no overlap (GH1595)
- Fix bug in DataFrame.set_index (GH1592)
- Don’t ignore axes in boxplot if by specified (GH1565)
- Fix Panel .ix indexing with integers bug (GH1603)
- Fix Partial indexing bugs (years, months, ...) with PeriodIndex (GH1601)
- Fix MultiIndex console formatting issue (GH1606)
- Unordered index with duplicates doesn’t yield scalar location for single entry (GH1586)
- Fix resampling of tz-aware time series with “anchored” freq (GH1591)
- Fix DataFrame.rank error on integer data (GH1589)
- Selection of multiple SparseDataFrame columns by list in __getitem__ (GH1585)
• Override Index.tolist for compatibility with MultiIndex (GH1576)
• Fix hierarchical summing bug with MultiIndex of length 1 (GH1568)
• Work around numpy.concatenate use/bug in Series.set_value (GH1561)
• Ensure Series/DataFrame are sorted before resampling (GH1580)
• Fix unhandled IndexError when indexing very large time series (GH1562)
• Fix DatetimeIndex intersection logic error with irregular indexes (GH1551)
• Fix unit test errors on Python 3 (GH1550)
• Fix .ix indexing bugs in duplicate DataFrame index (GH1201)
• Better handle errors with non-existing objects in HDFStore (GH1254)
• Don’t copy int64 array data in DatetimeIndex when copy=False (GH1624)
• Fix resampling of conforming periods quarterly to annual (GH1622)
• Don’t lose index name on resampling (GH1631)
• Support python-dateutil version 2.1 (GH1637)
• Fix broken scatter_matrix axis labeling, esp. with time series (GH1625)
• Fix cases where extra keywords weren’t being passed on to matplotlib from Series.plot (GH1636)
• Fix BusinessMonthBegin logic for dates before 1st bday of month (GH1645)
• Ensure string alias converted (valid in DatetimeIndex.get_loc) in DataFrame.xs / __getitem__ (GH1644)
• Fix use of string alias timestamps with tz-aware time series (GH1647)
• Fix Series.max/min and Series.describe on len-0 series (GH1650)
• Handle None values in dict passed to concat (GH1649)
• Fix Series.interpolate with method='values' and DatetimeIndex (GH1646)
• Fix IndexError in left merges on a DataFrame with 0-length (GH1628)
• Fix DataFrame column width display with UTF-8 encoded characters (GH1620)
• Handle case in pandas.io.data.get_data_yahoo where Yahoo! returns duplicate dates for most recent business
day
• Avoid downsampling when plotting mixed frequencies on the same subplot (GH1619)
• Fix read_csv bug when reading a single line (GH1553)
• Fix bug in C code causing monthly periods prior to December 1969 to be off (GH1570)

36.19 pandas 0.8.0

Release date: 6/29/2012

36.19.1 New Features

• New unified DatetimeIndex class for nanosecond-level timestamp data
• New Timestamp datetime.datetime subclass with easy time zone conversions, and support for nanoseconds
- New PeriodIndex class for timespans, calendar logic, and Period scalar object
- High performance resampling of timestamp and period data. New resample method of all pandas data structures
- New frequency names plus shortcut string aliases like ‘15h’, ‘1h30min’
- Time series string indexing shorthand (GH222)
- Add week, dayofyear array and other timestamp array-valued field accessor functions to DatetimeIndex
- Add GroupBy.prod optimized aggregation function and ‘prod’ fast time series conversion method (GH1018)
- Implement robust frequency inference function and inferred_freq attribute on DatetimeIndex (GH391)
- New tz_convert and tz_localize methods in Series / DataFrame
- Convert DatetimeIndexes to UTC if time zones are different in join/setops (GH864)
- Add limit argument for forward/backward filling to reindex, fillna, etc. (GH825 and others)
- Add support for indexes (dates or otherwise) with duplicates and common sense indexing/selection functionality
- Series/DataFrame.update methods, in-place variant of combine_first (GH961)
- Add match function to API (GH502)
- Add Cython-optimized first, last, min, max, prod functions to GroupBy (GH994, GH1043)
- Dates can be split across multiple columns (GH1227, GH1186)
- Add experimental support for converting pandas DataFrame to R data.frame via rpy2 (GH350, GH1212)
- Can pass list of (name, function) to GroupBy.aggregate to get aggregates in a particular order (GH610)
- Can pass dicts with lists of functions or dicts to GroupBy aggregate to do much more flexible multiple function aggregation (GH642, GH610)
- New ordered_merge functions for merging DataFrames with ordered data. Also supports group-wise merging for panel data (GH813)
- Add keys() method to DataFrame
- Add flexible replace method for replacing potentially values to Series and DataFrame (GH929, GH1241)
- Add ‘kde’ plot kind for Series/DataFrame.plot (GH1059)
- More flexible multiple function aggregation with GroupBy
- Add pct_change function to Series/DataFrame
- Add option to interpolate by Index values in Series.interpolate (GH1206)
- Add max_colwidth option for DataFrame, defaulting to 50
- Conversion of DataFrame through rpy2 to R data.frame (GH1282, )
- Add keys() method on DataFrame (GH1240)
- Add new match function to API (similar to R) (GH502)
- Add dayfirst option to parsers (GH854)
- Add method argument to align method for forward/backward fillin (GH216)
- Add Panel.transpose method for rearranging axes (GH695)
- Add new cut function (patterned after R) for discretizing data into equal range-length bins or arbitrary breaks of your choosing (GH415)
- Add new qcut for cutting with quantiles (GH1378)
• Add `value_counts` top level array method (GH1392)
• Added Andrews curves plot tupe (GH1325)
• Add lag plot (GH1440)
• Add autocorrelation_plot (GH1425)
• Add support for tox and Travis CI (GH1382)
• Add support for Categorical use in GroupBy (GH292)
• Add any and all methods to DataFrame (GH1416)
• Add `secondary_y` option to Series.plot
• Add experimental lreshape function for reshaping wide to long

36.19.2 Improvements to existing features

• Switch to klib/khash-based hash tables in Index classes for better performance in many cases and lower memory footprint
• Shipping some functions from scipy.stats to reduce dependency, e.g. Series.describe and DataFrame.describe (GH1092)
• Can create MultiIndex by passing list of lists or list of arrays to Series, DataFrame constructor, etc. (GH831)
• Can pass arrays in addition to column names to DataFrame.set_index (GH402)
• Improve the speed of “square” reindexing of homogeneous DataFrame objects by significant margin (GH836)
• Handle more dtypes when passed MaskedArrays in DataFrame constructor (GH406)
• Improved performance of join operations on integer keys (GH682)
• Can pass multiple columns to GroupBy object, e.g. grouped[[col1, col2]] to only aggregate a subset of the value columns (GH383)
• Add histogram / kde plot options for scatter_matrix diagonals (GH1237)
• Add inplace option to Series/DataFrame.rename and sort_index, DataFrame.drop_duplicates (GH805, GH207)
• More helpful error message when nothing passed to Series.reindex (GH1267)
• Can mix array and scalars as dict-value inputs to DataFrame ctor (GH1329)
• Use DataFrame columns’ name for legend title in plots
• Preserve frequency in DatetimeIndex when possible in boolean indexing operations
• Promote datetime.date values in data alignment operations (GH867)
• Add `order` method to Index classes (GH1028)
• Avoid hash table creation in large monotonic hash table indexes (GH1160)
• Store time zones in HDFStore (GH1232)
• Enable storage of sparse data structures in HDFStore (GH85)
• Enable Series.asof to work with arrays of timestamp inputs
• Cython implementation of DataFrame.corr speeds up by > 100x (GH1349, GH1354)
• Exclude “nuisance” columns automatically in GroupBy.transform (GH1364)
• Support functions-as-strings in GroupBy.transform (GH1362)
• Use index name as xlabel/ylabel in plots (GH1415)
• Add convert_dtype option to Series.apply to be able to leave data as dtype=object (GH1414)
• Can specify all index level names in concat (GH1419)
• Add dialect keyword to parsers for quoting conventions (GH1363)
• Enable DataFrame[bool_DataFrame] += value (GH1366)
• Add retries argument to get_data_yahoo to try to prevent Yahoo! API 404s (GH826)
• Improve performance of reshaping by using O(N) categorical sorting
• Series names will be used for index of DataFrame if no index passed (GH1494)
• Header argument in DataFrame.to_csv can accept a list of column names to use instead of the object’s columns (GH921)
• Add raise_conflict argument to DataFrame.update (GH1526)
• Support file-like objects in ExcelFile (GH1529)

36.19.3 API Changes

• Rename pandas._series to pandas.lib
• Rename Factor to Categorical and add improvements. Numerous Categorical bug fixes
• Frequency name overhaul, WEEKDAY/EOM and rules with @ deprecated. get_legacy_offset_name backwards compatibility function added
• Raise ValueError in DataFrame.__nonzero__, so “if df” no longer works (GH1073)
• Change BDay (business day) to not normalize dates by default (GH506)
• Remove deprecated DataMatrix name
• Default merge suffixes for overlap now have underscores instead of periods to facilitate tab completion, etc. (GH1239)
• Deprecation of offset, time_rule timeRule parameters throughout codebase
• Series.append and DataFrame.append no longer check for duplicate indexes by default, add verify_integrity parameter (GH1394)
• Refactor Factor class, old constructor moved to Factor.from_array
• Modified internals of MultiIndex to use less memory (no longer represented as array of tuples) internally, speed up construction time and many methods which construct intermediate hierarchical indexes (GH1467)

36.19.4 Bug Fixes

• Fix OverflowError from storing pre-1970 dates in HDFStore by switching to datetime64 (GH179)
• Fix logical error with February leap year end in YearEnd offset
• Series([False, nan]) was getting casted to float64 (GH1074)
• Fix binary operations between boolean Series and object Series with booleans and NAs (GH1074, GH1079)
• Couldn’t assign whole array to column in mixed-type DataFrame via .ix (GH1142)
• Fix label slicing issues with float index values (GH1167)
• Fix segmentation caused by empty groups passed to groupby (GH1048)
• Fix occasionally misbehaving reindexing in the presence of NaN labels (GH522)
• Fix imprecise logic causing weird Series results from .apply (GH1183)
• Unstack multiple levels in one shot, avoiding empty columns in some cases. Fix pivot table bug (GH1181)
• Fix formatting of MultiIndex on Series/DataFrame when index name coincides with label (GH1217)
• Handle Excel 2003 #N/A as NaN from xlrd (GH1213, GH1225)
• Fix Timestamp locale-related deserialization issues with HDFStore by moving to datetime64 representation (GH1081, GH809)
• Fix DataFrame.duplicated/drop_duplicates NA value handling (GH557)
• Actually raise exceptions in fast reducer (GH1243)
• Fix various timezone-handling bugs from 0.7.3 (GH969)
• GroupBy on level=0 discarded index name (GH1313)
• Better error message with unmergeable DataFrames (GH1307)
• Series.__repr__ alignment fix with unicode index values (GH1279)
• Better error message if nothing passed to reindex (GH1267)
• More robust NA handling in DataFrame.drop_duplicates (GH557)
• Resolve locale-based and pre-epoch HDF5 timestamp deserialization issues (GH973, GH1081, GH179)
• Implement Series.repeat (GH1229)
• Fix indexing with namedtuple and other tuple subclasses (GH1026)
• Fix float64 slicing bug (GH1167)
• Parsing integers with commas (GH796)
• Fix groupby improper data type when group consists of one value (GH1065)
• Fix negative variance possibility in nanvar resulting from floating point error (GH1090)
• Consistently set name on groupby pieces (GH184)
• Treat dict return values as Series in GroupBy.apply (GH823)
• Respect column selection for DataFrame in in GroupBy.transform (GH1365)
• Fix MultiIndex partial indexing bug (GH1352)
• Enable assignment of rows in mixed-type DataFrame via .ix (GH1432)
• Reset index mapping when grouping Series in Cython (GH1423)
• Fix outer/inner DataFrame.join with non-unique indexes (GH1421)
• Fix MultiIndex groupby bugs with empty lower levels (GH1401)
• Calling fillna with a Series will have same behavior as with dict (GH1486)
• SparseSeries reduction bug (GH1375)
• Fix unicode serialization issue in HDFStore (GH1361)
• Pass keywords to pyplot.boxplot in DataFrame.boxplot (GH1493)
• Bug fixes in MonthBegin (GH1483)
• Preserve MultiIndex names in drop (GH1513)
• Fix Panel DataFrame slice-assignment bug (GH1533)
• Don’t use locals() in read_* functions (GH1547)

36.20 pandas 0.7.3

Release date: April 12, 2012

36.20.1 New Features

• Support for non-unique indexes: indexing and selection, many-to-one and many-to-many joins (GH1306)
• Added fixed-width file reader, read_fwf (GH952)
• Add group_keys argument to groupby to not add group names to MultiIndex in result of apply (GH938)
• DataFrame can now accept non-integer label slicing (GH946). Previously only DataFrame.ix was able to do so.
• DataFrame.apply now retains name attributes on Series objects (GH983)
• Numeric DataFrame comparisons with non-numeric values now raises proper TypeError (GH943). Previously raise "PandasError: DataFrame constructor not properly called!"
• Add kurt methods to Series and DataFrame (GH964)
• Can pass dict of column -> list/set NA values for text parsers (GH754)
• Allows users specified NA values in text parsers (GH754)
• Parsers checks for openpyxl dependency and raises ImportError if not found (GH1007)
• New factory function to create HDFStore objects that can be used in a with statement so users do not have to explicitly call HDFStore.close (GH1005)
• pivot_table is now more flexible with same parameters as groupby (GH941)
• Added stacked bar plots (GH987)
• scatter_matrix method in pandas/tools/plotting.py (GH935)
• DataFrame.boxplot returns plot results for ex-post styling (GH985)
• Short version number accessible as pandas.version.short_version (GH930)
• Additional documentation in panel.to_frame (GH942)
• More informative Series.apply docstring regarding element-wise apply (GH977)
• Notes on rpy2 installation (GH1006)
• Add rotation and font size options to hist method (GH1012)
• Use exogenous / X variable index in result of OLS.y_predict. Add OLS.predict method (GH1027, GH1008)

36.20.2 API Changes

• Calling apply on grouped Series, e.g. describe(), will no longer yield DataFrame by default. Will have to call unstack() to get prior behavior
• NA handling in non-numeric comparisons has been tightened up (GH933, GH953)
• No longer assign dummy names key_0, key_1, etc. to groupby index (GH1291)

### 36.20.3 Bug Fixes

- Fix logic error when selecting part of a row in a DataFrame with a MultiIndex index (GH1013)
- Series comparison with Series of differing length causes crash (GH1016).
- Fix bug in indexing when selecting section of hierarchically-indexed row (GH1013)
- DataFrame.plot(logy=True) has no effect (GH1011).
- Broken arithmetic operations between SparsePanel-Panel (GH1015)
- Unicode repr issues in MultiIndex with non-ASCII characters (GH1010)
- DataFrame.lookup() returns inconsistent results if exact match not present (GH1001)
- DataFrame arithmetic operations not treating None as NA (GH992)
- DataFrameGroupBy.apply returns incorrect result (GH991)
- Series.reshape returns incorrect result for multiple dimensions (GH989)
- Series.std and Series.var ignores ddof parameter (GH934)
- DataFrame.append loses index names (GH980)
- DataFrame.plot(kind='bar') ignores color argument (GH958)
- Inconsistent Index comparison results (GH948)
- Improper int dtype DataFrame construction from data with NaN (GH846)
- Removes default ‘result’ name in groupby results (GH995)
- DataFrame.from_records no longer mutate input columns (GH975)
- Use Index name when grouping by it (GH1313)

### 36.21 pandas 0.7.2

**Release date:** March 16, 2012

#### 36.21.1 New Features

- Add additional tie-breaking methods in DataFrame.rank (GH874)
- Add ascending parameter to rank in Series, DataFrame (GH875)
- Add sort_columns parameter to allow unsorted plots (GH918)
- IPython tab completion on GroupBy objects

#### 36.21.2 API Changes

- Series.sum returns 0 instead of NA when called on an empty series. Analogously for a DataFrame whose rows or columns are length 0 (GH844)
36.21.3 Improvements to existing features

- Don’t use groups dict in Grouper.size (GH860)
- Use khash for Series.value_counts, add raw function to algorithms.py (GH861)
- Enable column access via attributes on GroupBy (GH882)
- Enable setting existing columns (only) via attributes on DataFrame, Panel (GH883)
- Intercept __builtin__.sum in groupby (GH885)
- Can pass dict to DataFrame.fillna to use different values per column (GH661)
- Can select multiple hierarchical groups by passing list of values in .ix (GH134)
- Add level keyword to drop for dropping values from a level (GH159)
- Add coerce_float option on DataFrame.from_records (GH893)
- Raise exception if passed date_parser fails in read_csv
- Add axis option to DataFrame.fillna (GH174)
- Fixes to Panel to make it easier to subclass (GH888)

36.21.4 Bug Fixes

- Fix overflow-related bugs in groupby (GH850, GH851)
- Fix unhelpful error message in parsers (GH856)
- Better err msg for failed boolean slicing of dataframe (GH859)
- Series.count cannot accept a string (level name) in the level argument (GH869)
- Group index platform int check (GH870)
- concat on axis=1 and ignore_index=True raises TypeError (GH871)
- Further unicode handling issues resolved (GH795)
- Fix failure in multiindex-based access in Panel (GH880)
- Fix DataFrame boolean slice assignment failure (GH881)
- Fix combineAdd NotImplemented for SparseDataFrame (GH887)
- Fix DataFrame.to_html encoding and columns (GH890, GH891, GH909)
- Fix na-filling handling in mixed-type DataFrame (GH910)
- Fix to DataFrame.set_value with non-existant row/col (GH911)
- Fix malformed block in groupby when excluding nuisance columns (GH916)
- Fix inconsistent NA handling in dtype=object arrays (GH925)
- Fix missing center-of-mass computation in ewmcov (GH862)
- Don’t raise exception when opening read-only HDF5 file (GH847)
- Fix possible out-of-bounds memory access in 0-length Series (GH917)
36.22 pandas 0.7.1

Release date: February 29, 2012

36.22.1 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

36.22.2 Improvements to existing features

- Improve performance and memory usage of fillna on DataFrame
- Can concatenate a list of Series along axis=1 to obtain a DataFrame (GH787)

36.22.3 Bug Fixes

- Fix memory leak when inserting large number of columns into a single DataFrame (GH790)
- Appending length-0 DataFrame with new columns would not result in those new columns being part of the resulting concatenated DataFrame (GH782)
- Fixed groupby corner case when passing dictionary grouper and as_index is False (GH819)
- Fixed bug whereby bool array sometimes had object dtype (GH820)
- Fix exception thrown on np.diff (GH816)
- Fix to_records where columns are non-strings (GH822)
- Fix Index.intersection where indices have incomparable types (GH811)
- Fix ExcelFile throwing an exception for two-line file (GH837)
- Add clearer error message in csv parser (GH835)
- Fix loss of fractional seconds in HDFStore (GH513)
- Fix DataFrame join where columns have datetimes (GH787)
- Work around numpy performance issue in take (GH817)
- Improve comparison operations for NA-friendliness (GH801)
- Fix indexing operation for floating point values (GH780, GH798)
- Fix groupby case resulting in malformed dataframe (GH814)
- Fix behavior of reindex of Series dropping name (GH812)
• Improve on redundant groupby computation (GH775)
• Catch possible NA assignment to int/bool series with exception (GH839)

36.23  pandas 0.7.0

Release date: 2/9/2012

36.23.1 New Features

• New 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 concat function for concatenating DataFrame or Panel objects along an axis. Can form union or intersection of the other axes. Improves performance of DataFrame.append (GH468, GH479, GH273)
• Handle differently-indexed output values in DataFrame.append (GH498)
• Can pass list of dicts (e.g., a list of shallow JSON objects) to DataFrame constructor (GH526)
• Add reorder_levels method to Series and DataFrame (GH534)
• Add dict-like get function to DataFrame and Panel (GH521)
• DataFrame.iterrows method for efficiently iterating through the rows of a DataFrame
• Added DataFrame.to_panel with code adapted from LongPanel.to_long
• reindex_axis method added to DataFrame
• Add level option to binary arithmetic functions on DataFrame and Series
• Add level option to the reindex and align methods on Series and DataFrame for broadcasting values across a level (GH542, GH552, others)
• Add attribute-based item access to Panel and add IPython completion (PR GH554)
• Add logy option to Series.plot for log-scaling on the Y axis
• Add index, header, and justify options to DataFrame.to_string. Add option to (GH570, GH571)
• Can pass multiple DataFrames to DataFrame.join to join on index (GH115)
• Can pass multiple Panels to Panel.join (GH115)
• Can pass multiple DataFrames to DataFrame.append to concatenate (stack) and multiple Series to Series.append too
• 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)
• Add verbose option to read_csv and read_table to show number of NA values inserted in non-numeric columns (GH614)
• Can pass a list of dicts or Series to DataFrame.append to concatenate multiple rows (GH464)
• Add level argument to DataFrame.xs for selecting data from other MultiIndex levels. Can take one or more levels with potentially a tuple of keys for flexible retrieval of data (GH371, GH629)
• New crosstab function for easily computing frequency tables (GH170)
• Can pass a list of functions to aggregate with groupby on a DataFrame, yielding an aggregated result with hierarchical columns (GH166)
• Add integer-indexing functions iget in Series and irow/iget in DataFrame (GH628)
• Add new Series.unique function, significantly faster than numpy.unique (GH658)
• Add new cummin and cummax instance methods to Series and DataFrame (GH647)
• Add new value_range function to return min/max of a dataframe (GH288)
• Add drop parameter to reset_index method of DataFrame and added method to Series as well (GH699)
• Add isin method to Index objects, works just like Series.isin (GH GH657)
• Implement array interface on Panel so that ufuncs work (re: GH740)
• Add sort option to DataFrame.join (GH731)
• Improved handling of NAs (propagation) in binary operations with dtype=object arrays (GH737)
• Add abs method to Pandas objects
• Added algorithms module to start collecting central algos

36.23.2 API Changes

• Label-indexing with integer indexes now raises KeyError if a label is not found instead of falling back on location-based indexing (GH700)
• Label-based slicing via ix or [] on Series will now only work if exact matches for the labels are found or if the index is monotonic (for range selections)
• Label-based slicing and sequences of labels can be passed to [] on a Series for both getting and setting (GH86)
• // operator (getitem and setitem) will raise KeyError with integer indexes when an index is not contained in the index. The prior behavior would fall back on position-based indexing if a key was not found in the index which would lead to subtle bugs. This is now consistent with the behavior of .ix on DataFrame and friends (GH328)
• Rename DataFrame.delevel to DataFrame.reset_index and add deprecation warning
• Series.sort (an in-place operation) called on a Series which is a view on a larger array (e.g. a column in a DataFrame) will generate an Exception to prevent accidentally modifying the data source (GH316)
• Refactor to remove deprecated LongPanel class (GH552)
• Deprecated Panel.to_long, renamed to to_frame
• Deprecated colSpace argument in DataFrame.to_string, renamed to col_space
• Rename precision to accuracy in engineering float formatter (GH GH395)
• The default delimiter for read_csv is comma rather than letting csv.Sniffer infer it
• Rename col_or_columns argument in DataFrame.drop_duplicates (GH GH734)
36.23.3 Improvements to existing features

- 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)
- Don’t print length by default in Series.to_string, add length option (GH 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)
- Some performance enhancements in constructing a Panel from a dict of DataFrame objects
- Made Index._get_duplicates a public method by removing the underscore
- Prettier printing of floats, and column spacing fix (GH395, GH571)
- Add bold_rows option to DataFrame.to_html (GH586)
- Improve the performance of DataFrame.sort_index by up to 5x or more when sorting by multiple columns
- Substantially improve performance of DataFrame and Series constructors when passed a nested dict or dict, respectively (GH540, GH621)
- Modified setup.py so that pip / setuptools will install dependencies (GH GH507, various pull requests)
- Unstack called on DataFrame with non-MultiIndex will return Series (GH GH477)
- Improve DataFrame.to_string and console formatting to be more consistent in the number of displayed digits (GH395)
- Use bottleneck if available for performing NaN-friendly statistical operations that it implemented (GH91)
- Monkey-patch context to traceback in DataFrame.apply to indicate which row/column the function application failed on (GH614)
- Improved ability of read_table and read_clipboard to parse console-formatted DataFrames (can read the row of index names, etc.)
- Can pass list of group labels (without having to convert to an ndarray yourself) to groupby in some cases (GH659)
- Use kind argument to Series.order for selecting different sort kinds (GH668)
• Add option to Series.to_csv to omit the index (GH684)
• Add delimiter as an alternative to sep in read_csv and other parsing functions
• Substantially improved performance of groupby on DataFrames with many columns by aggregating blocks of
columns all at once (GH745)
• Can pass a file handle or StringIO to Series/DataFrame.to_csv (GH765)
• Can pass sequence of integers to DataFrame.irow(icol) and Series.iget, (GH GH654)
• Prototypes for some vectorized string functions
• Add float64 hash table to solve the Series.unique problem with NAs (GH714)
• Memoize objects when reading from file to reduce memory footprint
• Can get and set a column of a DataFrame with hierarchical columns containing “empty” ("") lower levels without
passing the empty levels (PR GH768)

36.23.4 Bug Fixes

• Raise exception in out-of-bounds indexing of Series instead of seg-faulting, regression from earlier releases
(GH495)
• Fix error when joining DataFrames of different dtypes within the same typeclass (e.g. float32 and float64)
(GH486)
• Fix bug in Series.min/Series.max on objects like datetime.datetime (GH GH487)
• Preserve index names in Index.union (GH501)
• Fix bug in Index joining causing subclass information (like DateRange type) to be lost in some cases (GH500)
• Accept empty list as input to DataFrame constructor, regression from 0.6.0 (GH491)
• Can output DataFrame and Series with ndarray objects in a dtype=object array (GH490)
• Return empty string from Series.to_string when called on empty Series (GH GH488)
• Fix exception passing empty list to DataFrame.from_records
• Fix Index.format bug (excluding name field) with datetimes with time info
• Fix scalar value access in Series to always return NumPy scalars, regression from prior versions (GH510)
• Handle rows skipped at beginning of file in read_* functions (GH505)
• Handle improper dtype casting in set_value methods
• Unary ‘-’ / __neg__ operator on DataFrame was returning integer values
• Unbox 0-dim ndarrays from certain operators like all, any in Series
• Fix handling of missing columns (was combine_first-specific) in DataFrame.combine for general case (GH529)
• Fix type inference logic with boolean lists and arrays in DataFrame indexing
• Use centered sum of squares in R-square computation if entity_effects=True in panel regression
• Handle all NA case in Series.{corr, cov}, was raising exception (GH548)
• Aggregating by multiple levels with level argument to DataFrame, Series stat method, was broken (GH545)
• Fix Cython buf when converter passed to read_csv produced a numeric array (buffer dtype mismatch when
passed to Cython type inference function) (GH GH546)
• Fix exception when setting scalar value using .ix on a DataFrame with a MultiIndex (GH551)
• Fix outer join between two DateRanges with different offsets that returned an invalid DateRange
• Cleanup DataFrame.from_records failure where index argument is an integer
• Fix Data.from_records failure when passed a dictionary
• Fix NA handling in {Series, DataFrame}.rank with non-floating point dtypes
• Fix bug related to integer type-checking in .ix-based indexing
• Handle non-string index name passed to DataFrame.from_records
• DataFrame.insert caused the columns name(s) field to be discarded (GH527)
• Fix erroneous in monotonic many-to-one left joins
• Fix DataFrame.to_string to remove extra column white space (GH571)
• Format floats to default to same number of digits (GH395)
• Added decorator to copy docstring from one function to another (GH449)
• Fix error in monotonic many-to-one left joins
• Fix __eq__ comparison between DateOffsets with different relativedelta keywords passed
• Fix exception caused by parser converter returning strings (GH583)
• Fix MultiIndex formatting bug with integer names (GH601)
• Fix bug in handling of non-numeric aggregates in Series.groupby (GH612)
• Fix TypeError with tuple subclasses (e.g. namedtuple) in DataFrame.from_records (GH611)
• Catch misreported console size when running IPython within Emacs
• Fix minor bug in pivot table margins, loss of index names and length-1 ‘All’ tuple in row labels
• Add support for legacy WidePanel objects to be read from HDFStore
• Fix out-of-bounds segfault in pad_object and backfill_object methods when either source or target array are empty
• Could not create a new column in a DataFrame from a list of tuples
• Fix bugs preventing SparseDataFrame and SparseSeries working with groupby (GH666)
• Use sort kind in Series.sort / argsort (GH668)
• Fix DataFrame operations on non-scalar, non-pandas objects (GH672)
• Don’t convert DataFrame column to integer type when passing integer to __setitem__ (GH669)
• Fix downstream bug in pivot_table caused by integer level names in MultiIndex (GH678)
• Fix SparseSeries.combine_first when passed a dense Series (GH687)
• Fix performance regression in HDFStore loading when DataFrame or Panel stored in table format with datetimes
• Raise Exception in DateRange when offset with n=0 is passed (GH683)
• Fix get/set inconsistency with .ix property and integer location but non-integer index (GH707)
• Use right dropna function for SparseSeries. Return dense Series for NA fill value (GH730)
• Fix Index.format bug causing incorrectly string-formatted Series with datetime indexes (GH726, GH758)
• Fix errors caused by object dtype arrays passed to ols (GH759)
• Fix error where column names lost when passing list of labels to DataFrame.__getitem__. (GH662)
• Fix error whereby top-level week iterator overwrote week instance
• Fix circular reference causing memory leak in sparse array / series / frame, (GH663)
• Fix integer-slicing from integers-as-floats (GH670)
• Fix zero division errors in nanops from object dtype arrays in all NA case (GH676)
• Fix csv encoding when using unicode (GH705, GH717, GH738)
• Fix assumption that each object contains every unique block type in concat, (GH708)
• Fix sortedness check of multiindex in to_panel (GH719, 720)
• Fix that None was not treated as NA in PyObjectHashtable
• Fix hashing dtype because of endianness confusion (GH747, GH748)
• Fix SparseSeries.dropna to return dense Series in case of NA fill value (GH GH730)
• Use map_infer instead of np.vectorize. handle NA sentinels if converter yields numeric array, (GH753)
• Fixes and improvements to DataFrame.rank (GH742)
• Fix catching AttributeError instead of NameError for bottleneck
• Try to cast non-MultiIndex to better dtype when calling reset_index (GH726 GH440)
• Fix #1.QNAN0’ float bug on 2.6/win64
• Allow subclasses of dicts in DataFrame constructor, with tests
• Fix problem whereby set_index destroys column multiindex (GH764)
• Hack around bug in generating DateRange from naive DateOffset (GH770)
• Fix bug in DateRange.intersection causing incorrect results with some overlapping ranges (GH771)

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36.24 pandas 0.6.1

Release date: 12/13/2011

36.24.1 API Changes

- Rename `names` argument in DataFrame.from_records to `columns`. Add deprecation warning
- Boolean get/set operations on Series with boolean Series will reindex instead of requiring that the indexes be exactly equal (GH429)

36.24.2 New Features

- Can pass Series to DataFrame.append with ignore_index=True for appending a single row (GH430)
- Add Spearman and Kendall correlation options to Series.corr and DataFrame.corr (GH428)
- Add new `get_value` and `set_value` methods to Series, DataFrame, and Panel to very low-overhead access to scalar elements. df.get_value(row, column) is about 3x faster than df[column][row] by handling fewer cases (GH437, GH438). Add similar methods to sparse data structures for compatibility
- Add Qt table widget to sandbox (GH435)
- DataFrame.align can accept Series arguments, add axis keyword (GH461)
- Implement new SparseList and SparseArray data structures. SparseSeries now derives from SparseArray (GH463)
- `max_columns / max_rows` options in set_printoptions (GH453)
- Implement Series.rank and DataFrame.rank, 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 (GH GH114)
• Add Series.from_csv function (GH482)

36.24.3 Improvements to existing features

• Improve memory usage of DataFrame.describe (do not copy data unnecessarily) (GH425)
• Use same formatting function for outputting floating point Series to console as in DataFrame (GH420)
• DataFrame.delevel will try to infer better dtype for new columns (GH440)
• Exclude non-numeric types in DataFrame.{corr, cov}
• Override Index.astype to enable dtype casting (GH412)
• Use same float formatting function for Series.__repr__ (GH420)
• Use available console width to output DataFrame columns (GH453)
• Accept ndarrays when setting items in Panel (GH452)
• Infer console width when printing __repr__ of DataFrame to console (PR GH453)
• Optimize scalar value lookups in the general case by 25% or more in Series and DataFrame
• Can pass DataFrame/DataFrame and DataFrame/Series to rolling_corr/rolling_cov (GH462)
• 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 GH158)
• MultiIndex.get_level_values can take the level name
• More helpful error message when DataFrame.plot fails on one of the columns (GH478)
• Improve performance of DataFrame.{index, columns} attribute lookup

36.24.4 Bug Fixes

• Fix O(K^2) memory leak caused by inserting many columns without consolidating, had been present since 0.4.0 (GH467)
• DataFrame.count should return Series with zero instead of NA with length-0 axis (GH423)
• Fix Yahoo! Finance API usage in pandas.io.data (GH419, GH427)
• Fix upstream bug causing failure in Series.align with empty Series (GH434)
• Function passed to DataFrame.apply can return a list, as long as it’s the right length. Regression from 0.4 (GH432)
• Don’t “accidentally” upcast scalar values when indexing using .ix (GH431)
• Fix groupby exception raised with as_index=False and single column selected (GH421)
• Implement DateOffset.__ne__ causing downstream bug (GH456)
• Fix __doc__-related issue when converting py -> pyo with py2exe
• Bug fix in left join Cython code with duplicate monotonic labels
• Fix bug when unstacking multiple levels described in GH451
• Exclude NA values in dtype=object arrays, regression from 0.5.0 (GH469)
• Use Cython map_infer function in DataFrame.applymap to properly infer output type, handle tuple return values and other things that were breaking (GH465)
• Handle floating point index values in HDFStore (GH454)
• Fixed stale column reference bug (cached Series object) caused by type change / item deletion in DataFrame (GH473)
• Index.get_loc should always raise Exception when there are duplicates
• Handle differently-indexed Series input to DataFrame constructor (GH475)
• Omit nuisance columns in multi-groupby with Python function
• Buglet in handling of single grouping in general apply
• Handle type inference properly when passing list of lists or tuples to DataFrame constructor (GH484)
• Preserve Index / MultiIndex names in GroupBy.apply concatenation step (GH GH481)

36.24.5 Thanks

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36.25 pandas 0.6.0

Release date: 11/25/2011
### 36.25.1 API Changes

- Arithmetic methods like `sum` will attempt to sum `dtype=object` values by default instead of excluding them (GH382)

### 36.25.2 New Features

- Add `melt` function to `pandas.core.reshape`
- Add `level` parameter to group by level in Series and DataFrame descriptive statistics (GH313)
- Add `head` and `tail` methods to Series, analogous to to DataFrame (PR GH296)
- Add `Series.isin` function which checks if each value is contained in a passed sequence (GH289)
- Add `float_format` option to `Series.to_string`
- Add `skip_footer` (GH291) and `converters` (GH343) options to `read_csv` and `read_table`
- Add proper, tested weighted least squares to standard and panel OLS (GH GH303)
- Add `drop_duplicates` and `duplicated` functions for removing duplicate DataFrame rows and checking for duplicate rows, respectively (GH319)
- Implement logical (boolean) operators `&`, `|`, `^` on DataFrame (GH347)
- Add `Series.mad`, mean absolute deviation, matching DataFrame
- Add `QuarterEnd` DateOffset (GH321)
- Add matrix multiplication function `dot` to DataFrame (GH65)
- Add `orient` option to `Panel.from_dict` to ease creation of mixed-type Panels (GH359, GH301)
- Add `DataFrame.from_dict` with similar `orient` option
- Can now pass list of tuples or list of lists to `DataFrame.from_records` for fast conversion to DataFrame (GH357)
- Can pass multiple levels to `groupby`, e.g. `df.groupby(level=[0, 1])` (GH GH103)
- Can sort by multiple columns in `DataFrame.sort_index` (GH92, GH362)
- Add fast `get_value` and `put_value` methods to DataFrame and micro-performance tweaks (GH360)
- Add `bar` plot option to `DataFrame.plot` (GH348)
- Add `idxmin` and `idxmax` functions to Series and DataFrame for computing index labels achieving maximum and minimum values (GH286)
- Add `read_clipboard` function for parsing DataFrame from OS clipboard, should work across platforms (GH300)
- Add `nunique` function to Series for counting unique elements (GH297)
- DataFrame constructor will use Series name if no columns passed (GH373)
- Support regular expressions and longer delimiters in `read_table/read_csv`, but does not handle quoted strings yet (GH364)
- Add `DataFrame.to_html` for formatting DataFrame to HTML (GH387)
- MaskedArray can be passed to DataFrame constructor and masked values will be converted to NaN (GH396)
- Add `DataFrame.boxplot` function (GH368, others)
- Can pass extra args, kwds to `DataFrame.apply` (GH376)
36.25.3 Improvements to existing features

- Raise more helpful exception if date parsing fails in DateRange (GH298)
- Vastly improved performance of GroupBy on axes with a MultiIndex (GH299)
- Print level names in hierarchical index in Series repr (GH305)
- Return DataFrame when performing GroupBy on selected column and as_index=False (GH308)
- Can pass vector to on argument in DataFrame.join (GH312)
- Don’t show Series name if it’s None in the repr, also omit length for short Series (GH317)
- Show legend by default in DataFrame.plot, add legend boolean flag (GH324)
- Significantly improved performance of Series.order, which also makes np.unique called on a Series faster (GH327)
- Faster cythonized count by level in Series and DataFrame (GH341)
- Raise exception if dateutil 2.0 installed on Python 2.x runtime (GH346)
- Significant GroupBy performance enhancement with multiple keys with many “empty” combinations
- New Cython vectorized function map_infer speeds up Series.apply and Series.map significantly when passed elementwise Python function, motivated by GH355
- Cythonized cache_readonly, resulting in substantial micro-performance enhancements throughout the codebase (GH361)
- Special Cython matrix iterator for applying arbitrary reduction operations with 3-5x better performance than np.apply_along_axis (GH309)
- Add raw option to DataFrame.apply for getting better performance when the passed function only requires an ndarray (GH309)
- Improve performance of MultiIndex.from_tuples
- Can pass multiple levels to stack and unstack (GH370)
- Can pass multiple values columns to pivot_table (GH381)
- Can call DataFrame.delevel with standard Index with name set (GH393)
- Use Series name in GroupBy for result index (GH363)
- Refactor Series/DataFrame stat methods to use common set of NaN-friendly function
- Handle NumPy scalar integers at C level in Cython conversion routines

36.25.4 Bug Fixes

- Fix bug in DataFrame.to_csv when writing a DataFrame with an index name (GH290)
- DataFrame should clear its Series caches on consolidation, was causing “stale” Series to be returned in some corner cases (GH304)
- DataFrame constructor failed if a column had a list of tuples (GH293)
- Ensure that Series.apply always returns a Series and implement Series.round (GH314)
- Support boolean columns in Cythonized groupby functions (GH315)
- DataFrame.describe should not fail if there are no numeric columns, instead return categorical describe (GH323)
• Fixed bug which could cause columns to be printed in wrong order in DataFrame.to_string if specific list of columns passed (GH325)
• Fix legend plotting failure if DataFrame columns are integers (GH326)
• Shift start date back by one month for Yahoo! Finance API in pandas.io.data (GH329)
• Fix DataFrame.join failure on unconsolidated inputs (GH331)
• DataFrame.min/max will no longer fail on mixed-type DataFrame (GH337)
• Fix read_csv / read_table failure when passing list to index_col that is not in ascending order (GH349)
• Fix failure passing Int64Index to Index.union when both are monotonic
• Fix error when passing SparseSeries to (dense) DataFrame constructor
• Added missing bang at top of setup.py (GH352)
• Change is_monotonic on MultiIndex so it properly compares the tuples
• Fix MultiIndex outer join logic (GH351)
• Set index name attribute with single-key groupby (GH358)
• Bug fix in reflexive binary addition in Series and DataFrame for non-commutative operations (like string concatenation) (GH353)
• setupeg.py will invoke Cython (GH192)
• Fix block consolidation bug after inserting column into MultiIndex (GH366)
• Fix bug in join operations between Index and Int64Index (GH367)
• Handle min_periods=0 case in moving window functions (GH365)
• Fixed corner cases in DataFrame.apply/pivot with empty DataFrame (GH378)
• Fixed repr exception when Series name is a tuple
• Always return DateRange from asfreq (GH390)
• Pass level names to swaplavel (GH379)
• Don’t lose index names in MultiIndex.droplevel (GH394)
• Infer more proper return type in DataFrame.apply when no columns or rows depending on whether the passed function is a reduction (GH389)
• Always return NA/NaN from Series.min/max and DataFrame.min/max when all of a row/column/values are NA (GH384)
• Enable partial setting with .ix / advanced indexing (GH397)
• Handle mixed-type DataFrames correctly in unstack, do not lose type information (GH403)
• Fix integer name formatting bug in Index.format and in Series.__repr__
• Handle label types other than string passed to groupby (GH405)
• Fix bug in .ix-based indexing with partial retrieval when a label is not contained in a level
• Index name was not being pickled (GH408)
• Level name should be passed to result index in GroupBy.apply (GH416)
36.25.5 Thanks

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36.26 pandas 0.5.0

Release date: 10/24/2011

This release of pandas includes a number of API changes (see below) and cleanup of deprecated APIs from pre-0.4.0 releases. There are also bug fixes, new features, numerous significant performance enhancements, and includes a new ipython completer hook to enable tab completion of DataFrame columns accesses and attributes (a new feature).

In addition to the changes listed here from 0.4.3 to 0.5.0, the minor releases 4.1, 0.4.2, and 0.4.3 brought some significant new functionality and performance improvements that are worth taking a look at.

Thanks to all for bug reports, contributed patches and generally providing feedback on the library.

36.26.1 API Changes

- `read_table`, `read_csv`, and `ExcelFile.parse` default arguments for `index_col` is now None. To use one or more of the columns as the resulting DataFrame’s index, these must be explicitly specified now.
- Parsing functions like `read_csv` no longer parse dates by default (GH GH225)
- Removed `weights` option in panel regression which was not doing anything principled (GH155)
- Changed `buffer` argument name in `Series.to_string` to `buf`
• `Series.to_string` and `DataFrame.to_string` now return strings by default instead of printing to sys.stdout

• Deprecated `nanRep` argument in various `to_string` and `to_csv` functions in favor of `na_rep`. Will be removed in 0.6 (GH275)

• Renamed `delimiter` to `sep` in `DataFrame.from_csv` for consistency

• Changed order of `Series.clip` arguments to match those of `numpy.clip` and added (unimplemented) `out` argument so `numpy.clip` can be called on a Series (GH272)

• Series functions renamed (and thus deprecated) in 0.4 series have been removed:
  – `asOf`, use `asof`
  – `toDict`, use `to_dict`
  – `toString`, use `to_string`
  – `toCSV`, use `to_csv`
  – `merge`, use `map`
  – `applymap`, use `apply`
  – `combineFirst`, use `combine_first`
  – `_firstTimeWithValuse` use `first_valid_index`
  – `_lastTimeWithValuse` use `last_valid_index`

• DataFrame functions renamed / deprecated in 0.4 series have been removed:
  – `asMatrix` method, use `as_matrix` or `values` attribute
  – `combineFirst`, use `combine_first`
  – `getXS`, use `xs`
  – `merge`, use `join`
  – `fromRecords`, use `from_records`
  – `fromcsv`, use `from_csv`
  – `toRecords`, use `to_records`
  – `toDict`, use `to_dict`
  – `toString`, use `to_string`
  – `toCSV`, use `to_csv`
  – `_firstTimeWithValuse` use `first_valid_index`
  – `_lastTimeWithValuse` use `last_valid_index`
  – `DataMatrix` is no longer needed
  – `rows()` method, use `index` attribute
  – `cols()` method, use `columns` attribute
  – `dropEmptyRows()`, use `dropna(how='all')`
  – `dropIncompleteRows()`, use `dropna()`
  – `tapply(f)`, use `apply(f, axis=1)`
  – `tgroupby(keyfunc, aggfunc)`, use `groupby` with `axis=1`
36.26.2 Deprecations Removed

- `indexField` argument in `DataFrame.from_records`
- `missingAtEnd` argument in `Series.order`. Use `na_last` instead
- `Series.fromValue` classmethod, use regular `Series` constructor instead
- Functions `parseCSV`, `parseText`, and `parseExcel` methods in `pandas.io.parsers` have been removed
- `Index.asOfDate` function
- `Panel.getMinorXS` (use `minor_xs`) and `Panel.getMajorXS` (use `major_xs`)
- `Panel.toWide`, use `Panel.to_wide` instead

36.26.3 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
- Add `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
- Added column attribute access to DataFrame, e.g. `df.A` equivalent to `df['A']` if ‘A’ is a column in the DataFrame (GH213)
- Added IPython tab completion hook for `DataFrame` columns. (GH233, GH230)
- Implement `Series.describe` for `Series` containing objects (GH241)
- Add inner join option to `DataFrame.join` when joining on key(s) (GH248)
- Can select set of DataFrame columns by passing a list to `__getitem__` (GH GH253)
- Can use `&` and `|` to intersection / union Index objects, respectively (GH 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
- Implemented `Panel.take`
- Add `set_eng_float_format` function for setting alternate `DataFrame` floating point string formatting
- Add convenience `set_index` function for creating a `DataFrame` index from its existing columns

36.26.4 Improvements to existing features

- Major performance improvements in file parsing functions `read_csv` and `read_table`
- Added Cython function for converting tuples to ndarray very fast. Speeds up many MultiIndex-related operations
- File parsing functions like `read_csv` and `read_table` will explicitly check if a parsed index has duplicates and raise a more helpful exception rather than deferring the check until later
• Refactored merging / joining code into a tidy class and disabled unnecessary computations in the float/object case, thus getting about 10% better performance (GH211)
• Improved speed of DataFrame.xs on mixed-type DataFrame objects by about 5x, regression from 0.3.0 (GH215)
• With new DataFrame.align method, speeding up binary operations between differently-indexed DataFrame objects by 10-25%.
• Significantly sped up conversion of nested dict into DataFrame (GH212)
• Can pass hierarchical index level name to groupby instead of the level number if desired (GH223)
• Add support for different delimiters in DataFrame.to_csv (GH244)
• Add more helpful error message when importing pandas post-installation from the source directory (GH250)
• Significantly speed up DataFrame __repr__ and count on large mixed-type DataFrame objects
• Better handling of pyx file dependencies in Cython module build (GH271)

36.26.5 Bug Fixes

• read_csv / read_table fixes
  – Be less aggressive about converting float->int in cases of floating point representations of integers like 1.0, 2.0, etc.
  – “True”/”False” will not get correctly converted to boolean
  – Index name attribute will get set when specifying an index column
  – Passing column names should force header=None (GH257)
  – Don’t modify passed column names when index_col is not None (GH258)
  – Can sniff CSV separator in zip file (since seek is not supported, was failing before)
• Worked around matplotlib “bug” in which series[, np.newaxis] fails. Should be reported upstream to matplotlib (GH224)
• DataFrame.iteritems was not returning Series with the name attribute set. Also neither was DataFrame._series
• Can store datetime.date objects in HDFStore (GH231)
• Index and Series names are now stored in HDFStore
• Fixed problem in which data would get upcasted to object dtype in GroupBy.apply operations (GH237)
• Fixed outer join bug with empty DataFrame (GH238)
• Can create empty Panel (GH239)
• Fix join on single key when passing list with 1 entry (GH246)
• Don’t raise Exception on plotting DataFrame with an all-NA column (GH251, GH254)
• Bug min/max errors when called on integer DataFrames (GH241)
• DataFrame.iteritems and DataFrame._series not assigning name attribute
• Panel.__repr__ raised exception on length-0 major/minor axes
• DataFrame.join on key with empty DataFrame produced incorrect columns
• Implemented MultiIndex.diff (GH260)
• Int64Index.take and MultiIndex.take lost name field, fix downstream issue GH262
• Can pass list of tuples to Series (GH270)
• Can pass level name to DataFrame.stack
• Support set operations between MultiIndex and Index
• Fix many corner cases in MultiIndex set operations - Fix MultiIndex-handling bug with GroupBy.apply when returned groups are not indexed the same
• Fix corner case bugs in DataFrame.apply
• Setting DataFrame index did not cause Series cache to get cleared
• Various int32 -> int64 platform-specific issues
• Don’t be too aggressive converting to integer when parsing file with MultiIndex (GH285)
• Fix bug when slicing Series with negative indices before beginning

36.26.6 Thanks

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• Luca Beltrame
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36.27 pandas 0.4.3

Release date: 10/9/2011

is is largely a bugfix release from 0.4.2 but also includes a handful of new d enhanced features. Also, pandas can now be installed and used on Python 3 thanks Thomas Kluyver!.

36.27.1 New Features

• Python 3 support using 2to3 (GH200, Thomas Kluyver)
• Add name attribute to Series and added relevant logic and tests. Name now prints as part of Series.__repr__
• Add name attribute to standard Index so that stacking / unstacking does not discard names and so that indexed DataFrame objects can be reliably round-tripped to flat files, pickle, HDF5, etc.
• Add isnull and notnull as instance methods on Series (GH209, GH203)

36.27.2 Improvements to existing features

• Skip xldr-related unit tests if not installed
• Index.append and MultiIndex.append can accept a list of Index objects to concatenate together
• 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)
• Refactored Series.__repr__ to be a bit more clean and consistent
36.27.3 API Changes

- *Series.describe* and *DataFrame.describe* now bring the 25% and 75% quartiles instead of the 10% and 90% deciles. The other outputs have not changed
- *Series.toString* will print deprecation warning, has been de-camelCased to *to_string*

36.27.4 Bug Fixes

- Fix broken interaction between *Index* and *Int64Index* when calling intersection. Implement *Int64Index.intersection*
- *MultiIndex.sortlevel* discarded the level names (GH202)
- Fix bugs in groupby, join, and append due to improper concatenation of *MultiIndex* objects (GH201)
- Fix regression from 0.4.1, *isnull* and *notnull* ceased to work on other kinds of Python scalar objects like *datetime.datetime*
- Raise more helpful exception when attempting to write empty DataFrame or LongPanel to *HDFStore* (GH204)
- Use stdlib csv module to properly escape strings with commas in *DataFrame.to_csv* (GH206, Thomas Kluyver)
- Fix Python ndarray access in Cython code for sparse blocked index integrity check
- Fix bug writing Series to CSV in Python 3 (GH209)
- Miscellaneous Python 3 bugfixes

36.27.5 Thanks

- Thomas Kluyver
- rsamson

36.28 pandas 0.4.2

**Release date:** 10/3/2011

is is a performance optimization release with several bug fixes. The new *Int64Index* and new merging / joining Cython code and related Python frastructure are the main new additions

36.28.1 New Features

- Added fast *Int64Index* type with specialized join, union, intersection. Will result in significant performance enhancements for int64-based time series (e.g. using NumPy’s datetim64 one day) and also faster operations on DataFrame objects storing record array-like data.
- Refactored *Index* classes to have a *join* method and associated data alignment routines throughout the codebase to be able to leverage optimized joining / merging routines.
- Added *Series.align* method for aligning two series with choice of join method
- Wrote faster Cython data alignment / merging routines resulting in substantial speed increases
- Added *is_monotonic* property to *Index* classes with associated Cython code to evaluate the monotonicity of the *Index* values
• Add method `get_level_values` to `MultiIndex`
• Implemented shallow copy of `BlockManager` object in `DataFrame` internals

### 36.28.2 Improvements to existing features

• Improved performance of `isnull` and `notnull`, a regression from v0.3.0 (GH187)
• Wrote templating / code generation script to auto-generate Cython code for various functions which need to be available for the 4 major data types used in pandas (float64, bool, object, int64)
• 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`
• Improved performance of `DateRange.union` with overlapping ranges and non-cacheable offsets (like Minute). Implemented analogous fast `DateRange.intersection` for overlapping ranges.
• 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
• Added informative Exception when passing dict to DataFrame groupby aggregation with axis != 0

### 36.28.3 API Changes

### 36.28.4 Bug Fixes

• Fixed minor unhandled exception in Cython code implementing fast groupby aggregation operations
• Fixed bug in unstacking code manifesting with more than 3 hierarchical levels
• Throw exception when step specified in label-based slice (GH185)
• Fix `isnull` to correctly work with np.float32. Fix upstream bug described in GH182
• Finish implementation of `as_index=False` in groupby for DataFrame aggregation (GH181)
• Raise SkipTest for pre-epoch HDFStore failure. Real fix will be sorted out via datetime64 dtype

### 36.28.5 Thanks

• Uri Laserson
• Scott Sinclair

### 36.29 pandas 0.4.1

**Release date:** 9/25/2011

is is primarily a bug fix release but includes some new features and improvements
36.29.1 New Features

- Added new `DataFrame` methods `get_dtypes` and property `dtypes`.
- Setting of values using `.ix` indexing attribute in mixed-type DataFrame objects has been implemented (fixes GH135).
- `read_csv` can read multiple columns into a `MultiIndex`. DataFrame’s `to_csv` method will properly write out a `MultiIndex` which can be read back (GH151, thanks to Skipper Seabold).
- Wrote fast time series merging/joining methods in Cython. Will be integrated later into `DataFrame.join` and related functions.
- Added `ignore_index` option to `DataFrame.append` for combining unindexed records stored in a DataFrame.

36.29.2 Improvements to existing features

- Some speed enhancements with internal Index type-checking function.
- `DataFrame.rename` has a new `copy` parameter which can rename a DataFrame in place.
- Enable unstacking by level name (GH142).
- Enable sortlevel to work by level name (GH141).
- `read_csv` can automatically “sniff” other kinds of delimiters using `csv.Sniffer` (GH146).
- Improved speed of unit test suite by about 40%.
- Exception will not be raised calling `HDFStore.remove` on non-existent node with where clause.
- Optimized `_ensure_index` function resulting in performance savings in type-checking Index objects.

36.29.3 API Changes

36.29.4 Bug Fixes

- Fixed DataFrame constructor bug causing downstream problems (e.g. `.copy()` failing) when passing a Series as the values along with a column name and index.
- Fixed single-key groupby on DataFrame with `as_index=False` (GH160).
- `Series.shift` was failing on integer Series (GH154).
- `unstack` methods were producing incorrect output in the case of duplicate hierarchical labels. An exception will now be raised (GH147).
- Calling `count` with level argument caused reduceat failure or segfault in earlier NumPy (GH169).
- Fixed `DataFrame.corrwith` to automatically exclude non-numeric data (GH144).
- Unicode handling bug fixes in `DataFrame.to_string` (GH138).
- Excluding OLS degenerate unit test case that was causing platform specific failure (GH149).
- Skip blosc-dependent unit tests for PyTables < 2.2 (GH137).
- Calling `copy` on `DateRange` did not copy over attributes to the new object (GH168).
- Fix bug in `HDFStore` in which Panel data could be appended to a Table with different item order, thus resulting in an incorrect result read back.
36.29.5 Thanks

- Yaroslav Halchenko
- Jeff Reback
- Skipper Seabold
- Dan Lovell
- Nick Pentreath

36.30 pandas 0.4.0

Release date: 9/12/2011

36.30.1 New Features

- `pandas.core.sparse` module: “Sparse” (mostly-NA, or some other fill value) versions of `Series`, `DataFrame`, and `Panel`. For low-density data, this will result in significant performance boosts, and smaller memory footprint. Added `to_sparse` methods to `Series`, `DataFrame`, and `Panel`. See online documentation for more on these.

- Fancy indexing operator on `Series` / `DataFrame`, e.g. via `.ix` operator. Both getting and setting of values is supported; however, setting values will only currently work on homogeneously-typed `DataFrame` objects. Things like:
  - `series.ix[[d1, d2, d3]]`
  - `frame.ix[5:10, ['C', 'B', 'A']], frame.ix[5:10, 'A':'C']`
  - `frame.ix[date1:date2]`

- Significantly enhanced `groupby` functionality
  - Can `groupby` multiple keys, e.g. `df.groupby(['key1', 'key2'])`. Iteration with multiple groupings products a flattened tuple
  - “Nuisance” columns (non-aggregatable) will automatically be excluded from `DataFrame` aggregation operations
  - Added automatic “dispatching to `Series` / `DataFrame` methods to more easily invoke methods on groups. e.g. `s.groupby(crit).std()` will work even though `std` is not implemented on the `GroupBy` class

- Hierarchical / multi-level indexing
  - New the `MultiIndex` class. Integrated `MultiIndex` into `Series` and `DataFrame` fancy indexing, slicing, `__getitem__` and `__setitem`, reindexing, etc. Added `level` keyword argument to `groupby` to enable grouping by a level of a `MultiIndex`

- New data reshaping functions: `stack` and `unstack` on `DataFrame` and `Series`
  - Integrate with `MultiIndex` to enable sophisticated reshaping of data

- `Index` objects (labels for axes) are now capable of holding tuples

- `Series.describe`, `DataFrame.describe`: produces an R-like table of summary statistics about each data column

- `DataFrame.quantile`, `Series.quantile` for computing sample quantiles of data across requested axis

- Added general `DataFrame.dropna` method to replace `dropIncompleteRows` and `dropEmptyRows`, deprecated those.
• **Series** arithmetic methods with optional `fill_value` for missing data, e.g. `a.add(b, fill_value=0)`. If a location is missing for both it will still be missing in the result though.
• `fill_value` option has been added to `DataFrame.{add, mul, sub, div}` methods similar to `Series`
• Boolean indexing with `DataFrame` objects: `data[data > 0.1] = 0.1` or `data[data> other] = 1`.
• `pytz` / tzinfo support in `DateRange`
  – `tz_localize`, `tz_normalize`, and `tz_validate` methods added
• Added `ExcelFile` class to `pandas.io.parsers` for parsing multiple sheets out of a single Excel 2003 document
• `GroupBy` aggregations can now optionally broadcast, e.g. produce an object of the same size with the aggregated value propagated
• Added `select` function in all data structures: reindex axis based on arbitrary criterion (function returning boolean value), e.g. `frame.select(lambda x: 'foo' in x, axis=1)`
• `DataFrame.consolidate` method, API function relating to redesigned internals
• `DataFrame.insert` method for inserting column at a specified location rather than the default `__setitem__` behavior (which puts it at the end)
• `HDFStore` class in `pandas.io.pytables` has been largely rewritten using patches from Jeff Reback from others. It now supports mixed-type `DataFrame` and `Series` data and can store `Panel` objects. It also has the option to query `DataFrame` and `Panel` data. Loading data from legacy `HDFStore` files is supported explicitly in the code
• Added `set_printoptions` method to modify appearance of `DataFrame` tabular output
• `rolling_quantile` functions; a moving version of `Series.quantile / DataFrame.quantile`
• Generic `rolling_apply` moving window function
• New `drop` method added to `Series, DataFrame, etc.` which can drop a set of labels from an axis, producing a new object
• `reindex` methods now sport a `copy` option so that data is not forced to be copied then the resulting object is indexed the same
• Added `sort_index` methods to `Series` and `Panel`. Renamed `DataFrame.sort` to `sort_index`. Leaving `DataFrame.sort` for now.
• Added `skipna` option to statistical instance methods on all the data structures
• `pandas.io.data` module providing a consistent interface for reading time series data from several different sources

### 36.30.2 Improvements to existing features

• The 2-dimensional `DataFrame` and `DataMatrix` classes have been extensively redesigned internally into a single class `DataFrame`, preserving where possible their optimal performance characteristics. This should reduce confusion from users about which class to use.
  – Note that under the hood there is a new essentially “lazy evaluation” scheme within respect to adding columns to `DataFrame`. During some operations, like-typed blocks will be “consolidated” but not before.
• `DataFrame` accessing columns repeatedly is now significantly faster than `DataMatrix` used to be in 0.3.0 due to an internal Series caching mechanism (which are all views on the underlying data)
• Column ordering for mixed type data is now completely consistent in `DataFrame`. In prior releases, there was inconsistent column ordering in `DataMatrix`
• Improved console / string formatting of `DataMatrix` with negative numbers
• Improved tabular data parsing functions, `read_table` and `read_csv`:
Added `skiprows` and `na_values` arguments to `pandas.io.parsers` functions for more flexible IO

- `parseCSV` and `read_csv` functions and others in `pandas.io.parsers` now can take a list of custom NA values, and also a list of rows to skip

- Can slice `DataFrame` and get a view of the data (when homogeneously typed), e.g. `frame.xs(idx, copy=False)` or `frame.ix[idx]`

- Many speed optimizations throughout `Series` and `DataFrame`

- Eager evaluation of groups when calling `groupby` functions, so if there is an exception with the grouping function it will raised immediately versus sometime later on when the groups are needed

- `datetools.WeekOfMonth` offset can be parameterized with `n` different than 1 or -1.

- Statistical methods on `DataFrame` like `mean`, `std`, `var`, `skew` will now ignore non-numerical data. Before a not very useful error message was generated. A flag `numeric_only` has been added to `DataFrame.sum` and `DataFrame.count` to enable this behavior in those methods if so desired (disabled by default)

- `DataFrame.pivot` generalized to enable pivoting multiple columns into a `DataFrame` with hierarchical columns

- `DataFrame` constructor can accept structured / record arrays

- `Panel` constructor can accept a dict of `DataFrame`-like objects. Do not need to use `from_dict` anymore (`from_dict` is there to stay, though).

### 36.30.3 API Changes

- The `DataMatrix` variable now refers to `DataFrame`, will be removed within two releases

- `WidePanel` is now known as `Panel`. The `WidePanel` variable in the pandas namespace now refers to the renamed `Panel` class

- `LongPanel` and `Panel` / `WidePanel` now no longer have a common subclass. `LongPanel` is now a subclass of `DataFrame` having a number of additional methods and a hierarchical index instead of the old `LongPanelIndex` object, which has been removed. Legacy `LongPanel` pickles may not load properly

- Cython is now required to build `pandas` from a development branch. This was done to avoid continuing to check in cythonized C files into source control. Builds from released source distributions will not require Cython

- Cython code has been moved up to a top level `pandas/src` directory. Cython extension modules have been renamed and promoted from the `lib` subpackage to the top level, i.e.

  - `pandas.lib.tseries -> pandas._tseries`
  - `pandas.lib.sparse -> pandas._sparse`

- `DataFrame` pickling format has changed. Backwards compatibility for legacy pickles is provided, but it’s recommended to consider PyTables-based `HDFStore` for storing data with a longer expected shelf life

- A `copy` argument has been added to the `DataFrame` constructor to avoid unnecessary copying of data. Data is no longer copied by default when passed into the constructor

- Handling of boolean dtype in `DataFrame` has been improved to support storage of boolean data with NA / NaN values. Before it was being converted to float64 so this should not (in theory) cause API breakage

- To optimize performance, Index objects now only check that their labels are unique when uniqueness matters (i.e. when someone goes to perform a lookup). This is a potentially dangerous tradeoff, but will lead to much better performance in many places (like `groupby`).

- Boolean indexing using `Series` must now have the same indices (labels)

- Backwards compatibility support for `begin/end/nPeriods` keyword arguments in `DateRange` class has been removed
• More intuitive / shorter filling aliases `ffill` (for pad) and `bfill` (for backfill) have been added to the functions that use them: `reindex`, `asfreq`, `fillna`.

• `pandas.core.mixins` code moved to `pandas.core.generic`

• `buffer` keyword arguments (e.g. `DataFrame.toString`) renamed to `buf` to avoid using Python built-in name

• `DataFrame.rows()` removed (use `DataFrame.index`)

• Added deprecation warning to `DataFrame.cols()`, to be removed in next release

• `DataFrame` deprecations and de-camelCasing: `merge`, `asMatrix`, `toDataMatrix`, `_firstTimeWithValue`, `_lastTimeWithValue`, `toRecords`, `fromRecords`, `tgroupby`, `toString`

• `pandas.io.parsers` method deprecations
  – `parseCSV` is now `read_csv` and keyword arguments have been de-camelCased
  – `parseText` is now `read_table`
  – `parseExcel` is replaced by the `ExcelFile` class and its `parse` method

• `fillMethod` arguments (deprecated in prior release) removed, should be replaced with `method`

• `Series.fill`, `DataFrame.fill`, and `Panel.fill` removed, use `fillna` instead

• `groupby` functions now exclude NA / NaN values from the list of groups. This matches R behavior with NAs in factors e.g. with the `tapply` function

• Removed `parseText`, `parseCSV` and `parseExcel` from pandas namespace

• `Series.combineFunc` renamed to `Series.combine` and made a bit more general with a `fill_value` keyword argument defaulting to NaN

• Removed `pandas.core.pytools` module. Code has been moved to `pandas.core.common`

• Tacked on `groupName` attribute for groups in `GroupBy` renamed to `name`

• Panel/LongPanel `dims` attribute renamed to `shape` to be more conformant

• Slicing a `Series` returns a view now

• More Series deprecations / renaming: `toCSV` to `to_csv`, `asOf` to `asof`, `merge` to `map`, `applymap` to `apply`, `toDict` to `to_dict`, `combineFirst` to `combine_first`. Will print `FutureWarning`.

• `DataFrame.to_csv` does not write an “index” column label by default anymore since the output file can be read back without it. However, there is a new `index_label` argument. So you can do `index_label='index'` to emulate the old behavior

• `datetools.Week` argument renamed from `dayOfWeek` to `weekday`

• `timeRule` argument in `shift` has been deprecated in favor of using the `offset` argument for everything. So you can still pass a time rule string to `offset`

• Added optional `encoding` argument to `read_csv`, `read_table`, `to_csv`, `from_csv` to handle unicode in python 2.x

### 36.30.4 Bug Fixes

• Column ordering in `pandas.io.parsers.parseCSV` will match CSV in the presence of mixed-type data

• Fixed handling of Excel 2003 dates in `pandas.io.parsers`

• `DateRange` caching was happening with high resolution `DateOffset` objects, e.g. `DateOffset(seconds=1)`. This has been fixed

• Fixed `__truediv__` issue in `DataFrame`
• Fixed DataFrame.toCSV bug preventing IO round trips in some cases
• Fixed bug in Series.plot causing matplotlib to barf in exceptional cases
• Disabled Index objects from being hashable, like ndarrays
• Added __ne__ implementation to Index so that operations like ts[ts != idx] will work
• Added __ne__ implementation to DataFrame
• Bug / unintuitive result when calling fillna on unordered labels
• Bug calling sum on boolean DataFrame
• Bug fix when creating a DataFrame from a dict with scalar values
• Series.{sum, mean, std, ...} now return NA/NaN when the whole Series is NA
• NumPy 1.4 through 1.6 compatibility fixes
• Fixed bug in bias correction in rolling_cov, was affecting rolling_corr too
• R-square value was incorrect in the presence of fixed and time effects in the PanelOLS classes
• HDFStore can handle duplicates in table format, will take

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36.31 pandas 0.3.0

Release date: February 20, 2011

36.31.1 New features

- `corrwith` function to compute column- or row-wise correlations between two DataFrame objects
- Can boolean-index DataFrame objects, e.g. `df[df > 2] = 2`, `px[px > last_px] = 0`
- Added comparison magic methods (`__lt__`, `__gt__`, etc.)
- Flexible explicit arithmetic methods (add, mul, sub, div, etc.)
- Added `reindex_like` method
- Added `reindex_like` method to WidePanel
- Convenience functions for accessing SQL-like databases in `pandas.io.sql` module
- Added (still experimental) HDFStore class for storing pandas data structures using HDF5 / PyTables in `pandas.io.pytables` module
- Added WeekOfMonth date offset
- `pandas.rpy` (experimental) module created, provide some interfacing / conversion between rpy2 and pandas

36.31.2 Improvements to existing features

- Unit test coverage: 100% line coverage of core data structures
- Speed enhancement to rolling `{median, max, min}`
- Column ordering between DataFrame and DataMatrix is now consistent: before DataFrame would not respect column order
- Improved `{Series, DataFrame}.plot` methods to be more flexible (can pass matplotlib Axis arguments, plot DataFrame columns in multiple subplots, etc.)

36.31.3 API Changes

- Exponentially-weighted moment functions in `pandas.stats.moments` have a more consistent API and accept a `min_periods` argument like their regular moving counterparts.
- `fillMethod` argument in Series, DataFrame changed to `method`, `FutureWarning` added.
- `fill` method in Series, DataFrame/DataMatrix, WidePanel renamed to `fillna`, `FutureWarning` added to `fill`
- Renamed `DataFrame.getXS` to `xs`, `FutureWarning` added
- Removed `cap` and `floor` functions from DataFrame, renamed to `clip_upper` and `clip_lower` for consistency with NumPy
36.31.4 Bug Fixes

- Fixed bug in IndexableSkiplist Cython code that was breaking rolling_max function
- Numerous numpy.int64-related indexing fixes
- Several NumPy 1.4.0 NaN-handling fixes
- Bug fixes to pandas.io.parsers.parseCSV
- Fixed DateRange caching issue with unusual date offsets
- Fixed bug in DateRange.union
- Fixed corner case in IndexableSkiplist implementation
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pandas, 1